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Should Acutec Invest in Additive Manufacturing for Production Purposes in the Near Future?



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by

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Submitted to The Department of Economics

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I hereby recognize and pledge to fulfill my responsibilities as defined in the Honor Code and to maintain the integrity of both myself and the College as a whole.

Signature:

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Acknowledgements ii
Table of Contents iii
List of Tables iv
Abstract v
Introduction 1
Chapter 1: Literature Review 4
I. Basics of Additive Manufacturing and Key Terms 4
II. Advantages and Obstacles of Adoption 4
III. Estimating Costs of Additive Manufacturing 8
IV. Contribution to the Literature 12
Chapter 2: Theoretical Analysis 14
I. Firm Behavior Theory 14
II. Supply Chain Management & Vertical Integration Theory 15
III. First-mover Advantage Theory 16
Chapter 3: An Empirical Analysis 20
I. The Data Set 20
a. Sources of Data 20
b. Compilation of Data 20
II. The Regression Model 21
a. The Model (On-Time Delivery) 21
b. The Model (Scrap) 21
c. Explanation: Dependent and Independent Variables 22
d. Control Variables 24
e. Summary Statistics 25
III. Regression Results (On-Time Delivery) 26
a. Interpreting Coefficients 27
IV. Regression Results (Scrap) 29
a. Interpreting Coefficients 29
V. Potential for Biases and Error 30
VI. Cost Analysis 32
VII. Conclusion 33
Chapter 4: Application of Findings and Closing Remarks 34
I. Summary of Study 34
II. Recommendations to Acutec 36
III. Possible Extensions of Research 36
IV. Conclusion 37
Appendix 38
A. Summary Statistics 38
B. Variable Correlation Matrix 39
C. Variable Inflation Factors 40
D. List of Competitors & Web Pages 41
References 42
About the Author 45

List of Tables

1.1 Three Axis Model of Manufactured Parts…….. 5

1.2 Additive Cost Model (Ruffo et al.)…… 9

1.3 Additive Cost Model (Hopkins & Dickens)…… 10

3.1 Regression Results (On-Time Delivery)…….…. 26

3.2 Regression Results (Scrap)…….…. 29

Abstract

The aim of this study is to determine if Acutec should adopt additive manufacturing for production purposes in the near future. In order to answer this question, a review of the relevant literature and relevant theories are included. After this, an empirical analysis was performed on data collected for a part that was identified as a potential candidate for early adoption. The empirical analysis includes regressions that analyze the contributing factors of scrap and on-time delivery for the traditional manufacturing method that is currently in use, as well as a brief cost analysis to determine if, economically speaking, such a transition is viable. My overall hypothesis that this study aims to prove is; if Acutec adopts additive manufacturing, then the potential gains in at least one of the three important customer metrics (scrap, on-time delivery, and cost), through integration of the supply chain or minimizing cost, will offset the costs of adoption for a single part, or help to maintain a new competency that will provide a first-mover advantage. I found that the identified part would not be suitable for early adoption. However, this does not disqualify additive manufacturing in general. In fact, it is argued that the adoption of additive manufacturing will be very important for Acutec's continued success.

Introduction

In 2011 value added from manufacturing worldwide reached $11.3 trillion. The US was the second largest manufacturer in this period, contributing 17% of all goods produced (Thomas & Gilbert, 2014). However, additive manufacturing contributed just $246 million of the approximate $2 trillion of US manufacturing, or about 0.01% (Thomas & Gilbert, 2014). Opinions on additive manufacturing among business owners have been wide ranging. On the one hand, CEO of General Electric Jeff Immelt, views the technology as a game changer and has initiated a plan to invest $3.5 billion in order to produce over 100,000 parts for the LEAP and GE9X engines (Conner et al. 2014). On the other is CEO Terry Gou of Foxconn who has stated publicly, "3D printing is a gimmick and has no commercial value" (Conner et al. 2014). Yet there are tremendous advantages to manufacturing and designing parts additively. Additively designed parts are intended to capitalize on the freedom of complexity offered by the technique which serves to minimize the amount of material necessary, keeping costs low. This is important to note because additive manufacturing is not nearly as effective on traditionally designed parts as it is with parts that were designed with additive in mind. Additively designed parts make it possible to reduce the amount of material (and thus production time) significantly, reducing the weight of the part, while still keeping the necessary strength properties through the use of geometries that would be time consuming, or often impossible, to recreate with traditional subtractive processes. Similarly, the additional material on a conventionally designed part adds unnecessary time and material to production, reducing the potential profit per part. Thus, for the future sustainability and growth of the investment it might be important to develop a broader picture of the state of adoption within the industry.

There is certainly plenty of potential for additive manufacturing to grow. The aerospace industry, in particular, is situated to benefit tremendously from adopting. Huang et al. studied the effect

of AM on energy consumption for commercial aerospace applications. As of 2009, the world's aircraft consumed 250 million tons (12% of transport sector) of oil equivalents and was responsible for 9% of greenhouse gas emissions. This consumption is expected to triple by 2050 as globalization continues (Huang et al., 2016). Huang et al. estimate that, by aggressively adopting AM to produce light weight parts for just commercial flight, one could reduce airplane fuel consumption by 6.4% (2016). Further savings would be realized if the same principles were applied to military flight which accounts for about 19% of aviary fuel consumption (Huang et al., 2016). Fuel savings are just one reason of many why AM is forecasted to be a $50 billion industry within the next 15 years (Thomas & Gilbert, 2014).

The goal of this project is to determine whether or not Acutec Precision Aerospace Inc. should invest in additive manufacturing for production purposes in the immediate future. After a review of the literature, I turn to the economic theories used to construct my hypothesis. Such theories encompass topics such as: behavior of the firm, supply chain management, and first-mover advantage. Finally, I will analyze firm data on three key metrics important to the customer on a specific part, which is currently manufactured in a traditional manner, to better assess my economic theory. The first metric is the cost of production. The second metric, quality, refers to the number of scrap parts produced. Lastly, on-time delivery simply reflects whether an order was fulfilled by the date Acutec promised the customer. On the basis of such analysis, my resulting hypothesis is: if Acutec adopts additive manufacturing, then the potential gains in at least one of the three important customer metrics, through integration of the supply chain or minimizing cost, will offset the costs of adoption for a single part, or help to maintain a new competency that will provide a first-mover advantage.

This question is important because it affects the future profitability of Acutec, which employs well over 300 people with good paying jobs in a town where the income per capita is $19,704 as of 2013 (City-Data.com). Acutec also provides its employees with health insurance at little cost to the employee.

So if additive manufacturing turns out to be the newest disruptive technology in manufacturing and Acutec loses its competitive edge during the long process of adopting this difficult technology it could have disastrous effects for an already struggling community.

Chapter 1: Literature Review

I. Basics of Additive Manufacturing and Key Terms:

When considering adopting any new technology it is important to familiarize oneself with the vocabulary associated with it. Additive manufacturing (AM), as defined by the American Section of the International Association of Testing Materials (ASTM), is "the process of joining materials to make objects from 3D model data, usually layer upon layer, as opposed to subtractive methodologies, such as traditional machining" (Mellor et al., 2014). There is a wide array of technologies that can make a part additively out of metals including but not limited to: Laser Beam Melting (LBM), Electron Beam Melting (EBM), Laser Metal Deposition (LMD), Selective Laser Melting (SLM), Direct Metal Laser Sintering (DMLS), and Laser Metal Fusion (LMF). Most of these machine type terminologies, and others that one might come across, are trademarks of manufacturers and, despite their various names, these machines generally produce parts very similarly (Herzog et al., 2016). One important distinguishing characteristic is the way that a machine feeds material to the heat source. For this there are two main methods; direct energy deposition and powder bed fusion. With powder bed fusion the build plate is in a bed of metal powder. After every pass of the laser the build plate and constructed object gets lowered and more powder is rolled on top of the previously melted layer to be melted by another pass of the laser. This is in contrast to direct energy deposition (DED), in DED the powder is deposited from one or more nozzles simultaneously with the heat source which could be a laser, arc beam, or electron beam (Herzog et al., 2016).

II. Advantages and Obstacles of Adoption:

According to Ford (2014), additive manufacturing has the potential to reduce the costs of storing, moving, and distributing raw materials, mid-process, and end-usable parts by giving firms the

ability to produce parts on demand without need of tooling and setup. However, additive manufacturing may not be for all parts and product lines as Conner et al. (2014) point out. The low production rate and relatively constant returns to scale of both time and production cost make additive suitable for low volume and high value parts (Conner et al. 2014). They also created a three dimensional model to reference manufactured parts on the basis of production volume, complexity, and customization. Production volume is simply the number of parts made in a given timeframe (i.e. Lot size or order quantity) where complexity refers to the number of geometric features and the location of said features that would make a part difficult to manufacture through subtractive or formative methods. Finally, customization refers to the uniqueness of a part design. The authors use these attributes to represent the sides of a cube, depicted in Figure 1.1, which make up the eight regions that can classify any manufactured part.



Figure 1.1 (Conner et al., 2014)

The region that interests me the most, as it best describes the products that Acutec creates, would be region 2, manufacturing for the few. The authors point out that fixturing and tooling costs are very substantial on low volume production and that additive manufacturing might reduce cost and or lead time by eliminating the need for tooling and fixtures. They also point out, however, that if a part is also low complexity and low customization it might be wise to diversify to regions outside of region 2 in order to reduce exposure to pressures from other technologies such as CNC milling (Conner et al. 2014). These authors take care to note the continuous scales for customization and complexity with relation to cost. Traditionally increases in these two categories would lead to increased cost, but

with additive manufacturing such increases become free as complex geometries are crafted as easily as simple ones. This radically changes part design as many of the traditional design principles are no longer relevant. One example cited by Conner et al. (2014) is GE's LEAP engine fuel nozzles which were previously made with twenty conventionally fabricated titanium parts welded together. After redesigning the system for AM the assembly was reduced to just a single part that increased durability and reduced weight by 25% (Conner et al. 2014). Additionally this reduces costs related to part tracking, and quality issues related to welds as well as reducing the amount of raw material purchased since there is not material lost in chips as one would see in subtractive manufacturing. This article was helpful in understanding the relationships between complexity, volume, and customization for additive manufacturing, but it failed to address many of the other serious barriers to entry that additive manufacturing has, as its aim is to simply classify parts mathematically into categories as a rapid way to determine if a more extensive cost benefit analysis would likely be fruitful.

One such barrier to entry is the high machine cost, Vartanian and McDonald (2016) generously estimate that a machine with a build volume of 1 cubic foot or greater could cost between $700,000 and $1,000,000. Other barriers include: limited material selection, material costs remain high, and process speeds are relatively slow. Additionally, additive manufacturing poses a plethora of new problems from an engineering standpoint that need to be controlled for in the planning stages. Studies have shown that, due to the layering technique used in AM, even part orientation can create directional dependencies that can alter the mechanical properties of a part. Process parameters, such as heat source temperature and layer thickness, can also profoundly change the mechanical properties of the part. Even the amount of recycled material used has been shown to have an effect on final dimensions and properties of the part (Monzon et al., 2014). Yet these issues are not just engineering issues, but also standardization issues. The fact is that two manufacturers supplying the same part, even using the same equipment and material, could produce parts that have different characteristics. Thus, as Mellor et

al. point out, the lagging technical standards for AM is one of the greatest barriers for some manufacturers. Many industries that would benefit from AM also require extensive quality and material certifications due to the critical nature of the component (Mellor et al., 2014).

There has been significant progress towards the creation of international standards for additive, but the effort is still a work in progress. Two organizations are of particular relevance where standardization is concerned. The first is ASTM, which I have mentioned previously. In 2009, ASTM created their Committee 42 on Additive Manufacturing Technologies (Monzon et al., 2014). The second organization of note is the International Organization for Standardization (ISO), which established a similar effort in 2011 with the creation of Committee TC261. ISO TC261, as the late comer, has divided its efforts into two groups; one attempting to create original standards for AM, and the other working to adopt external organization standards (Monzon et al., 2014). The adoption of external standards generally occurs in two ways; the first is fast tracking the other party's standard, and the second is to negotiate directly with the external body on common content where both parties provide input. In fact, in July 2013, at a meeting held in the UK, ISO TC261 and ASTM F42 agreed to jointly develop AM standards so as to minimize overlapping efforts and create a single international standard for additive manufacturing (Monzon et al., 2014) The current list of approved standards for additive manufacturing are as follows (ASTM):

- **F2924- 14** - Standard Specification for Additive Manufacturing Titanium-6 Aluminum-4 Vanadium with Powder Bed Fusion
- **F3001-14** - Standard Specification for Additive Manufacturing Titanium-6 Aluminum-4 Vanadium ELI (Extra Low Interstitial) with Powder Bed Fusion
- **F3049-14** - Standard Guide for Characterizing Properties of Metal Powders Used for Additive Manufacturing Processes

- **F3055-14a** - Standard Specification for Additive Manufacturing Nickel Alloy (UNS N07718) with Powder Bed Fusion
- **F3056-14e1** - Standard Specification for Additive Manufacturing Nickel Alloy (UNS N06625) with Powder Bed Fusion
- **F3091 / F3091M-14** - Standard Specification for Powder Bed Fusion of Plastic Materials
- **F3184-16** - Standard Specification for Additive Manufacturing Stainless Steel Alloy (UNS S31603) with Powder Bed Fusion
- **F3187-16** - Standard Guide for Directed Energy Deposition of Metals Terminology
- **ISO / ASTM52900-15** - Standard Terminology for Additive Manufacturing – General Principles & Terminology
- **F2971-13** - Standard Practice for Reporting Data for Test Specimens Prepared by Additive Manufacturing
- **F3122-14** - Standard Guide for Evaluating Mechanical Properties of Metal Materials Made via Additive Manufacturing Processes
- **ISO / ASTM52921-13** - Standard Terminology for Additive Manufacturing-Coordinate Systems and Test Methodologies

III. Estimating Costs of Additive Manufacturing:

There is a consensus among scholars that the main driver of the adoption of additive manufacturing, or any technological advance, is the net benefit, which may be directed to develop or sustain a competitive advantage. Thus, in order to determine if my case example part would make a good candidate for early adoption of AM for Acutec it will be essential to estimate the production cost for the new additive process. Through my research I have discovered four studies, which aimed to provide costing models for additive manufacturing.

The first such study was conducted by Hopkins and Dickens in 2003. This study considered the scenario in which a single part was produced at 90% up-time, or utilization, during the course of a single year without taking into account overhead costs. The traditional manufacturing used for comparison in this study was injection molding, whose costs were assessed and compared to three separate types of AM equipment; fused deposition modeling, laser sintering, and stereolithography. The paper found that due to relatively high tooling costs of traditional injection molding, for these parts, it was cost effective to manufacture additively (Hopkins & Dickens, 2003). Granted traditional injection molding eventually did gain advantage through economies of scale. Yet these gains weren't realized for laser sintering until quantity of levers produced was greater than 14,000 (Hopkins & Dickens, 2003). The main real world implication of this study was to simply empirically prove that AM could offer a cost effective solution for manufacturing rather than simply produce rapid prototypes. Additionally, this study served to inform business owners on the relative costs of different platforms of AM technology. Where this research really fell short was in the fact that it allocates indirect costs over the total quantity produced, which is based on the assumption that a machine is producing at 90% utilization.

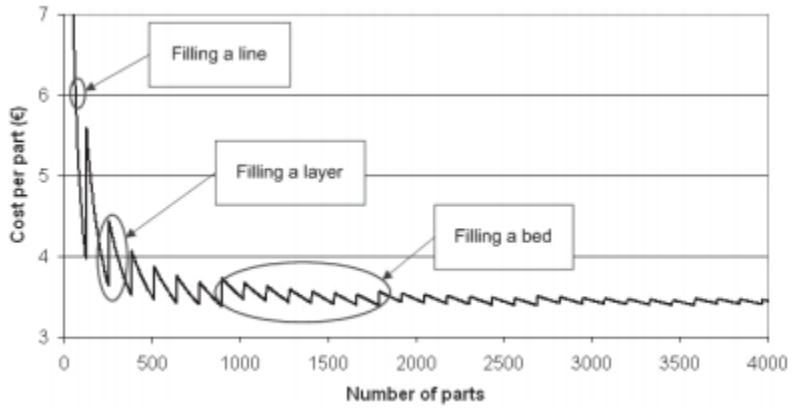

Figure 1.2 (Ruffo et al.,2006)

Ruffo et al. (2006) provided a new model, which featured a jagged downward curve that flattened out, rather than the straight line of Hopkins and Dickens. This new model was more precise, accounting for indirect costs at every quantity rather than amortizing costs over the maximum producible quantity. It also reflected the change in the curve associated with adding a new row or vertical layer as well as the change in cost associated with starting a new run due to filling the machine capacity. Together these

improvements give the Ruffo model the characteristic saw tooth, downward curving shape that you see in Figure 1.2. The main distinctions between the Ruffo model compared to the Hopkins model are: 1) the Ruffo model examines more categories of cost 2) Labor was considered as a direct cost amortized over the quantity of parts in the Hopkins model rather than an indirect cost (operator salary) as presented in the Ruffo model 3) material recycling was considered in the Ruffo model 4) the laser sintering machines were similar but not the same 5) the Ruffo model used a more realistic 57% utilization rate rather than the 90% used in the Hopkins model (Hopkins & Dickens, 2003). These

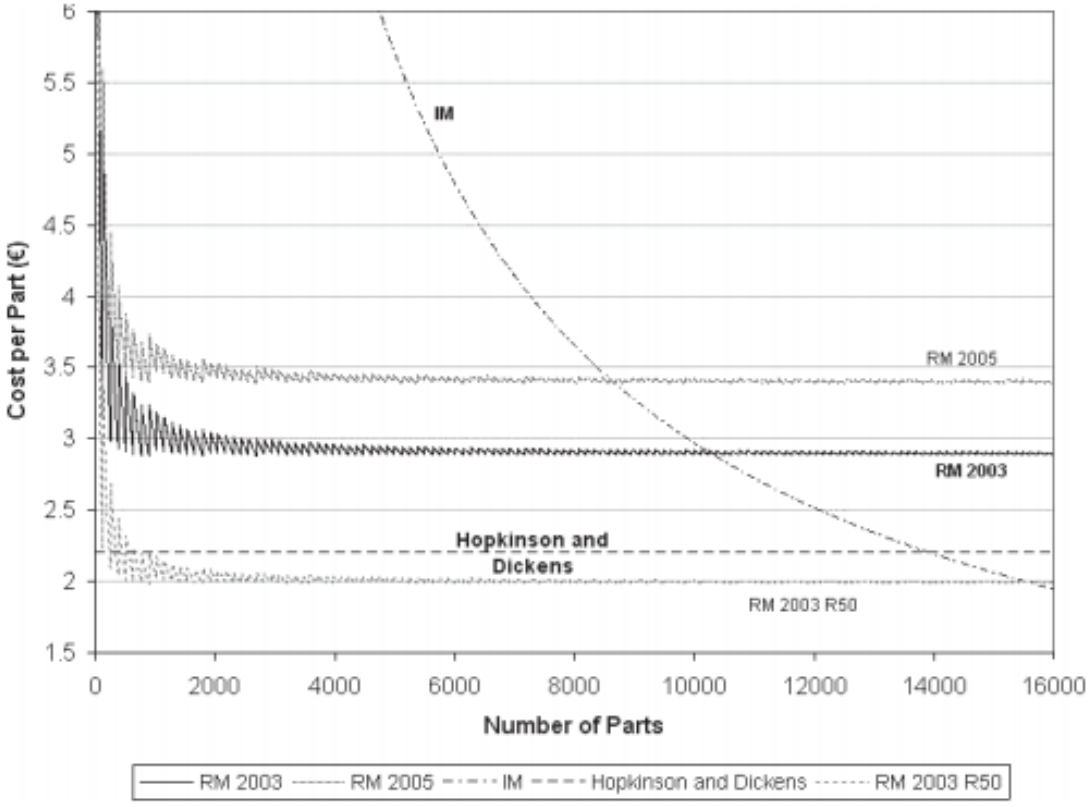

Figure 1.3 (Hopkins & Dickens, 2003)

distinctions account for the difference between RM2005 (Ruffo cost function) and Hopkinson and Dickens cost model in Figure 1.3. Yet this study did have one limitation addressed by Ruffo and Hague in 2007. The study only used a singular part. This ignores AM's ability to produce multiple parts at the same time, allowing for greater build space optimization which, in turn, reduces the cost. By comparing

three separate mathematical methods for assigning cost for mixed components against producing each of the two sample parts exclusively, Ruffo and Hague's 2007 study concluded that there are, in fact, cost savings associated with mixed parts production.

Baumers et al. (2016) sought to continue this systematic analysis of monetary costs. The authors collected data for two machines, one DMLS and one EBM, to create a workable production function that they then use to make speculations on the future of AM. One large contribution of this model compared to previous models was that they used an algorithm that determined the layouts that maximize the occupied space of any number of five sample parts on the build plates for each machine in order to optimize the build space and reduce cost. This is important as it has been shown that technical efficiency, and space utilization, is necessary for models of AM resource consumption (Baumers et al., 2016). Authors Baumers et al. do make several important assertions about cost structure, and the future of additive manufacturing, which are applicable to this analysis of AM.

The first finding they discuss is that system productivity (at least with the previous generation of technology used in the experiment) was a primary driver of cost. The deposition rate of the DMLS and EBM machines tested were only 37.58 and 69.24 g/h respectively (Baumers et al., 2016). Which can be compared to traditional machining rates which are often cited around 100 kg/h. Larger volume build spaces would allow higher build quantities to amortize some of the warm up and cool down times, as well as other fixed expenses, which would reduce cost per part. In the end the greatest cost reducer would likely be deposition rates that more closely resemble those of traditional manufacturing.

Baumers et al. (2016) also found through their research that, contrary to popular belief, opportunities for capitalizing on economies of scale can be found. Generally speaking such gains are made either by reducing indivisibilities or by a physical scale up of technology that reduces per unit cost. Tooling would be a classic example of an opportunity to reduce indivisibilities by using tools completely

rather than discarding a tool that still can be used to make more parts. However, AM does not require tooling. Instead AM could increase build volume to spread costs, develop more continuous build styles, or deposit multiple layers at once. EOS has already taken this to heart with the M 400-4 which has a much larger build volume (400mm X 400mm X 400mm) and four lasers, each with their own build quadrant (EOS). This is relevant because it shows that some economies of scale may be possible for additive manufacturing which means that saying that AM will never be profitable for high-volume products might be premature.

While the findings of this paper were very insightful, perhaps an equal take-away was the way the authors created their cost function and the level of depth the authors went into for the indirect costs associated with both AM platforms. Finally, the author states that he endeavored on his research because he believed "a systematic analysis of the monetary cost associated with the operation of AM, as one of the most critical determinants of the net benefit obtainable from the technology's use, forms an excellent starting point for future analysis of the economic impact of AM adoption" (Baumers et al., 2016). They also identify the common uncertainty that business owners face when determining whether or not to adopt a new technology and hope to provide some insight.

IV. Contribution to the Literature:

Previous research has made several leaps in the way of improving costing models for generic additive manufacturing cases. It is my hope that I can further the knowledge base for business owners that was started by Baumers et al. (2016) analysis through the assessing feasibility for an early case adoption part for a relatively small manufacturing firm in a real business case scenario, using real world data on the existing traditional manufacturing methods. My aim is to not only compare the costs between technologies for this part, but also to analyze the driving factors of cost as well as the other two customer metrics that drive success in the aerospace industry. By also studying the drivers of quality

and on-time delivery, for the traditional method I hope I might make inferences as to how adoption would affect these areas as well. This would be the first such analysis for AM, especially for a supplier of predesigned parts. Right now a majority of the literature surrounds advances made in material and structure improvements or the benefits of designing for additive through case studies where massive efficiency gains were made. Very few, if any, study the possibility of an established traditional manufacturing supplier adopting AM for a traditionally designed part.

Chapter 2: Theoretical Analysis

I. Firm Behavior Theory:

In any industry it can be assumed that firms operate as profit maximizers. In order to do so it is important to understand that profit is calculated as total revenue, the amount a firm receives for the sale of its output, less the total cost, or the market value of the inputs a firm uses in production (Mankiw, 2012). For the product of concern in this study, available actions related to profit maximization are limited by the fact that Acutec is engaged in a long term agreement for this product. Meaning prices and quantity demanded are relatively constant, thus gains on the revenue side of the equation are unlikely. As such, by adopting additive manufacturing, Acutec would be attempting to reduce production cost, thus increasing profit.

When considering total cost, it is important to understand the difference between explicit and implicit costs. Explicit costs are input costs that require an outlay of money by the firm (Mankiw, 2012). Examples of such costs would include, but are not limited to; machine costs, material costs, energy costs, and labor costs. In contrast, implicit costs are the input costs that do not require an outlay of money by the firm (Mankiw, 2012). While I will not make any attempt to calculate such costs for the purpose of this study, it is important to understand that such costs do exist. Implicit costs will likely be fairly high if Acutec should decide to adopt additive manufacturing. A notable example of an implicit cost is the forgone benefit of investing this large sum of money that Acutec would be diverting towards this project in other facets of the company. So the added benefit that Acutec would have gotten from investing in other avenues such as new machines, or in information technology in order to improve information flow throughout the shop. In this same way, Acutec also bears the implicit cost of devoting countless engineering hours to the development of this very difficult technology rather than performing every day engineering tasks.

As for explicit expenditures, it is important to distinguish between fixed and variable costs. This distinction is a simple one, fixed costs, unlike variable costs, are those that do not vary with the quantity of output produced. Thus, machine costs would be a perfect example of a fixed as it is a one-time expenditure. Similarly, material costs would be a good example of a variable cost, as the amount of material varies directly with the quantity of parts produced. This will be particularly helpful in determining the proper costing model for AM as certain cost may or may not vary with quantity. I am hoping that my research will show that the adoption of AM, while having high fixed costs (machine price), will benefit from potentially lower material costs (current castings cost $720-861.40) and other lower variable costs. Additionally, AM does not require tooling which could be considered either a fixed or variable cost. Tooling often does need to be replaced due to wear from use, however, this might mean a tool needs several replacements per build of a given part or the tool might be expected to last indefinitely for a given job. Regardless of classification, AM promises to eliminate this sizable cost.

II. Supply Chain Management & Vertical Integration Theory:

While the decision to adopt additive manufacturing is, in the long term, a decision to add to the core competencies of the shop, the motivation and short term benefit can largely be discussed as a vertical integration of the supply chain. The vertical chain of production, or supply chain, is the series of steps in a production process which describes the process of transitioning raw material into finished product. A firm is said to be vertically integrated if it participates in more than one successive stage in the vertical chain. Therefore, as one large effect of adoption of the case study part for additive manufacturing will be to cut out the casting supplier from the chain of production, and produce the part additively from scratch, it could be said that Acutec is vertically integrating an upstream process. Through this integration, Acutec has the potential to benefit in a variety of ways. First, vertical integration cuts out the transaction costs associated with using a supplier, specifically the transportation

cost. Another benefit is that Acutec gains control over an important input good, the casting, which could allow them to adapt to rapidly changing demand without missing deliveries due to obnoxiously long material lead times (12-14 weeks). Additionally, Acutec could potentially reduce the quantity and cost associated with keeping castings on hand. On the other hand, making these castings additively would likely result in a higher average cost, as economies of scale are much more difficult to achieve additively. Thus it will likely be better to outsource the castings except when the lead times and/or costs of outsourcing become great enough to merit producing at a greater cost in house.

III. First-mover Advantage Theory:

First-mover advantages describe a positive outcome resulting from technological leadership in a given technology adoption choice. In order to discuss potential first-mover advantages, however, we must first understand what makes a particular technology desirable for firms. Once a technology is found to be desirable, we must then consider timing of entrance; more specifically, whether the firm stands to benefit from being a technology leader or follower. Each strategy can be beneficial; however, if a firm is considering taking a leadership role it should evaluate the technology on the bases of: 1) sustainability of the technological change 2) first-mover advantages 3) first-mover disadvantages (Porter, 1985).

Porter rightly points out, “technological change is not important for its own sake, but it is important if it affects competitive advantage or industry structure” (Porter, 1985). In order to affect competitive advantage the technological change must affect the drivers of cost and/or differentiation. That is the change should reduce the cost of producing or set the firm or product apart from its competitors. Alternately, a technological change might also be suitable if it can reshape industry structure in a way that the firm can capitalize on. This means that if Acutec is to consider AM, then adoption must reduce costs, costing drivers, or differentiate Acutec’s product (manufacturing services). The former is the aim

of the empirical portion of this study and the latter would be true as it adds a capability (AM) which differentiates Acutec from its competitors.[1] Finally, adopting AM can also reshape the industry structure in several key ways. For one, it changes the buyer/seller power dynamics by allowing Acutec the option to choose to produce the castings additively in-house, this could potentially be used as a bargaining chip for Acutec to negotiate better prices. Additionally, Acutec could patent the AM process of creating the part, forcing any customer who wishes to have the part made additively to go through Acutec. Finally, adding AM to Acutec's repertoire would change industry structure by opening up a new market segment previously inaccessible.

If AM is in fact a desirable option then timing of entry must be considered. Generally speaking, firms tend to view technology leadership as a means of achieving differentiation and technological followership as the approach for minimizing cost. However, each strategy can positively affect both aspects of competitive advantage. Ultimately, the decision of being a leader or follower comes down to sustainability, first-mover advantages, and first-mover disadvantages.

Porter identifies the sustainability of technological innovation as a function of four factors: 1) the source of the technological change 2) the presence or absence of sustainable cost or differentiation advantaged in technology development 3) relative technological skill 4) rate of technological diffusion (Porter, 1985). AM technology is disadvantaged by the fact that the source of technological change is external, and thus more accessible for follower adoption. As for the second factor, AM leadership should provide Acutec with a greater market segment than competitors allowing for greater absolute R&D expenditure in order to maintain competitive advantage. Technological leadership should provide an advantageous head start that could be used to develop the skills and relationships necessary to distinguish Acutec as relatively more skilled than their competitors, adding to the sustainability of the

[1] This claim was verified after checking the capabilities of 27 of Acutec's competitors, for a complete list refer to Appendix D

innovation. Finally, the rate of technological diffusion might be very high given the availability of AM technology and support services.

AM had a mixed score on sustainability, the main detraction being that the machines and support services are widely available, however, being a leader allows Acutec to stay ahead of the competition on the learning curve and attract a larger market share to aid in continuous R&D. Yet, sustainability only accounts for one of three factors discussed by Porter, first-mover advantages and disadvantages also play a key role.

Perhaps the most important first-mover advantage is the reputational effect that Acutec could capitalize on. As a leader Acutec has the opportunity to market itself as unique by being the first traditional and additive manufacturing supplier in the market for aerospace/power generation manufacturing services. Additionally, Acutec will be the first to serve buyers, allowing the establishment of loyalty and increasing the potential for future business. However, this advantage is contingent upon the ability of the firm to communicate this leadership through advertisement, word-of-mouth, and accolades. Acutec could also lock in future sales by leveraging switching costs for a competitive advantage. Switching costs might be as simple as the disruption in supply chain caused by moving to a new supplier or accepting a firm that is not as advanced on the learning curve and may not be as effective of a producer. The act of switching would impose the costs of the new firm's lack of experience as well as any logistical costs associated with changing suppliers. Finally, Acutec could benefit from institutional barriers that serve to limit competition. Patents or LTA's would be plausible institutional barriers that Acutec could benefit from as a first-mover. By patenting the process of making specific parts additively Acutec can expect 100% of future business for that part when additive manufacturing is required helping to guarantee future business.

There are still potential disadvantages for being a first-mover that also need to be considered. Pioneering cost, demand uncertainty, and the specificity of investment to early generations of cost factors are all potential disadvantages of AM. Pioneering costs include those associated with gaining proper approvals, educating buyers, developing training procedures, and even absorbing high input costs while supply is limited (Porter, 1985). Each of these costs could be mitigated as a follower. Additionally, demand uncertainty is a real concern, because Acutec rarely makes design decisions as a supplier, and thus must rely on customer demand for additively manufactured goods being great enough to warrant a relatively large expenditure. Lastly, AM machines have been making leaps in productivity recently, meaning Acutec could potentially buy a machine that is state of the art at the time of purchase, but wildly obsolete well before it has produced enough to rationalize the expenditure.

It is my expectation that the potential gains, in reputation and market share, from being a first mover will outweigh the potential disadvantages of being an early adopter under conditions of uncertain demand. These advantages can then be sustained through proper management and continued investment in AM R&D in order to solidify Acutec as the leading supplier of AM services for its market, expanding their claim as a one-stop shop for manufacturing services in a rapidly changing industry.

Chapter 3: Empirical Analysis

I. The Data Set

a. Sources of Data

Data used in my regression analysis was gathered directly from the databases of my object of study, Acutec Precision Aerospace Inc. The entirety of this data was either extracted directly from, or derived from, information collected from several of the tables within the database connected to Acutec's enterprise resource planning software JobBOSS.

This study focuses on the analysis of aggregated data on eight technically different parts, chosen because of their near identical nature and shared long term agreement. Due to the confines of proprietary knowledge descriptions of this part must be kept vague and identifying information must be omitted from this report. The best description of the part that can be given is to describe its function as a fuel-injection housing for a land or marine turbine.

b. Compilation of data

When compiling the data, I pulled the information from the several tables into a single excel document and used the Acutec specific job number, as well as customer part and casting numbers, to connect the many variables. My final dataset contains data at the build level, meaning that each "data point" represents a group of parts produced at the same time for a single order. However, not all of the data is collected at the build level. Some data is collected at the operation level and had to be transformed. For example, operator experience is actually derived from calculating the time between the employee's hiring date and the day that said employee posted time on an operation. This operational level data was then averaged over the build to get the average operator experience. After compiling and transforming the data, I then eliminated any data points that were missing values and narrowed the scope of my data to jobs

that started, and were completed, between January 1st, 2015 and December 31st, 2016. This left me with 200 viable data points for examination.

II. The Regression Model

a. Model 1 (On-Time Delivery)

The first regression in this study aims to analyze the effects of the independent variables with respect to on-time delivery. Due to the nature of on-time delivery (a binary dummy variable) a probit regression would generally be preferred. However, after a preliminary run of my regression, not all of my variables of interest were statistically significant. In the hopes that my insignificant variables of interest had joint significance, I decided to use a standard OLS regression so that I could perform the necessary F-test. The regression equation is as follows:

$$\text{On-time Delivery} = \alpha + \beta 1\ \text{Build ID} + \beta 2\ \text{Date Changes} + \beta 3\ \text{Quantity Changes} + \beta 4\ \text{Make Quantity} + \beta 5\ \text{Total Hours} + \beta 6\ \text{Scrap} + \beta 7\ \text{Operator Experience} + \beta 8\ \text{Operator Experience Hours} + \beta 9\ \text{Time Available} - \text{Total Required Lead} + \beta 10\ \text{Job 2} + \beta 11\ \text{Job 3} + \beta 12\ \text{Job 4} + \beta 13\ \text{Job 5} + \beta 14\ \text{Job 6} + \beta 15\ \text{Job 7} + \beta 16\ \text{Job 8} + \varepsilon$$

b. Model 2 (Scrap)

The second regression in this study models the count of scrap at the build level. Due to the fact that Acutec has a <1% scrap rate for this part, there is an excess of zeros in the data that cannot be explained by a normal distribution. In cases such as these there are four possible types of regressions to use; Poisson regression, negative binomial regression, zero-inflated Poisson regression, and zero-inflated negative binomial regression. Generally speaking, the Poisson regression is preferred so long as the variance equals (or approximates) the mean. In this data set the mean is 0.27 and the variance is 0.48. Since this requirement is not obviously met, my starting point was the negative binomial regression. Thus, I began by running a zero-inflated negative binomial regression with vuong and zip commands following the regression.

The purpose of the vuong command is to provide a test of the zero-inflated results against the negative binomial regression. If the Stata regression results have a significant z-test score then the zero-inflated model would be preferred. The second additional command, zip, compares the zero –inflated negative binomial model against the zero-inflated Poisson model. For this test, if the likelihood-ratio for alpha is significant then the zero-inflated negative binomial model is preferred. After running this command, I found that the Vuong test resulted in a z score of 1.15 with a p-value of 0.1255 which means that there is not sufficient evidence that, for the negative binomial model, zero-inflation would be preferred. Additionally, I found that the chibar^2 of the likelihood-ratio test was 0.000 and the p-value was 1.00 (not significant), meaning that the zero-inflated Poisson model is preferred. After this, I needed to verify that zero-inflated Poisson was indeed preferred over the standard model. For this, I ran my regression as a zero-inflated Poisson with the additional command of vuong to once again perform a Vuong test which compares these two options (standard and inflated). Once more a significant z-test would indicate that the zero-inflated model would be preferred (that is a large positive z value). The z value for this test was 2.91, which provides strong evidence that the zero-inflated model is preferred. The final zero-inflated Poisson regression used was:

Scrap = α + β1 Make Quantity + β2 Build ID + β3 Total Hours + β3 Operator Experience + β4 Operator Experience Hours + β5 Job 2 + β6 Job 3 + β7 Job 4 + β8 Job 5 + β9 Job 6 + β10 Job 7 + β11 Job 8 + ε

c. Explanation: Dependent Variable and Independent Variables

The dependent variable in this first regression, on-time delivery, is a simple dummy variable that indicates whether an order was shipped by the date the customer requested or not. As a dummy variable, the possible outcomes are 1 (if the order is late) and 0 (if the order is

on time). Other variables in my regression fall into two simple categories, variables of interest and control variables. Variables of interest for this regression would be any that would be directly affected by the adoption of additive manufacturing. In this regression, additive can be expected to affect three key attributes: machine time, scrap, and lead time. The three variables in the regression that are changed in one way or another by these attributes, or variables of interest, would be: Total Hours, Scrap, and (Time Available – Total Required Lead). The first variable of interest, total hours, is simply the total amount of time recorded by machinists for a given build. One would expect that additional hours would correlate to a higher incidence of late deliveries (specifically if those hours are unplanned). After consulting Linear AMS, and receiving a quoted run-time of approximately 150 hours per part, it is clear that total hours would increase significantly with the adoption of AM. Scrap, the second variable of interest, is simply the number of defective parts found during the course of a build. Time spent machining, or reworking, bad parts is time not spent fulfilling the order, thus a higher incidence of scrap would likely affect Acutec's ability to produce on time. Considering the abnormally low scrap rate, it is likely that (at least initially) the scrap rate for additive would be substantially higher for AM. Finally, the last variable of interest, time available less total required lead, is a proxy for the shops anticipated ability to complete an order on time given sufficient scheduling capacity. This value is calculated by, first, finding the time available, which can be accomplished by calculating the working days between the order date and the promised date. Then, using a formula that I created I estimated the required lead for the order. This formula used machining time that was based on the times used for quoting and job scheduling, to which I added a day for every additional process (which is fairly standard practice). After finding these two values I calculated the difference, which is the value that I used in my regression. This variable ended up having both positive and negative integers, indicating that there are occasions when Acutec simply

does not have enough time to be expected to fulfil the order. The effect that adopting AM would have on this variable is unclear as the lead-time required for material would reduce significantly, but the lead-time required for manufacturing would increase substantially. Not to mention that the time available is customer driven and impossible to estimate ahead of time.

The second regression's dependent variable, Scrap, is simply a count of the defective parts for an order. For this regression, the only variable of interest would be Total Hours, which was described above. Again the reason for my interest in this variable is that it is one of the only variables that will be affected by adopting additive manufacturing.

d. Control Variables

When considering the independent variables it is important to distinguish between variables of interest (those that are of central importance to my thesis) and control variables. Control variables are simply "outside" factors that may affect the dependent variable. By observing these variables, we can control for the variation that they create, allowing for a more accurate analysis. These control variables are:

a. Build ID represents the chronological order of the builds. This variable is a proxy variable that should account for the experiential gains of the shop as more orders are completed. This gain in experience should reduce errors in planning and production, increasing the likelihood that the order would be completed on time. The added shop experience would also likely reduce the chance of scrap parts as operators learn from their mistakes.
b. Date Changes is a count variable that represents the number of times Acutec's customer service representatives had to change the promised date due to a customer request. It would be expected that having more changes would increase the likelihood of scheduling

errors and conflicts, thus reducing the probability of producing the order on time. (This variable is not present in the scrap regression)

c. Quantity Changes is another count variable that reflects the number of times a customer requests a change in the overall quantity of the order. If the order quantity increases then it could potentially cause a late order due to a lack of material as well as inadequate time or capacity for completion. (This variable is not present in the scrap regression)

d. Make Quantity is simply the number of parts that needs to be made for the order. More parts create a greater opportunity for scrap, and potential for delays that could result in a late delivery.

e. Operator Experience is the average number of years for the operators who posted time on a given build. One would assume that more experienced operators would be more likely to complete an order on time as well as scrap fewer parts.

f. Operator Experience Hours is an interaction term between Operator Experience and Total Hours.

g. Job1 –Job8 are eight variables that represent the eight Acutec jobs (chosen for their similarity) which make up the aggregated data. These variables were included to account for any minute differences between jobs that might affect on-time delivery or scrap rate.

e. *Summary Statistics*

In order to get a more complete understanding of the data set it is important to look at the summary statistics. In the spirit of brevity, this section will only cover the most important findings. However, for a complete list, refer to Appendix A. This data set has a total of 200 observations. Each of these observations corresponds to a build, which has a make quantity (the number of parts to be manufactured for a given order/build). The make quantities of the 200 observations range between 3 and 36 parts, but have a mean of 15.55 parts. The machining

time to complete each build ranges from 17 to 213 hours, depending primarily on the make quantity. The mean of the machining time is 75.31 hours, which, if divided by the mean make quantity, equates to about 4.8 hours per part. This is perfectly in line with my estimation for required lead time. As for my first dependent variable, On-Time Delivery, the mean was 0.33. As a dummy variable, we can interpret this as 33% of deliveries being late. In real numbers this means that 66 of 200 orders were not completed on time. The second dependent variable in this study, scrap, had a range of 0 to 4 and a mean of 0.27. Of the 200 observations, only 34 have values that were greater than zero. In other words, of the 3,110 parts produced, only 54 were determined to be scrap. This equates to a 1.7% scrap rate.

III. Regression Results (On-time Delivery)

3.1 Regression Results (On-Time Delivery) Observations: 200 Robust R^2: 0.4547

On-Time Delivery	Coefficient	Standard Error	T-Stat.	P>[t]
Build ID	-0.004574	0.000643	-7.12	0.000
Date Changes	-0.125296	0.023548	-0.53	0.595
Quantity Changes	0.048276	0.022308	2.16	0.032
Make Quantity	-0.010959	0.009743	-1.12	0.262
Total Hours	0.011452	0.003552	3.22	0.001
Operator Experience	0.120035	0.049694	2.42	0.017
Time Available - Total Req'd Lead	0.000363	0.000651	0.56	0.577
Scrap	0.063782	0.041961	1.52	0.130
Experience Hours	-0.001642	0.041000	-2.58	0.011
Job2	0.190384	0.125296	1.52	0.130
Job3	-0.109545	0.119347	-0.92	0.360
Job4	-0.120984	0.115194	-1.05	0.295
Job5	-0.171443	0.131874	-1.30	0.195
Job6	-0.037710	0.134257	-0.28	0.779
Job7	0.139609	0.175945	0.79	0.429
Job8	0.632450	0.233277	2.71	0.007
Constant	0.099566	0.273646	0.36	0.716

a. Interpreting Coefficients

These results show that Total Hours is statistically significant at the 1% level. The coefficient for Total Hours is approximately 0.0115, which means that an additional hour of machine time would correspond to a 1.15% increase in the likelihood of a late delivery, all else held equal. Given that the mean value of this variable is 75.31 hours, it can be safely stated that Total Hours also has economic significance, as it has a sufficiently large effect on whether or not the order will be delivered on time. My other two variables of interest, Scrap and Time Available – Total Required Lead, did not have independent statistical significance. However, just because these variables are not independently significant does not mean that they are not jointly significant. Using an F-test one can test these variables for joint significance. However, after determining the F-statistic was only 1.89 (which is well below the required 3.09 needed for rejection)I rejected my null hypothesis. This means that Scrap and Time Available – Total Required Lead are not jointly significant. After making this determination, it was necessary to check if the variables should be included in the first place. To do so a comparison of two models (one model with the questionable variables and one without) adjusted R^2 values was necessary. The adjusted R^2 values differed by less than 0.004. This was not enough to justify eliminating two variables of interest from my regression. Despite their theoretical importance, these variables lacked statistical significance, which could be explained by unobserved terms that caused a downward bias of my coefficient. One reason that the variable Scrap might not have a significant effect is the abnormally low scrap rate of 1.7%. As for the second variable that was insignificant, Time Available – Total Required Lead, it would appear that, because of the abnormally large range (-182 to 463) and high standard deviation (85.53) compared to the mean (58.51), the data was simply inconsistent and therefore could not generate a significantly large effect in either direction.

While only one of three of my variables of interest were statistically significant, it is still important to discuss the coefficients of the rest of the independent variables. Build ID, for instance, was statistically significant with a coefficient of about -.005. This means that with each new build, the likelihood of a late delivery is reduced by 0.5%, holding all else equal. This is a fairly small change, so the economic significance of such a change would be limited. After that, if we look at the two customer change variables, Date Changes and Quantity Changes, only quantity changes had a significant effect at the 10% level. The coefficient on Quantity Changes (0.048276) means that, holding all else equal, with each additional quantity change the customer requests, there is about a 4.8% greater chance of a late delivery. This makes logical sense, especially in the case of a quantity increase, because the scheduled start might not leave sufficient time to complete the order or there simply may not be enough material available for the additional parts. The two experience variables were both statistically significant but of opposite signs. Operator Experience had a coefficient of 0.12 meaning that each additional year of experience correlates to a 12% higher instance of late deliveries, all else constant. This was opposite of the direction that was expected, however, it might be that more experienced machinists take more care in checking their work, or that they have a more difficult time with the technological portion of being a machinist (as more experience often means older). The other variable related to experience, Experience Hours, had a coefficient of about -0.0016 which means that at a given level of experience, an additional hour of work would reduce the chance of a late delivery by 0.16%. In other words, for a given level of experience, an additional hour of work would lead to a marginal increase in the probability of on-time delivery (1.15% for the additional hour) by 0.16% if all else is held constant. Which makes sense as one would expect that efficiency would increase over time, despite the additional time increasing the likelihood of a late shipment. The last of the significant variables is Job 8. The coefficient on Job 8 means that

Job 8 is 63% more likely to be late, all else held equal, than Job 1. This can be explained by the number of occurrences of each job, Job 1 appeared 34 times in my dataset while Job 8 appeared only 6 times. Thus, a single late delivery on Job 8 would represent a 5.67 times greater effect than the same late delivery would have for Job 1.

IV. Regression Results (Scrap)

3.2 Regression Results (Scrap) Observations: 200

Scrap	IRR	Standard Error	Z-Stat.	P>[z]
Build ID	1.002109	0.002820	0.75	0.454
Make Quantity	1.118056	0.047396	2.63	0.008
Total Hours	0.975105	0.026997	-0.91	0.363
Operator Experience	0.739265	0.198733	-1.12	0.261
Experience Hours	1.003516	0.003643	0.97	0.334
Job2	1.675568	0.736527	1.17	0.240
Job3	0.305151	0.158508	-2.29	0.022
Job4	0.393488	0.168624	-2.18	0.030
Job5	0.347798	0.210107	-1.75	0.080
Job6	0.432421	0.364471	-0.99	0.320
Job7	0.243047	0.218647	-1.57	0.116
Job8	0.797506	0.757293	-0.24	0.812
Constant	1.365033	2.413325	0.18	0.860
Inflate(Make Quantity)	0.031489	0.070421	0.45	0.655
Constant	0.007969	1.305433	0.01	0.995

a. Interpreting Coefficients

The fist note to make with this regression is that the effects of the variables aren't normal coefficients, but incidence rate ratios (IRR). What this means is that the numbers are to be interpreted as the frequency of an event with relation to one. In other words, when interpreting the IRR for Make Quantity, which is statistically significant at the 1% level, one can say that, with each additional unit, the chance of an incidence of scrap is about 1.12 times as

high (or 12% higher). The only other statistically significant variables are job variables, which were included to control for bias, and have little significance to this study.

V. Potential for Biases and Error

Most empirical studies have a potential for bias and error, specifically in the form of multicollinearity, heteroscedasticity, and specification errors. The first type of error that I tested for was heteroscedasticity; to do so I ran the estat hettest command in Stata, which is the equivalent of the Breush-Pagan test. The result of which was a chi^2 of 8.17 which is sufficiently high to reject the null hypothesis of a constant variance and conclude that heteroscedasticity was indeed present. To correct for this I used only robust standard errors. Additionally, after generating a correlation matrix and running the estat vif command in Stata (variation inflation factors for the dependent variables), it was determined that only three of my variables suffer from any multicollinearity. Variables that have a correlation value greater than 0.8 or a variation inflation factor of 10 or greater are generally considered to be suffering from multicollinearity. These three variables are Total Hours, Operator Experience, and Experience Hours. The fact that Experience Hours is an interaction term of the other two makes it perfectly logical that they would be highly correlated.

After checking for multicollinearity and correcting for heteroscedasticity I had to check for the final type of error, specification error, which has four parts; omission of important variables, inclusion of irrelevant variables, failure to follow functional form, and measurement error. Omission of variables can be tested for with a Ramsey RESET test. The result of running this test in Stata was an F-statistic of 4.71 which is great enough to accept the null hypothesis that there is in fact missing variables. This result is not surprising, the process of manufacturing and processing a precision part is so complicated that it would be nearly impossible to fully

capture. Even slight temperature variations on the shop floor is said to be enough to put a machine out of tolerance.

While the inclusion of irrelevant variables was minimized during the process of finding the preferred regression, not all of the variables are statistically significant which has the potential to cause bias in the results. Another issue that was corrected for in the process of finding the preferred regression was functional form. Both Scrap and Total Hours were tested to determine if a squared shape would better suited to the data. However, after adding the squared variables to the regression both were found to be statistically insignificant. As a result, both variables were dropped from the preferred regression as the insignificance indicated that they did not follow an exponential form. There could have been other functional form issues that were not checked for, but does not seem to be the case.

Finally, there are also measurement errors that make up specification error. This is probably the greatest potential for bias and error as it was necessary to rely on others to input data correctly and anytime there is manual entry of information there will be human error. For one, all data used has the potential for a typographical error (missed number, wrong number, extra number, etc.). Or an operator might have failed to report a scrap part, intentionally input time that was incorrect, or failed to enter a time altogether (any observation that didn't have any time posted would have been dropped, but not if there were multiple operators and only one failed to report). As for the change data (quantity and date), it is quite possible that Acutec customer service representatives had to change a quantity or date simply because they were correcting their own error or that of a coworker, which would over inflate the data. The simple fact of the matter is that humans are fallible and any time human entry of data is required on a regular basis, there will be errors. Additionally, for the variable operator experience, a simple

average of the years experienced for all employees would not be the best measure. While it was not feasible, given the available data, a better measure of operator experience would have been an average that was weighted on the number of hours worked so as to better account for the results of the experience of each worker in relation to the dependent variable.

VI. Cost Analysis

Initially, the intention for this portion of the study was to have an in depth analysis of the cost of both additive and traditional manufacturing. The end goal of which would have been to estimate a cost model similar to that of preceding researchers Baumers et al. (2016), Ruffo et al. (2006), and Hopkins & Dickens(2003) for this specific part. After which, using real data from the traditional manufacturing process that Acutec currently uses, an equivalent cost model could be compared to that of AM to determine at what levels of output additive manufacturing would be cost effective. However, as data was collected, this plan quickly became infeasible and wholly irrelevant. The first issue was the wholly incomplete costing data for Acutec's current traditional approach. The best estimation for cost that was available was generic values used for quoting; the only actual data collected was machining hours and scrap. The number of hours posted would not account for machine utilization (percentage of time the machine is in use) which would greatly impact the real cost of running the machine. Nor do the generic hourly rates for machining, labor, and overhead actually relate to real costs, they are simply generic quoting prices that, while good enough for estimating the cost of a job, would not be realistic enough to maintain the academic integrity of this study. However, after outsourcing some of the additive manufacturing cost estimation to Linear AMS (a company that provides training and support services to companies looking to adopt additive manufacturing) it was determined that AM costs would be prohibitively high. In fact, on the SLM 280 machine, the 5.61 kg of material needed to additively produce a single part and support structures would cost approximately

$1,250. To put this in context, the castings for the current traditional manufacturing process are $720-861.40 per casting for traditional manufacturing. This fact alone makes further investigation into cost for this part a hopeless endeavor, especially if you consider that Linear AMS also estimated that a single part would take 150-170 hours. Even at minimum wage (which is far less than any operator would be paid) labor cost would be higher than $1,050. After considering just the cost of material and the absolute bare minimum labor, the cost of AM would exceed the total revenue per part ($1,740) by $560.

VII. Conclusion

Ultimately, my findings from this empirical analysis are limited due to a lack of statistically significant results. For the On-Time Delivery regression, it can be said that the total number of machining hours has a statistically and economically significant effect that makes late delivery more likely. The other two variables of interest, Scrap and Time Available – Total Required Lead, were not statistically significant. With respect to the regression for scrap, only Make Quantity was statistically significant. Due to the fact that the make quantity is determined by the order a customer places, this really doesn't provide much insight towards my hypothesis as it will not be affected by the adoption of additive manufacturing. The cost analysis did provide very significant, albeit negative results, by demonstrating that this part cannot be produced additively for a profit so long as the material cost remains at its current level. These results will be discussed in greater detail and with regards to the overall thesis of the paper in the next section titled *Application of Findings and Closing Remarks.*

Chapter 4: Application of Findings and Closing Remarks

I. Summary of Study

The central thesis this study aims to prove is; if Acutec adopts additive manufacturing, then the potential gains in at least one of the three important customer metrics (cost, scrap, on-time delivery), through integration of the supply chain or minimizing cost, will offset the costs of adoption for a single part, or help to maintain a new competency that will provide a first-mover advantage. After the empirical analysis, only one of these claims can be unequivocally dismissed, that is that additive manufacturing will reduce cost for this part.

In the theoretical analysis portion of this study it was explained that firms act as profit maximizers (profit being defined as total revenue less total cost). Additionally, due to the nature of the long-term agreement on this part, there is very little room for increasing profit through greater volume or new pricing strategies. Thus, cost minimization is the only route to increased profits for this part. After determining that the material cost, when combined with the bare minimum labor cost, is substantially greater than the total revenue on the part, we can conclude that a profit maximizing firm would not chose to adopt additive manufacturing for this part, as the implication of such a high material cost would be that AM does not minimize cost. Additionally, due to the low scrap rate of traditional manufacturing (1.7%) for this part, the gains to be had by reducing scrap are relatively low and unlikely to be achieved for quite some time. Finally, while the casting lead times for this part are incredibly high (12-14 weeks) for this part, the machining time per part is relatively low at approximately 4-5 hours a part. This is compared to the 150-170 hours per part that was estimated by Linear AMS. That comes out to 2,250-2,550 machining hours to complete the average 15 part order (18-22 weeks running two 10 hour shifts 5 days a week). This means that total production time would increase, making on-time delivery

less likely, especially if we allow the assumption that additive manufacturing will behave similarly to traditional manufacturing where an added hour of machining time correlates to 1.15% greater chance of a late delivery, all else held constant. From this we can infer that the benefits for on-time delivery gained from integrating the supply chain are not sufficient to outweigh the slow production rates of current additive technology for this part.

The final claim of my thesis is impossible to prove ex-ante (before adoption). The claim in reference is that by adopting AM and becoming a first-mover, Acutec will gain a competitive advantage through cost minimization or differentiation. While the cost minimization portion of this claim is debunked, the differentiation portion remains true. Acutec would be a first mover for their market. However, the effect of this competitive advantage is debatable. We cannot estimate the reputational effects of adopting this technology, and it is difficult to estimate the business that AM would generate for Acutec. It is clear, however, that AM is quickly becoming a major player in the industry, and that this will soon be negatively affecting Acutec if we do not adapt. One strikingly clear example of this is present in the phasing out of the GENX engine in favor of the newer GE9X. Acutec currently has an entire cell of machines devoted to making the fuel injection nozzles for the GENX engine. However, GE, since redesigning for the GE9X, has combined 20 parts in the fuel injection system (including the fuel injection nozzle that Acutec produces for the GENX) and begun producing this part additively (Conner et al., 2014). Currently, as Acutec does not yet have additive capabilities, this shift means a loss of business that we cannot hope to get back without AM, and it will likely not be the last such loss. Thus, while this part was a poor transition part, it cannot be said that AM is a bad investment for Acutec. Rather, all that can be said is that this part would not be a good fit for AM technology.

II. Recommendation to Acutec

It is my recommendation that Acutec continue to search for a suitable transition part, or simply take the leap of faith required to invest in this technology with the hope that the contracts will follow once the process is operational. If a transition part is to be found, it must certainly have a high profit-to-weight ratio in order to overcome the high material cost. Alternatively, it might be best to look into parts that are made from materials other than Inconel 625. Additionally, if Acutec wishes to see a sizeable reduction in scrap after introducing AM, it would be helpful to identify a part that has had repeated quality issues. One criterion that was used in determining the part for this study that should be maintained would be having a long term agreement. Due to the high investment cost of AM, it will be crucial to have the guarantee of continuing business in order to mitigate the risk and ensure a return on the investment. Additionally, in order to fully capitalize on the competitive advantage of differentiation of services it would be crucial to market this new technology in order to make customers aware of our new capability. While I do not believe that Acutec would benefit greatly from a large advertisement campaign as that would be expensive to reach our customers across the globe, one strategy that would be inexpensive and highly effective would be to promote the technology in the various shows and conventions that Acutec attends over the year. The Paris Air Show this summer, for instance, would be a phenomenal platform to reach new and existing customers this summer if enough progress towards adaption can be achieved. Additionally, Acutec could simply feature this new capability in the sales presentations that we give to several of our main customers each year. This strategy would reach our the key players in our target audience without wasting precious investment dollars that could be used for the actual adoption.

III. Possible Extension of Research

It is important to recognize that any research can be extended or improved. This report is certainly not an exception. The most obvious extension necessary in the future is duplicating this study for a part that is better suited to AM based off of the description given above. Perhaps the greatest extension of this research that could be done is to analyze AM after its adoption. Doing so would allow real comparison to be drawn between technologies using actual data rather than estimations and conjecture. Another extension that could be made would be to add variables and/or improve data collection so that the data that can be analyzed is more accurate. On this note, given the complex nature of precision manufacturing, it would be naïve to think that it is possible to quantify all the possible variables that affect scrap and on-time delivery. However, by adding in variables, such as queue time for each operation (for on-time delivery) and tolerance and feature data that would account for part complexity (for scrap) it is likely that one could vastly improve the regression models.

IV. Conclusion

The profound positive impact that Acutec has had on the Meadville community and its employee's welfare in general cannot be understated. Thus, it is crucial that Acutec continue to search for new opportunities to grow so that more of the Meadville community can share in their prosperity. While this study failed to prove that AM is suitable for the chosen part, I maintain that the technology will be fundamental for the aerospace industry and that Acutec would greatly benefit from its successful adoption as a first-mover.

Appendix A: Summary Statistics

Variable	Mean	Standard Deviation	Min.	Max.
Date Changes	2.66	2.38	0.00	14.00
Quantity Changes	1.39	1.64	0.00	9.00
On-Time Delivery	0.33	0.47	0.00	1.00
Make Quantity	15.55	4.40	3.00	36.00
Scrap	0.27	0.69	0.00	4.00
Total Hours	75.31	28.06	17.48	212.94
Operator Experience	4.70	1.78	0.47	11.84
Time Available - Total Req'd Lead	58.51	85.53	-181.50	462.50
Experience Hours	360.48	209.42	28.81	1396.69
Job 1	0.17	0.38	0.00	1.00
Job 2	0.06	0.24	0.00	1.00
Job 3	0.17	0.38	0.00	1.00
Job 4	0.33	0.47	0.00	1.00
Job 5	0.13	0.34	0.00	1.00
Job 6	0.07	0.26	0.00	1.00
Job 7	0.05	0.21	0.00	1.00
Job 8	0.03	0.17	0.00	1.00

Appendix B: Variable Correlation Matrix

Correlation Matrix	Date Changes	Quantity Changes	On-Time Delivery	Make Quantity	Scrap	Total Hours	Operator Experience	Time Available - Total Lead	Experience Hours
Date Changes	1.0000								
Quantity Changes	0.5954	1.0000							
On-Time Delivery	-0.0159	0.0798	1.0000						
Make Quantity	0.0328	0.1760	0.1181	1.0000					
Scrap	0.1442	0.0529	0.1413	0.1161	1.0000				
Total Hours	0.0420	0.1151	0.1439	0.6270	0.0193	1.0000			
Operator Experience	0.0127	0.0596	0.1253	0.0738	0.0521	0.1321	1.0000		
Time Available - Total Lead	0.6092	0.3421	-0.0058	-0.2545	0.0161	-0.1448	0.1238	1.0000	
Experience Hours	0.0356	0.1529	0.1415	0.4472	0.0631	0.7325	0.7344	-0.0194	1.0000

Appendix C: Variable Inflation Factors

Variable	VIF
Experience Hours	22.11
Total Hours	11.87
Operator Experience	10.42
Date Changes	3.18
Job 4	2.64
Time Available - Total Req'd Lead	2.42
Make Quantity	2.33
Job 3	2.08
Job 5	1.97
Quantity Changes	1.85
Job 8	1.66
Job 6	1.56
Build ID	1.50
Job 7	1.45
Job 2	1.45
Scrap	1.11
Mean VIF	4.35

Appendix D: List of Competitors

1. H&H Aero http://hhaero.com/
2. Duke Manufacturing http://duke-mfg.com/
3. MSI http://www.machspec.com/
4. Golden Dragon Aerospace https://www.b2match.eu/ninth-eu-china-cooperation-fair/participants/45
5. Noranco http://www.noranco.com/
6. RBC Bearings http://www.rbcbearings.com/
7. Pointe Precision http://pointeprecision.com/
8. Oberg Industries http://www.oberg.com/
9. Alard Machine http://www.alardmachine.com/
10. Tect http://www.tectcorp.com/
11. S&H Machine http://shmachine.com/
12. B&B Manufacturing http://www.bbmfg.com/
13. Fairview Machine Company http://fairviewmachine.us/
14. Mistequay Group http://www.mistequaygroup.com/
15. Spider Company http://www.spidercompany.com/
16. Southern Manufacturing Technologies, Inc http://www.smt-tampa.com/
17. SKS Machine http://www.sksmachine.com/
18. Mallory Highly Complex Machined Parts http://www.malcams.com/index.html
19. Dow Hydraulics http://www.dowhydraulics.com/
20. RS Precision http://rsprecision.com/
21. Aerostar Aerospace http://aerostaraerospace.com/
22. Coronado Manufacturing http://coronadomfg.com/
23. Absolute Technologies http://www.absolutetechnologies.com/
24. Vescio Manufacturing International http://vesciomfg.com/
25. Precision Aerospace Corp https://www.precision-aerospace.com/
26. Magnus Precision Manufacturing http://magnusprecision.com/
27. Thorund Inc https://www.thorudinc.com/

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This work was completed by Gregory Daniel Bras, student of economics at Allegheny College in the class of 2017. Gregory is a Brother of Phi Kappa Psi and has been a member of the Allegheny Men's Rugby team for all four years at Allegheny. In his time at Allegheny, Greg could often be found enjoying sunny days on various rooftops, the Phi Psi lawn, or frequenting his favorite watering hole: The Penny Bar. After graduation, Greg plans on accepting a position as an Account Manager at Acutec where he will work with the engineering department to facilitate the adoption of additive manufacturing. In addition to working full time at Acutec, Greg plans on attending Penn State Behrend to receive his Master's in Business.

