The impact of the Pandemic-Induced Semiconductor Shortage on Working Capital Management of U.S Industries

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Dissertation written under the supervision of professor Geraldo Manuel Alves Cerqueiro

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Abstract

This paper investigates the impacts of the pandemic-induced chip shortage on working capital management of U.S. industries. The methodology involves measuring the sensitivity of publicly traded firms' returns to the semiconductor industry through a 5-factor Fama and French model including the PHLX Semiconductor Index. Through obtained β values, industries were categorized into treated and control groups based on the average sensitivity of their respective firms to the chip industry. Aiming to isolate the effect of the semiconductor shortage, this study makes use of a Generalized Synthetic Control Method with Two-way Fixed Effects and Bootstrapping procedures. Working Capital Management is assessed through Days Sales Outstanding, Days Inventory Outstanding, Days Payable Outstanding, and Cash Conversion Cycle. Additionally, the respective turnover metrics of these items are also examined. Evidence is found supporting a decrease in DSO and an increase in Recevable Turnover, indicating a shift towards profitability and liquidity by impacted firms. A strategic increase in inventory can also be inferred from the obtained results, amidst the uncertain length of the shortage and increased consumer demand from 2021 onward. Firm size is to some extent relevant for the definition of credit policies of larger firms and shows evidence of expansive inventory capacity for SMEs. Furthermore, increased Cash Conversion Cycles can be observed for middle-sized firms after the shock. The findings contribute to the literature studying working capital management, the impact of the pandemic, and the consequent supply chain constraints on financial management.

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Resumo

Este artigo investiga os impactos da escassez de chips induzida pela pandemia na gestão do capital de giro das indústrias americanas. A metodologia envolve a medição da sensibilidade dos retornos das empresas cotadas na bolsa à indústria de semicondutores através de um modelo de Fama e French de 5 factores, incluindo o indice PHLX. Pelos valores β obtidos, os sectores foram classificados em grupos tratados e de controlo. Para isolar o efeito da escassez de semicondutores, este estudo utiliza um método de controlo sintético generalizado com efeitos fixos bidireccionais. A gestão do fundo de maneio é avaliada através dos dias de vendas pendentes, dias de inventário pendentes, dias de pagamentos pendentes e ciclo de conversão de caixa. Além disso, são também examinadas as respectivas métricas de rotação destes itens. São encontradas evidências que apoiam uma diminuição do DSO e um aumento da rotação das contas a receber, indicando uma mudança no sentido da rentabilidade e da liquidez por parte das empresas afectadas. Os resultados obtidos permitem inferir um aumento estratégico do inventário. A dimensão da empresa é relevante para a definição das políticas de crédito para empresas grandes e mostra indícios de uma capacidade de inventário alargada para as PME. Além disso, observa-se um aumento dos Ciclos de Conversão de Caixa para as empresas de média dimensão após o choque. Os resultados contribuem para a literatura que estuda a gestão do capital de giro, o impacto da pandemia e as consequentes restrições da cadeia de abastecimento na gestão financeira.

Título: O impacto da escassez de semicondutores induzida pela pandemia na gestão do fundo de maneio das empresas americanas

Nome: Johannes Borges Kuckertz

Palavras-Chave: Gestão do capital de giro, Pandemia, Escassez de semicondutores, Método de controlo sintético generalizado, EUA, Perturbação da cadeia de abastecimento

List of Abbreviations

WCM	Working Capital Management
DSO	Days Sales Outstanding
DIO	Days Inventory Outstanding
DPO	Days Payable Outstanding
CCC	Cash Conversion Cycle
RT	Receivable Turnover
IT	Inventory Turnover
PT	Payable Turnover
SCM	Synthetic Control Method
GSCM	Generalized Synthetic Control Method
GFC	Global Financial Crisis
ROA	Return on Assets

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1 Introduction

The outbreak of the COVID-19 pandemic, beginning at the end of 2019, affected the stability of nations and the everyday lives of many, introducing for an extended period the concept of a "New Normal", with lockdowns and severe restrictions to social contact (Jamaludin et al. (2020)). The crisis caused changes to work dynamics, consumer behavior, disruptions in manufacturing, and unexpected logistical challenges, ultimately having a profound impact on economies and financial markets across the globe (Sansa (2022)).

The changes brought by the pandemic also disturbed global supply chains, and one of the highest impacts was suffered in the supply of chips (Helper and Soltas (2021)). Mobile phones, computers, CNC machines, and most technological devices cannot be produced without semiconductors. It is possible to argue, that the more reliant an industry is on chips, the more severe the impact. Not only was the health crisis enough to induce the shortage, but it was even further aggravated by trade restrictions between the U.S. and China. These forces greatly disturbed the balance of supply and demand between upstream chip suppliers and downstream manufacturers in chip-intense industries. From the second quarter of 2020 onward, many manufacturers had no choice but to close parts of production lines affected by the shortage. The situation was aggravated by the surge in demand for chip-based products facilitating work from home, which require a different production process than those used for manufacturing (Bauer et al. (2020),Burkacky et al. (2020)).

In the U.S., this crisis put working capital management to the test. A proper working capital policy holds paramount importance as it guarantees short-term liquidity and cash flow, while also influencing long-term business sustainability (Richards and Laughlin (1980)). Managers were required to address challenges introduced by a crisis that had never been dealt with before, with lead times affected and fluctuations in the availability of key components (Demiraj et al. (2022)). It was necessary to think fast and construct strategies to address these issues in the short-term, but also consider the longer term to construct resilient policies that shield companies from such unexpected impact in the future (Frieske and Stieler (2022)).

All the problems involving the uncertainty brought by the pandemic and its influence on the chip shortage, raise a variety of questions. How did different industries react to the shortage? How was working capital impacted? Were the management team of firms ready to introduce policies to navigate the unprecedented crisis? And even more pressing, to what extent were the effects caused by the pandemic, and what portion can be attributed specifically to the semiconductor shortage?

To find out, this paper will assess the impact of the semiconductor shortage on U.S. industries. Following a 5-factor model approach, the sensitivity of different industries to fluctuations in the chip industry will be determined. This sensitivity will be used to categorize firms in a comparative study into treatment and control groups. The obtained control sample will then be used to create a counterfactual group to the treated firms, using a Generalized Synthetic Control Method. The objective of this approach is to isolate the effects of the semiconductor shortage on working capital items. To observe the impact across multiple periods after the shock introduced in the second quarter of 2020, the methodology will also make use of Two-way fixed effects, controlling for time- and firm-level variables.

This paper finds evidence that affected industries pursue liquidity-enhancing measures by decreasing the collection period of receivables. They also purposefully increase inventories in anticipation of demand increases and the uncertainty generated by the shortage, at the expense of the Inventory Turnover ratios ((Lind et al. (2012)), Helper and Soltas (2021)). This paper also finds that firm size is significant for larger firms in improving turnover of receivables and for small to medium-sized firms in shaping expansive inventory management practices. Furthermore, it finds that middle-sized firms suffer from an increase in CCC, which may originate from an attempt to maintain increases in sales amidst the pandemic scenario (Zimon and Tarighi (2021)). Counter-intuitively, few significant findings are made regarding the management of accounts payable, which was expected to be negotiated in a way to increase cash levels.

The motivation behind this research paper is to contribute to the literature on working capital management and add to the papers studying the impacts of COVID-19 and shortages on financial management. There are yet to be more studies published in this field, and as more data is retrieved from the post-pandemic period, a better assessment can be made of its implications. Additionally, the findings of this paper may provide valuable insights to CFOs, financial managers, and consultants in firms with high sensitivity to the semiconductor industry - seeking to construct policies that shield them from future unprecedented shortages.

The following Section 2 provides an overview of existing literature on supply chains and the chip shortage. It also elaborates on the literature on working capital management amidst the pandemic. Literature supporting the methodology is also reviewed. Lastly, the segment displays the hypotheses constructed based on the reviewed literature. Section 3 describes the data and its preparation. Section 4 covers the approach to establish the treatment and control group, as well as breaking down the working capital items that will be analyzed. This section also gives a detailed explanation of the regression setup, elaborating on the construction of the Generalized Synthetic Control Method. It also breaks down the different splits of the dataset that will be used for the regressions. Section 5 addresses and discusses the results, as well as robustness tests conducted. Lastly, Section 6 concludes the paper.

2 Literature Review & Hypotheses

This chapter aims to provide an overview and discuss relevant literature regarding working capital policy, the impact of COVID-19 on the semiconductor industry, as well as its impact on working capital management across different countries and industries. Additionally, it will also provide an overview of literature relevant to the methodology pursued in this paper.

2.1 Supply Chain & Semiconductor Crisis

Through the emergence of the coronavirus, an unprecedented health crisis triggered global disruption. This gave emergence to a crisis in the semiconductor field, as a consequence of the disruptions to supply chains and global trade networks. Semiconductors can be found in almost all electronic devices and a variety of machinery. The crisis brought a shift in demand through the introduction of remote work, but also the closure of factories and constraints to many businesses that were not ready for the disruption. With that, the semiconductor industry was pushed to its limits resulting in costly impacts on their operations (Burkacky et al. (2020)). The White House addressed the constraints through an official article published, highlighting the impact of the pandemic on the automotive industry which was raised through an underestimation of the post-pandemic demand and disrupted global supply chain. After the peak of the pandemic, a growth in jobs was recorded as well as an increase in consumer spending on vehicles and homes. Impacted industries were thus unable to meet the rising demand through the difficulties introduced by the pandemic and the semiconductor shortage. The Biden-Harris Administration thus created a Supply Chain Disruption Task Force that emphasized semiconductor manufacturing intending to bolster domestic production (Helper and Soltas (2021)).

In light of the challenges within the semiconductor supply chain shortage that impacted the U.S., Simchi-Levi et al. (2022) constructed a model to test the strength of the chip supply chain through disruptions and its effects on the value chain. They obtained results showing that a 10-day disruption can lead to a nearly 12-month impact. They argue that the supply chain vulnerability lies to some extent in its geographic concentration in the regions of Taiwan, South Korea, and China. While the U.S. has implemented legislation to bolster domestic production of semiconductors through the CHIPS and Science Act, the authors argue that moving production to the U.S. is not enough. Instead, having dual or multiple sources is crucial for the security of the supply chain, meaning that in case one segment of production fails, the dependent company still receives the product.

Frieske and Stieler (2022) investigates the impact of the COVID-19-induced semiconductor shortage on the German automotive industry. To obtain their results the authors conducted a market analysis across the OEM, Tier 1, Tier 2, and Tier 3 stages of the supply chain and conducted expert interviews to develop strategies for the short-term and long-term that will increase the resilience of the supply chain in the future. Frieske and Stieler (2022) find that the European and German automotive industries are heavily impacted by the semiconductor industry production capacities, yet have little power to influence the stability of the supply chain, potentially because of geographical concentration (Simchi-Levi et al. (2022)). They also reveal that new approaches for purchasing and adapted logistic strategies are being developed by the automotive industry to be more resistant to crises in the long term. This would include a change in operations, reflected by increased warehousing and dual sourcing, as also recommended by Simchi-Levi et al. (2022). They also suggest that the network of critical components is being strengthened by OEMs and suppliers and that changes are implemented on an incremental basis rather than providing a core change in strategy by OEMs.

Also studying the automotive industry, Ramani et al. (2022) constructed a mathematical model studying the relationship of chip suppliers and automotive manufacturing companies under COVID-19, obtaining the following implications: production should be prioritized for cars that provide better margins, stockpiling and expanding capacity help control the impact of shortages and firms should seek new sourcing strategies - like near-shoring or direct sourcing. They also point out the importance of better information coordination between the parties to address disruptions more promptly.

A study conducted by McKinsey (Bauer et al. (2020)) provides a directive on how semiconductor demand should shift in the short and mid-term. The article develops a framework to assist companies in adapting to changes in demand and additional uncertainties generated by the pandemic. The framework consists of five stages: resolve, addressing the immediate challenges introduced by COVID-19, resilience, dealing with short-term cash management challenges, return, which encompasses a detailed plan to return businesses to be able to scale faster through new production and demand planning, and reformulated sourcing and pricing strategies, reimagination, involving understanding macroeconomic developments' impact on the semiconductor industry dynamics. This includes understanding government stimulation packages and assessing shifts in sourcing, and reform, which requires management to monitor the regulatory and competitive landscape. Furthermore, a second McKinsey directive (Burkacky et al. (2020)) points out how the semiconductor industry can emerge stronger in a post-pandemic era, involving understanding how COVID-19 changed customer behavior and operations within the industry.

2.2 Working Capital Management and the Pandemic

This event study seeks to contribute to the literature on working capital management and the impact it suffered through COVID-19 across different industries. Managing working capital is crucial for effective cash flow management and profitability. It exists through the management of time between purchasing resources for production, selling them, and receiving the cash from its sales (Richards and Laughlin (1980)). Effective management of such can help improve operations and finances. While it addresses short-term obligations and liquidity, it also influences a business' longer-term strategy, by enabling higher cash positions. These proceeds can be used to fund research and development initiatives, as well as capital expenditures and payment of long-term debt (Lazaridis and Tryfonidis (2006)). Poor working capital management can lead to short-term bottlenecks rendering a firm unable to deliver products or meet short-term payments (Shin and Soenen (1998)). Efficient working capital management enables profitability by reducing inventory holding costs and converting sales to cash faster (Deloof (2003), Gill et al. (2010), Ren et al. (2019)). In this study, the focus is given to metrics that originate from the working capital items: accounts receivables, inventories, and accounts payable. While working capital is defined as the difference between current assets and current liabilities, the focus in this paper is given to non-cash current assets and non-interest-bearing current liabilities. The rationale for this is the involvement of these items in the operation cycle of a firm. These figures can be used to construct the metrics: DSO, DIO and DPO. Moreover, these metrics can be used to construct the Cash Conversion Cycle, which expresses the timeline a firm needs to receive cash from its sales, incur expenses from building and storing inventory, and pay suppliers (Richards and Laughlin (1980). Figure 1 expresses the relationship between all periods to construct the Cash Conversion Cycle. Furthermore, turnover ratios will also be assessed for the three balance sheet items to measure the efficiency in the collection of cash and inventory management, as well as how timely businesses pay suppliers (Deloof (2003)).

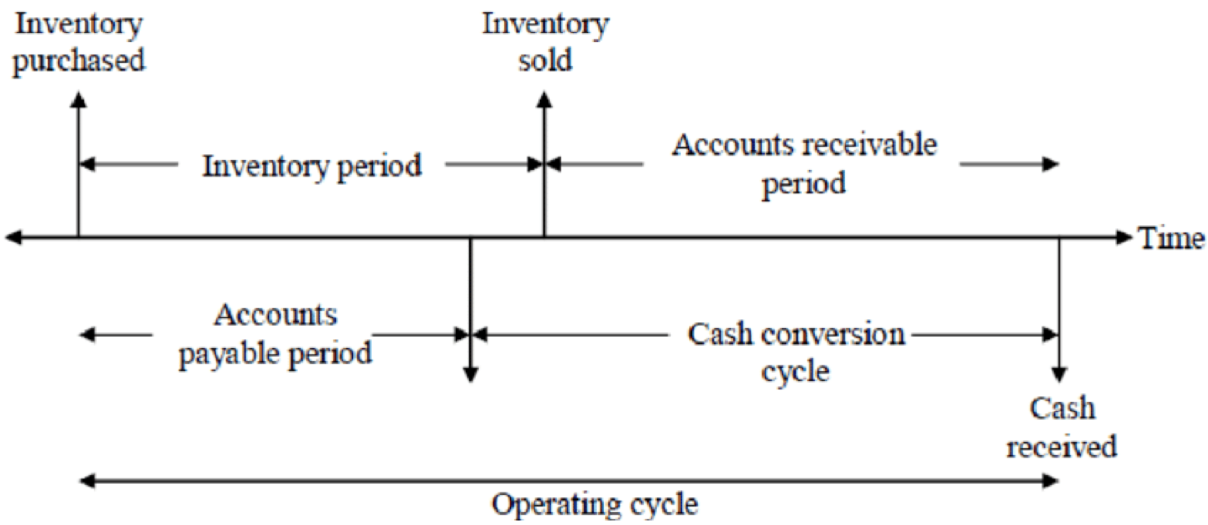

Figure 1: Cash Conversion Cycle (*Source: Richards and Laughlin (1980)*)

Firm-specific components can influence working capital items and the policies derived to manage them. In this study, they will be used to construct the counterfactual group for the treatment group through the GSCM. Lazaridis and Tryfonidis (2006) suggests that firms with higher leverage have lower levels of working capital and, thus need external financing to maintain their operations. Baños-Caballero et al. (2014) highlights how revenue growth can influence credit grants for trade and investments in inventory. Additionally, Chiou et al. (2006) also confirms sales growth as a determinant of working capital policies. Moreover, Baños-Caballero et al. (2014), as well as Moussawi et al. (2006) and Nazir et al. (2007) find that determinants of working capital policies are also dependent on firm size, with larger firms having a better ability to negotiate terms with clients and suppliers. Working Capital policies also differ greatly among different industries, being either of an aggressive or conservative nature (Nazir et al. (2007)). Hawawini et al. (1986) concludes a statistically significant industry effect on the working capital management directive of firms. They also show that this is due to firms embracing industry standards when establishing their approach to WCM.

Demiraj et al. (2022) assesses the importance of Working Capital Management (WCM) and how it influences profitability. They give the spotlight to the European automotive industry, studying the impact on profitability between pre-pandemic and pandemic periods. The authors make use of a panel regression approach to understand the impact of WCM components on Return on Assets (ROA). Their findings show that increases in the independent variables negatively impact ROA, with the effects of DSO and DIO overwhelming the effect of days payable outstanding. Zimon and Tarighi (2021) study the impact of COVID-19 on working capital management policies of SMEs in Poland. When assessing the turnover metrics of receivables, liabilities, and inventory, they find no significant results. Nevertheless, the control variables used are significant for all firms categorized as relatively large, showing that they increased receivables turnover due to a lack of problems to absorb customers, and had a higher liability turnover, indicating that they preferred to pay their debts with longer maturities. Also, they displayed a higher inventory turnover, possibly due to conservative working capital policies and increased inventory levels. They also find that a longer CCC strategy is associated with improved sales efficiency.

While outside the COVID-19 scenario, Lind et al. (2012) conducted a financial value chain analysis from 2006 to 2008 on WCM in the automotive industry. It found that improving its own CCC at the expense of value chain partners does not make a firm more competitive. Additionally, it found that CCC had little change in the observed period - but its determinants, DSO and DPO suffered from significant changes. It also observed an improvement in DSO in each stage of the automotive industry's supply chain. Their findings are relevant to this paper, as they also study how WCM is impacted in a crisis scenario.

There is also a large amount of studies of working capital management on profitability outside the COVID-19 pandemic scenario, that nevertheless provide relevancy to this study. Shin and Soenen (1998) finds a negative relationship between trade cycles and profitability for U.S. firms, indicating that controlling it and keeping it at lower levels is beneficial for profit and shareholder value. Based on this study, Deloof (2003) studies the relationship between working capital management and profitability for Belgian firms, assessing a sample of 1009 large firms in Belgium from 1992 to 1996. The author finds that reducing the number of days for accounts receivables and inventory increases profitability and that firms with lesser profitability make use of longer periods to pay their bills. Lazaridis and Tryfonidis (2006) extends the study of this relationship to Greece, by assessing firms listed on the Athens Stock Exchange, finding that all three components of CCC need to be kept at optimal levels to generate improved profitability. Gill et al. (2010) researched the same relationship in the United States, finding results that support the finding of Lazaridis and Tryfonidis (2006). Similarly, Altaf and Shah (2018) studied the impact of working capital management on profitability in Indian companies, finding an inverted U-shaped relationship between them. These results reinforce that companies must obtain an optimal level of working capital to balance their costs and benefits. Nazir et al. (2007) observe 208 listed companies in the Pakistani exchange KSE between 1998 and 2005, also finding a negative relationship between working capital policies and profitability. Similarly to Demiraj et al. (2022), García-Teruel and Martínez-Solano (2007) study the impact of WCM on SMEs in Spain and find that value can be created by reducing inventory days outstanding. Furthermore, decreasing the cash conversion cycle is also shown to have positive effects on the profitability of the sampled firms. Ren et al. (2019) study the relationship between CCC and profitability and China, and also finds consistent findings with the the aforementioned literature.

2.3 Factor Model Approach

To determine the sensitivity of industry groups to a semiconductor index, and to categorize them for the comparative event study, the approach in Beck et al. (2022) will be followed. They study the risk profile and systemic risk of different banks based on their specialization under Basel II introduced capital requirements. Their approach is relevant to this study as it focuses on understanding the sector concentration of banks. To do so, they make use of a factor model studying sampled banks' stock prices and how they are influenced by long-term specialization and differentiation, systemic risk, and financial sector exposure through sector-specific indices. Similarly, this study will also provide a factor model approach by gauging the sensitivity of firm returns against a semiconductor index under the five Fama and French factors (Fama and French (2015)), capturing value, size profitability, and investment premiums, as well as GDP.

In the methodological approach (Section 4.3), the control group will be used to create a synthetic control group as described in the next segment (Section 2.4).

2.4 Synthetic Control Method

This study follows Abadie et al. (2010), Abadie (2021), and Xu (2017) by making use of a Synthetic Control Method approach. Developed by Abadie et al. (2010), this method is particularly useful when analyzing interventions with limited treatment units and non-comparable control units. Furthermore, it's advantageous in scenarios where the parallel trends assumption is violated. SCM constructs a counterfactual group by creating a weighted combination of potential controls, closely mirroring the pre-intervention characteristics of the treated unit. This method was also demonstrated to be more efficient than two-way fixed effects and DID estimators, especially in handling time-varying confounders. Xu (2017) builds on this approach by constructing a Generalized Synthetic Control Method, that relaxes the SCM by enabling it to include Two-way Fixed Effects, allowing for the assessment of multiple treated units at once through multiple periods. This will be relevant to this paper, by allowing the observation of the development of WCM after the introduction of the semiconductor shock.

2.5 Hypotheses

Based on the reviewed literature, the following hypotheses will be assessed through the methodology applied in the study. All are to be put as a consequence of the semiconductor shortage and relative to the control group.

H1: Chip-dependent firms decrease their collection of payments period and increase Receivable Turnover due to liquidity pressure.

This hypothesis aligns with Lazaridis and Tryfonidis (2006), Ren et al. (2019), Deloof (2003) which addressed that firms implement receivable policies that ensure liquidity and profitability.

H2: Inventory management of treated firms suffer from an increase in DIO and decrease in Inventory Turnover.

This hypothesis is aligned with Demiraj et al. (2022), which argues that increases in inventory days may reflect a strategic decision in anticipation of a constrained supply chain. This strategic stockpiling is also suggested by Ramani et al. (2022) and Frieske and Stieler (2022) when studying the automotive industry.

H3: Treated firms' DPO increases and Payable turnover decreases, as accounts payable are renegotiated with suppliers to enable more flexibility.

Frieske and Stieler (2022) find that one strategy from the automotive industry is to renegotiate payments with suppliers, to construct a disruption-proof working capital policy.

H4: Larger treated firms have more ease in implementing working capital policies that ensure liquidity and profitability than smaller firms

Baños-Caballero et al. (2014), Lazaridis and Tryfonidis (2006) and Zimon and Tarighi (2021) argue that larger firms have stronger negotiating power with suppliers, can be more flexible with receivables collection, and have stronger inventory management when compared to small firms.

Having conducted a review of relevant literature in the working capital management field as well as providing insights into the pandemic-induced semiconductor shortage, it was possible to establish the hypotheses that will be tested throughout the paper. The next segment will elaborate on the data gathered for the approach that will be followed in this event study, as well as introduce all data preparations that aim to make the methodology have the most suitable outcome.

3 Data

3.1 Data for Treatment and Control Group

To determine the treatment and control group of the event study (Section 4.1), data on the monthly return of all firms across the US are gathered from 2004 to 2022 from the CRSPR Database. The database was searched for all available firms. The returns will be benchmarked against the PHLX Semiconductor index, retrieved from Thomson Reuters Refinitiv. Figures from the index are also be gathered from 2004 to 2022. The reason for starting from 2004 is because this is first point of available data for the PHLX index. The monthly U.S. risk-free rate and Fama and French factors are obtained from the Kenneth R. French Data Library. Data has also been retrieved from these since 2004.

3.2 Accounting data

Accounting data was sourced from the Compustat - Capital IQ North America database under the “Fundamental Quarterly” segment. The database was searched for all available firms, being identified through their Global Company Key and dating from January 2017 to June 2023. The data also identifies the NAICS code for each company, which will be used to place the firms into the event study’s groups. For all firms, the following data was obtained for each quarter: Revenue, Costs of goods sold, Inventory, Accounts Receivables, Accounts Payable, Long-term Debt and Total Assets. These variables will be used to construct the metrics described in Section 4.2.

3.3 Data Preparation

3.3.1 Data Quality and Consistency Checks

First, data normalization was performed to ensure consistency with standard quarter-end dates. At the beginning of data preparations, the sample consists of 10531 firms. The next steps will involve improving the suitability of the data for analysis. For this, a series of rigorous data quality processes were employed:

To ensure completeness of data, firms with incomplete records from January 2017 to June 2023 were excluded. The goal is to have 3 years of full data available before the shock and full data for the periods afterward until the second quarter of 2023. Thus, it is required that each firm has 26 periods of observation. After this procedure, 6239 firms are available with full data. Next, anomalies in the dataset will be addressed, by excluding companies with zero or negative values in the following key financial metrics: Revenue, Cost of Goods Sold, Inventory, Accounts Receivables, Accounts Payables, Long-term Debt, and Total Assets. After this step, 2959 firms are left in the dataset with complete and anomaly-free data.

The Synthetic Control Method requires predictor variables to be determined to construct the control group. For this study, these are leverage, revenue growth, and firm size. After calculating these metrics and again accounting for NAs, Infinite Values, or anomalies through removal, 1831 firms remain in the main dataset. A breakdown of the NAICS codes observed in this study can be observed in Table 4.

3.3.2 Treatment and Control Group Identification

Firms were categorized into treatment and control groups through a factor model approach, with their industry's grouping being determined through their β-values relative to the PHLX Semiconductor Index. The categorization utilized NAICS codes, focusing on the first three digits. This approach was adopted because the first three digits of NAICS codes represent the industry sub-sector, allowing one to address each industry without sacrificing data sufficiency for each sub-sector. The goal of this approach is to maintain robustness in the analysis that will be conducted.

3.3.3 Data Indexing

All quarterly data was indexed from *1* to *26*, with *1* representing Q1 2017 and *26* Q2 2023. The purpose of this is to facilitate data handling in the GSCM approach used.

Having established data completeness and quality, it is now possible to shift to the framework of the event study. First, the treatment and control groups using the factor model approach will be defined in two different ways. The importance of these approaches is to best isolate sectors that should suffer from higher impact facing the shortage versus industries that should be less impacted. Subsequently, the working capital ratios used in the study will be formally defined, as well as the regression setup constructed under the GSCM approach.

4 Methodology

4.1 Treatment and Control Group

The impact of the semiconductor shortage will be measured for different NAICS groups at 3 digits, representing their respective industries. The goal is to determine whether a 3-digit NAICS group falls under the treatment or control group for this study. To do this, the following approach is used:
First, the monthly risk-free adjusted returns of all sampled firms from the CRSPR database will be calculated, followed by the risk-free adjusted monthly returns of the PHLX Semiconductor Index. These will be used within a 5-factor Fama and French model, where the goal is to assess how the returns of these firms are related to trends in the semiconductor industry. The market index will be the risk-adjusted PHLX Semiconductor Index return. Additionally, GDP growth will also be used as an additional factor in the regression. The coefficient of interest is β_{PHLX}, measuring the sensitivity of an individual company's risk-free adjusted returns against the index. This will be averaged based on each firm's NAICS code to create β_{NAICS}, representing a given industry's sensitivity to the semiconductors market. Equation 1 describes this approach.

$$\begin{aligned} r_{\mathrm{i}} - r_f = R_f + \beta_{\mathrm{PHLX}} \times (\mathrm{PHLX} - r_f) + \beta_{\mathrm{SMB}} \times \mathrm{SMB} + \beta_{\mathrm{HML}} \times \mathrm{HML} \\ + \beta_{\mathrm{RMW}} \times \mathrm{RMW} + \beta_{\mathrm{CMA}} \times \mathrm{CMA} + \beta_{\mathrm{GDP}} \times \mathrm{GDP} \end{aligned} \tag{1}$$

where r_{i} is firm's i monthly return, r_f is the risk-free rate and $PHLX$ is the monthly return of the semiconductor index. GDP is the quarterly U.S GDP growth rate. The next variables are all determined by Fama and French, where SMB is the size premium, HML is the value premium, RMW is the profitability premium, and CMA is the investment premium. The coefficient of interest β_{PHLX} yields the sensitivity of the firm's i returns to the index returns. The measured β_{NAICS} summary statistics obtained from grouping the key coefficient from Equation 1 per 3-digit NAICS code are described in Table 1.

Statistic	β_{NAICS}
Mean	0.49
Median	0.49
Minimum	-0.63
1st Quartile	0.37
4th Quartile	0.57
Maximum	1.60

Table 1: Summary Statistics of β_{NAICS}

Two approaches will be used to set up the treated and control groups based on Equation 1. Under the first definition, NAICS groups fall into the treatment group if their respective β_{NAICS}

is higher than the median of 0.49. The control group will therefore be defined as the NAICS groups with a β_{NAICS} below the median. The distribution of β's for the different NAICS groups can be seen in Figure 2.

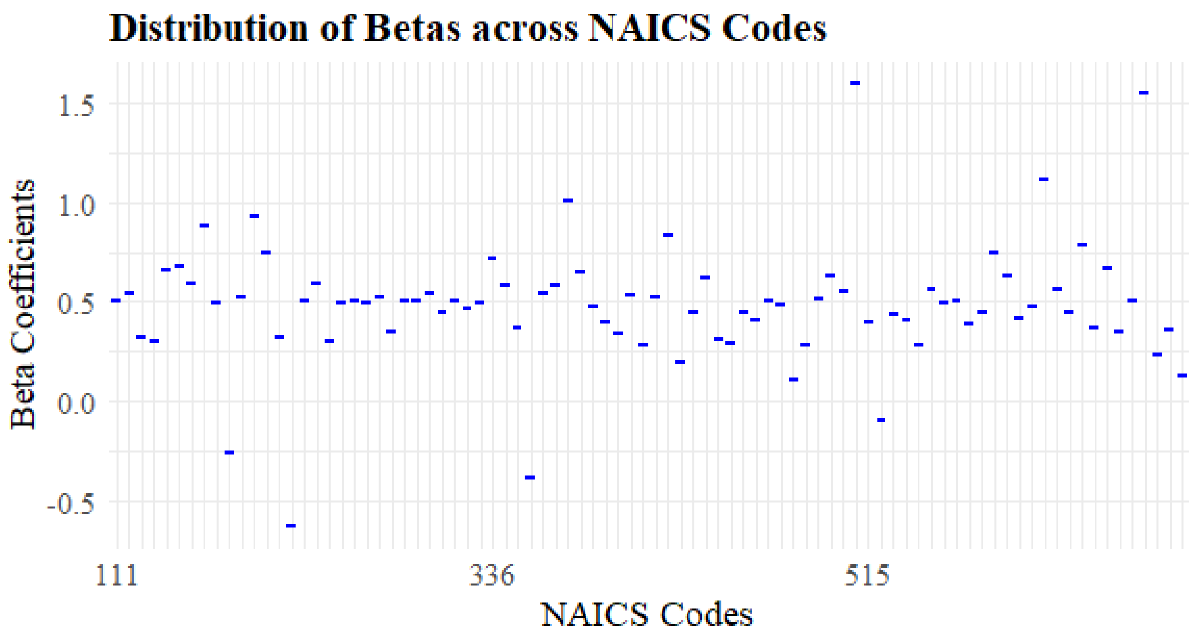

Figure 2: Distribution of β across NAICS codes

As can be observed from the figure, the distribution is concentrated near the median and average β_{NAICS} of 0.49. Thus, a second sample will be created, where the treatment group will be composed of industries with β_{NAICS} higher or equal to the 75th percentile (4th quartile) of 0.57 and the control group a lower or equal value to 0.37 (1st quartile). Table 5, in the Appendix, displays the 3-digit NAICS codes and their respective β_{NAICS}.

Having determined the classification for the two groups used in this study, the timing of the shock in this study will be determined.

Following the news of the semiconductor shortage and when it was recognized, the periods for pre-shortage and post-shortage will be defined as the second quarter of 2020. Since this study takes quarterly data from U.S. listed companies, a key detail is that earning reports are not released at the precise time of the quarter it is reporting. Instead, it is published several months later. For this reason, in this study, the shock will be recognized in the third quarter of 2020, where it's assumed that firms will already have recognized and reported the shock that fulfilled itself in the second quarter of 2020 and address it to shareholders along with measures that regulate working capital policies as well as other measures guided towards the pandemic.

Having determined the timing and groups that will be used in the regression setup in Section 4.3, the working capital ratios that will serve as dependent variables in the regressions will be presented and described in the next segment.

4.2 Working Capital Ratios

Proper working capital management is essential for firms to effectively manage assets and ensure liquidity and operational efficiency (Richards and Laughlin (1980), Deloof (2003), Demiraj et al. (2022)). The following metrics will be calculated to assess how working capital management practices change as a consequence of the pandemic for two built groups.

Turnover Ratios

$$\text{Inventory Turnover} = \frac{\text{COGS}}{\text{Inventory}} \tag{2}$$

where COGS = Cost of goods sold

$$\text{Receivables Turnover} = \frac{\text{Revenue}}{\text{Accounts Receivables}} \tag{3}$$

$$\text{Payable Turnover} = \frac{\text{COGS}}{\text{Accounts Payables}} \tag{4}$$

Turnover ratios measure how efficiently a company uses its working capital. Inventory turnover measures how often a firm's inventory is turned over relative to its COGS. A low ratio is expected to signal excess inventory or difficulty in turning inventory into sales. A high ratio may indicate strength in turning inventory into sales (Demiraj et al. (2022)). At the same time, a high ratio may reveal a company that possesses inefficient inventory stock. It is also relevant to address that a low inventory turnover may be advantageous during supply chain disruptions, as the one studied in this paper, should a company be increasing its inventory in anticipation of a shortage (Frieske and Stieler (2022), Lind et al. (2012)). Receivables turnover gauges how often a firm converts its receivables into cash. The higher the ratio, the more effective a company can do this conversion (Zimon and Tarighi (2021)). It also indicates the quality of its clients concerning their credit payments. A too high ratio, and a too conservative policy, may negatively impact a firm's business as customers may choose a competitor who offers credit with more flexibility. A low ratio, on the other hand, may indicate constrained credit policies with customers who do not meet their debt payments. It shows that a company may be struggling with converting its receivables into cash. Payable Turnover indicates how fast a company pays its suppliers. A high ratio implies that payments are made quickly and may be beneficial for the relationship with the supplier, as it reflects being a high-quality customer. A low turnover ratio, conversely, displays a longer time necessary to pay suppliers, implying cash flow difficulties and constraints in managing short-term liabilities. However, taking longer to pay a supplier, may also increase a firm's short-term cash position.

Working Capital Metrics

$$\text{Days Sales Outstanding (DSO)} = \frac{\text{Accounts Receivables}}{\text{Revenue}} \times 90 \tag{5}$$

$$\text{Days Inventory Outstanding (DIO)} = \frac{\text{Inventory}}{\text{COGS}} \times 90 \tag{6}$$

$$\text{Days Payables Outstanding (DPO)} = \frac{\text{Accounts Payables}}{\text{COGS}} \times 90 \tag{7}$$

$$\text{Cash Conversion Cycle (CCC)} = \text{DIO} + \text{DSO} - \text{DPO} \tag{8}$$

Working Capital metrics express in days how long it takes for a company to collect payments, sell its inventories, and pay suppliers. These are expressed through Equations (5) to (8). Equation (5) gauges how long it takes a given firm to collect its receivables. A lower value shows that it is quickly turning payments into cash. DIO is given by Equation (6) and shows how many days a company holds its inventory before selling it. DPO (Equation (7)) expresses how much time it takes for a firm to make its payments. A higher value implies that companies can delay their payments and use the cash to increase working capital or make short-term investments. Nevertheless, in some cases, they may indicate shortfalls and an inability to make payments. Since this paper observes quarterly data, the metrics are multiplied by 90 instead of 365, as done with annual data.
These metrics allow for the Cash Conversion Cycle (Figure 1), introduced by Richards and Laughlin (1980), to be calculated. It expresses the time it takes to convert resources into cash, considering the time from purchasing inventory, paying it, and receiving cash from the sale of inventory (Equation (8)).

The metrics presented in this section will be used to construct the regression models. Each item from Equations (2) to (8) will be assessed through a GSCM approach. Before pursuing this, data is processed one last time. The dataset is adjusted for anomalies in working capital metrics and ratios to ensure quality. Negative values of DSO, DPO, and DIO are removed from the dataset. These peculiarities originated through anomalies in reported Revenue and COGS figures, as well as abnormalities in accounts receivables, accounts payables, and inventory. Moreover, infinite values are removed for the metrics, including the Cash Conversion Cycle. Lastly, the 1st and 99th percentile for each of the Working Capital Metrics is calculated and finally also removed from the dataset. The goal of this procedure is once again to ensure high-quality data and account for any extreme values that could skew the results of the analysis, as well as worsen the quality of the counterfactual group that will be synthetically built in the next Section.

4.3 Regression Setup

This study employs the GSCM for an in-depth analysis of the semiconductor shortage's impact on U.S. industries' working capital management. Originating from the Synthetic Control Method (Abadie et al. (2010)), and extended through Xu (2017), it constructs a synthetic control group representing a counterfactual scenario, had the shock not happened. This allows for a more precise assessment of the shortage's impact. The counterfactual group is created by constructing best-matching control units based on a weighted combination of the control firms established in Section 4.1. The rationale of this approach is to provide a more flexible alternative to the Difference-in-Differences method, which contains the parallel trend assumption. Using an SCM, a counterfactual scenario is created that fulfills this requirement. Under the GSCM, Xu (2017) innovate the approach formerly introduced by Abadie et al. (2010) by combining it with linear fixed effects models. The benefits from this method encompass unique intercepts for each firm, in addition to time-specific coefficients. It can address circumstances in which the treatment is linked with unobserved time and firm-specific variations. Furthermore, it allows for the observation of multiple treated units and post-shock periods. Lastly, it includes a cross-validation process, which allows the selection of the best possible model in establishing the counterfactual group.

Having established an understanding of the approach used, the analysis unfolds in three distinct but interconnected approaches:

4.3.1 GSCM with the median-based sample

The treatment and control groups are based on their β_{NAICS} values, derived from a Factor Model approach against the PHLX Semiconductor Index described in Section 4.1. The median β_{NAICS} value will serve as the threshold, categorizing firms as treated if their industry's β_{NAICS} is above 0.49. Analogously, if the NAICS code of any firm fell below this figure, it will be addressed to the control group of firms that suffer less impact from the semiconductor sector. The counterfactual group will thus be built using these firms categorized in the control group.

4.3.2 GSCM with the quartile-bases sample

To further ensure a robust fragmentation between the control and treatment group, a more selective approach is pursued by only categorizing as treated firms in industries that have a β_{NAICS} higher than the 4th quartile values, and as control firms those firms in industries faring to equal or below the 1st quartile. All firms in industries in between are excluded. A key reason to pursue this can be identified from Figure 2. There is no high discrepancy between the β_{NAICS} values of different NAICS codes. By taking only the 1st and 4th quartiles, it might be possible to obtain a more robust figure and construct a higher-quality counterfactual group using the 1st quartile.

4.3.3 GSCM with Quintile-based firm-size subsetting

In the last GSCM approach, the dataset is split into quintiles based on firm size. This is measured as the average logarithm of a firm's revenue in the studied period. The goal is to assess the fourth hypothesis, that larger firms are more agile in anticipating and preparing for supply chain shortages, versus smaller firms that face constraints in their ability to address unexpected shocks. In doing so, this variable is removed as a predictor for the GSCM as it is controlled for through the separation of quintiles.

Throughout these approaches, the predictors in our Synthetic Control Method - firm size, revenue growth, and leverage ratio - play key roles in constructing the control group. The choice of these determinants follow Baños-Caballero et al. (2014), Chiou et al. (2006), Moussawi et al. (2006), and Deloof (2003). As these are key factors influencing working capital policies, it enables the construction of a control group with similar WCM characteristics to the treated firms in the pre-shock period, and the isolation of the effect of interest - the impact of the chip shortage.

Revenue growth is calculated as follows:

$$\frac{\text{Revenue}(t) - \text{Revenue}(t-1)}{\text{Revenue}(t-1)} \tag{9}$$

where t represents a given quarter.

Leverage Ratio is defined by the long-term debt to total assets ratio, and firm size is defined as follows:

$$\text{Firm Size} = \overline{\log(\text{Revenue})} \tag{10}$$

To compare turnover ratios between the treated and counterfactual group, the logarithmic transformation will be made for all ratios presented in Equations (2) to (4), to express results in percentage changes after the introduction of the shock.

The innovations in GSCM will be relevant to the methodology in allowing the analysis to capture variations across companies and the study's period. To do this, Two-way Fixed Effects at the firm- and time-level are introduced in the analysis, allowing for unobserved heterogeneity across these two dimensions to be controlled for. In other words, both company-specific and time-specific characteristics can be observed.

To increase the robustness of the obtained results, a Bootstrapping procedure will also be used. It will become especially useful as the sample size is reduced through the partitioning introduced in Section 4.3.2 and 4.3.3. Through multiple resampling of the data, in this study set to a thousand times, it captures variability and uncertainty in the dataset.

In addition to the predictors established, the following components are also added to obtain the best possible results:

A cross-validation procedure, whereby partitioning the dataset into training and validation sets, it's possible to select the best model, enhancing the robustness and generalizability of the findings. Parametric Inference, which offers a structured way to estimate the treatment effects and test hypotheses, ensuring reliability, as well as Parallel Computing, which speeds up the analysis given the complexity of data.

Using firm characteristics as determinants together with the aforementioned components to increase the robustness of results, it is expected that this framework enables the assessment of the semiconductor shortage's impact and the influence on constrained firms' management of working capital.

Having established the procedure for this study, determining the categorization of treatment and control group, the metrics of interest that compose working capital management, and the setup for the GSCM, the key findings will be presented and discussed in Section 5.

5 Results & Discussion

In this section, the obtained results from the descriptive statistics and GSCM approach will be discussed. First, the results for each working capital metric will be addressed for the pre- and post-treatment period across the median-based sample. Next, the results for the 1st and 4th β-based quartiles sample and lastly for the firm-size-based sample will be analyzed. Afterward, the results from the regression setup, which creates and uses the counterfactual group will be discussed.

Table 2 shows the descriptive statistics for the median-based sample, Table 6 and 7, the Appendix, show the descriptive figures for the sample split into quartiles and firm size, respectively. Descriptive statistics on Turnover metrics can be found in the Appendix on Tables 8 to 10. For the first sample, the treated group consists of 410 individual firms, and the control group, used in the regression setup to build the synthetic group consists of 552 firms. For the second sample, the 4th quartile consists of 172 firms and the 1st quartile of 224 companies.

5.1 Descriptive Statistics and Discussion

	Mean	Median	Max	Min
Days Inventory Outstanding				
Pre Q2 2020	102.07	84.02	658.12	3.15
Post Q2 2020	112.17	93.58	677.59	2.42
Days Sales Outstanding				
Pre Q2 2020	58.08	55.86	269.75	2.63
Post Q2 2020	59.26	56.09	338.52	3.08
Days Payables Outstanding				
Pre Q2 2020	49.13	45.47	197.62	5.92
Post Q2 2020	51.46	48.30	205.02	5.47
Cash Conversion Cycle				
Pre Q2 2020	111.02	94.00	637.21	7.23
Post Q2 2020	119.97	100.90	726.58	7.49

Table 2: Descriptive Working Capital Metrics - All Sample

Metrics assessing the collection of payments, DSO, show an average increase of one day for both mean and median values in DSO. These align with Receivable Turnover metrics, which also show almost no change for mean and median figures. The lack of change shows that while cash conversion of receivables may not have improved, it also did not worsen when the entire sample was perceived. It is expected that these metrics would either show increased efficiency, as a response to changes in policies with regards to sales made on credit or worsen, as impacts of overall supply chain constraints and the pandemic increase the difficulty of due payments for clients. The lack of change may support the argument made by Altaf and Shah (2018), that firms avoid deviating to either direction in working capital to not negatively influence profitability. Nevertheless, the maximum figures show a more substantial increase in payment collection days, increasing from 270 to 339 days, respectively, as well as decreased turnover efficiency, decreasing from a ratio of 34 to 29.

Inventory metrics expressed as DIO, show on average a 10-day increase from the pre-shock to the period of constrained supply chains (102 to 112 days), together with a 10-day increase in median value (84 to 94 days). The lack of increased efficiency in cash conversion of inventories is also captured in the descriptive statistics of Inventory Turnover, with both mean and median figures suffering slight reductions. This may follow the suggestion in Ramani et al. (2022) that one way for firms to circumvent the supply chain disruption is through stockpiling, anticipating longer periods of disrupted supply chains. Nevertheless, it could also reflect companies having difficulties in converting inventories to cash (Moussawi et al. (2006)).

Days Payable Outstanding also presents an increase in the average of 2 days, as well as a 2-day increase in the median. Turnover metrics for accounts payable suffer only from slight changes. In this case, these increases allow for firms to increase their cash positions by having more days to make due payments, thus also increasing the efficiency through payable turnover metrics. While the results do not present sizeable changes, they may also reflect a strategy to increase a firm's cash position during constrained periods. However, this may negatively impact profitability (Deloof (2003)), and also worsen relationships with suppliers (Ren et al. (2019), Lind et al. (2012)).

Finally, the CCC, which gauges the overall efficiency of working capital policies, displayed an increase in the mean from 111 to 120 days, with an increase in the median from 94 to 100 days. This increase indicates a general slowdown in the operational cycle of firms. Through the descriptive statistics, it's suggested that this is driven by extended DIO, as there is little observed change in DSO and DPO. While the minimum values are kept at similar levels, the increase of 90 days in the maximum values expresses that firm or industry-specific characteristics may influence the operational efficiency of firms. If such an effect persists through the approach from the regression setup, it may be the cause of concern, as shown by Shin and Soenen (1998). By studying two of the largest U.S. retailers at the time, they revealed that a 21-day difference in CCC between Walmart and Kmart inflicted a $198 million yearly financing expense to the latter. Nevertheless, it may also be a general pandemic effect in inventories suffered by firms across all industries in the United States.

The observed shifts in working capital metrics post-Q2 2020 reflect the broad impact of the supply chain disruption and the pandemic on operational efficiency. From the descriptive statistics for the overall sample, DIO seems to be the biggest driver of the increase in the CCC. Moreover, it is important to be cautious in concluding a worsening of operational efficiency, because the increased DIO may reflect a strategic decision. The regression approach will attempt to separate the effects, possibly mostly attributable to the pandemic - to the semiconductor shortage.

When shifting towards the descriptive statistics from the overall sample, where groups are segmented by the median value obtained from the factor model approach, to the 1st and 4th quartile-based sample (Table 6), the results mostly reflect those obtained in the greater sample. Mean and median values for DSO do not show high levels of difference. Similarly, trends in DIO are also mirrored in this subset, reinforcing the suggestion that either these figures increased due to purposefully increases in inventory, anticipating further shortages and supply chain disruptions (Frieske and Stieler (2022)), or difficulty for businesses to convert inventories into cash. The patterns in DPO are also consistent with the overall sample as well as patterns in the CCC. Similar to all metrics expressed in days, turnover metrics are also consistent with the median-based sample across all ratios. This leads to a similar conclusion to the one made in analyzing the entire dataset.

The descriptive statistics of working capital metrics across firm size quintiles provide a nuanced view of the impact of supply chain disruptions on different sizes of firms in the industry. The quintile-based approach, categorizing companies from Q1 (smallest) to Q5 (largest), offers an understanding of how firm size influences a company's financial health and resilience during the periods before and after the pandemic.

For DIO, there is a clear pattern observed where smaller firms (Q1 and Q2) had higher inventory conversion days compared to larger firms (Q4 and Q5), both before and after the second quarter of 2020. This suggests that smaller firms may have struggled more with inventory management or experienced longer inventory holding periods due to the scale of their business. It also may reflect the firm-specific effects of smaller firms. The increase in DIO post-Q2 2020 across all quintiles could indicate the widespread impact of the pandemic, causing inventory accumulation due to production delays and supply chain disruptions. These statistics also do not support findings by Moussawi et al. (2006), which observes that firm size negatively impacts WCM. As with the results from the two former samples, DSO remains relatively stable across all quintiles, with a slight increase post-Q2 2020. This consistency suggests a uniform impact of the pandemic and its induced disruptions across firms of different sizes in terms of receivables collection periods. It also indicates that the market conditions did not disproportionately impact the receivables collection efficiency of firms based on their size. Furthermore, larger firms (Q5) had a higher DPO compared to relatively smaller firms (Q1 to Q4), with only the smallest sampled firms having decreased DPO in the post-shock period. This could potentially reflect greater negotiation power or different credit terms with suppliers for larger and established businesses, as well as increased risk aversion from suppliers to smaller companies after introducing supply chain constraints. Post-Q2 2020, the increase in DPO for larger firms could suggest strategic extensions in accounts payable to conserve cash amidst the semiconductor shortage. These observations, while beneficial for cash positions, do not necessarily reflect a profitable strategy (Deloof (2003), Lind et al. (2012)).

Consistent with DIO and DPO observations, the CCC was higher for smaller firms pre-Q2 2020 and increased across all quintiles post-Q2 2020. This indicates that smaller firms face longer cycles in converting their resources into cash flows, which could have originated from the pandemic-induced overall supply chain constraints but were also exacerbated by the consequential semiconductor shortage.

Comparing these results with the median-sample and quartile-based analyses, it becomes evident that firm size plays a significant role in how companies weather challenges from the pandemic. While all firms experienced some degree of impact, the extent of this impact varies with firm size. Smaller firms generally faced longer inventory days and CCC, potentially highlighting their vulnerability to supply chain disruptions and market fluctuations. Conversely, larger firms, while also affected, displayed greater resilience possibly due to better resource allocation, stronger supplier relationships, or more robust financial structures. This differential impact shows the importance of careful consideration from management in constructing strategies for managing working capital, especially during industry-wide crises.

Having concluded the analysis of the descriptive results, a good foundation to grasp the averages of working capital metrics that reflect the pre-shock period to the period after the start of the pandemic is laid. The results highlight that DIO had the highest increase. This could be attributable to strategic reasons, and smaller firms bear the burden of facing longer inventory days and CCC. Through the GSCM approach presented in the next segment, the goal is to assess first, whether these changes are also reflected in the treated and counterfactual groups, and if they are caused by the semiconductor shortage. Furthermore, an additional goal is to confirm whether firm size impacts the changes in working capital policies introduced in the post-treatment period.

5.2 Methodology Results and Discussion

Table 3 displays the results from the Generalized Synthetic Control Method for the median-based sample, where firms considered as sensitive to the semiconductor shortage are classified as having an above median β_{NAICS} value, meaning they are more sensitive to trends in the semiconductor industry. It also displays results for the quartile-based sample, where treated firms are equal to or higher than the 4th quartile of β_{NAICS}. The counterfactual groups of the two samples are, respectively, based on firms with a below-median β_{NAICS} value and firms with β_{NAICS} below or lower than the 1st quartile value. The results from the first sample are displayed in the first column, while the second column displays the quartile-split results. The Appendix displays the detailed Two-Way Fixed Effects results showing the development and the coefficients for each period in Tables 11 and 12, with the Figures 3 and 4 displaying the panels for each metric analyzed under the two established samples. The treated group is represented by the black colored line, labeled *"Treated Average"*, and the counterfactual is represented by the blue dashed line, labeled *"Estimated Y(0) Average"*.

	All Sample		1st & 4th Quartile	
	ATT	S.E.	ATT	S.E.
Days Sales Outstanding (DSO)	-4.21** (0.01696)	1.763	-6.843*** (0.005814)	2.481
Days Inventory Outstanding (DIO)	-14.03 (0.1078)	8.101	-5.924 (0.6195)	11.93
Days Payables Outstanding (DPO)	0.1653 (0.9105)	1.471	3.218 (0.6334)	6.747
Cash Conversion Cycle (CCC)	-1.09 (0.8052)	4.421	-7.175 (0.582)	13.04
Receivables Turnover	0.04188** (0.04944)	0.02131	0.07678** (0.01274)	0.03082
Inventory Turnover	-0.1923** (0.04344)	0.09522	-0.23* (0.5957)	0.1221
Payables Turnover	0.-0.0023 (0.921)	0.0236	0.0399 (0.222)	0.03263

10% significance level (*); 5% significance level (**); 1% significance level (***)
p-Values in Parenthesis

Table 3: GSCM - Median and quartile-based sample results

It is possible to recognize a statistically significant reduction in DSO for both samples created through the GSCM. For the post-shock period in which the semiconductor shortage was officially recognized, DSO is on average reduced by 4.21 days when compared to the control group for the median-based sample, at a 5% significance level, and by 6.84 in comparison to the counterfactual group in the quartile-based sample at a 1% significance level. This supports the first hypothesis, establishing that treated firms reduce their collection period in response to the supply chain disruption. These are also aligned with the financial crisis period analysis conducted by Lind et al. (2012), which finds a decrease in DSO throughout almost the entire value chain of the automotive industry. These results reinforce that the chip shortage may have introduced changes to the working capital of treated firms (Ramani et al. (2022)). The reduction presented in this metric possibly reflects that firms are attempting to increase liquidity by being quicker in converting outstanding receivables into cash.

The findings for the Receivable Turnover metrics of both samples support this, displaying an increase of 4.2% and 7.7% (both significant at 10%-level) for the treated groups after the introduction of the chip shortage relative to the counterfactual groups, respectively. These further confirm a focus on credit policies by firms affected by the shortage, intending to improve liquidity and profitability (Lazaridis and Tryfonidis (2006), Gill et al. (2010)).

By using the two-way fixed effects approach, it is possible to obtain a granular assessment of the different impacts on the treated and control group over the assessed period through the first and fifth panels in Figures 3 and 4. First, it is possible to confirm that the synthetic control method worked in creating a counterfactual group, by showing that both lines follow similar courses in the pre-shock period. In the post-shock period, it is possible to recognize a statistically significant impact at the 5% level from the first quarter of 2021 onward (Table 11), inducing a diverging trend between the two groups. Similar results can be perceived for the quartile-based sample (Table 12). Both results correctly recognize the initial timing of the shock, highlighted in grey, with a spike for both treated and control groups, not significant, most likely due to the greater part of the impacts being attributable to the pandemic and greatly affecting both groups. Nevertheless, it suggests that the disparity that follows may be due to the semiconductor shortage. This gap reinforces a shift towards more strict working capital policies concerning the collection of payments. The changes made to DSO are supported by Baños-Caballero et al. (2014), which finds an equilibrium to trade cycles. Adjustments are promptly made because not being in equilibrium may induce high costs to businesses. This is further supported by the aforementioned assessment made by Shin and Soenen (1998) on the Walmart and Kmart case, which ultimately led to the insolvency of the latter.

When analyzing the GSCM-introduced results for inventory metrics, statistically significant results can only be observed for its turnover metrics. For the median-split sample, a decrease in turnover of 19.2% can be observed after the shock compared to the control group, significant at 5%, while a 23% decrease can be observed after the shock for the quartile-based sample, significant at 10%. These findings support the second hypothesis, that in addition to having difficulties in managing inventories through the general supply chain disruptions, chip-dependent firms suffered even greater consequences. As most papers linking WCM to profitability argue, this decrease may reflect a difficulty in converting inventories to sales and could induce higher costs to the operations of a company - for instance through warehousing (Ren et al. (2019)) - thus, preventing cash reserves from being used for profitable use cases (Demiraj et al. (2022)). However, it may still be questioned whether sales is the factor truly causing this ratio to worsen in the period of shortage. The shift to remote work greatly increased the demand for home-office technological appliances (Bauer et al. (2020)). And through the impossibility, at the time, of determining for how long the impact would last, it may be possible that the inventory policy at treated firms shifted to increasing inventory levels. This reflects the takeaways presented by Ramani et al. (2022) and Frieske and Stieler (2022). Their models suggest that firms in the automotive industry would benefit from expanding capacity and stockpiling, something that may be applied to other chip-reliant industries as well (Lind et al. (2012), Gill et al. (2010), Nazir et al. (2007)).

Further analysis may need to be conducted before determining whether the decrease in Inventory Turnover is due to weaker sales and less agility in inventory management or a consequence of the treated firms' forward-looking inventory management. From the second and fifth panels of Figures 3 and 4, it is possible to observe that the average number of days to sell inventories is increasing for both groups and turnover metrics are only decreasing, statistically significantly, for the treated groups. From Table 11 it is also possible to recognize that significant results are only introduced for Inventory Turnover after the 4th quarter post-shock (Q2 2021). This may support the argument for stockpiling because consumer demand rose with savings generated during pandemic periods. According to a White House statement (Helper and Soltas (2021)), automotive sales were at the highest level in 15 years between January and June 2021. This shields the perception that a highly chip-intensive sector like the automotive industry needed to expand capacity to keep up with demand amidst the shortage of key components to manufacture their final product. Furthermore, the White House publication also mentions the issue of more firms suffering from insufficient stock to attend to demand. Lastly, the shock shows a strong impact on the Inventory Days and Turnover for both samples and both the treated and counterfactual groups in the quarter of the shock introduction, again most likely introduced as a broader pandemic impact, which strongly increases the DIO and, conversely, reduces Inventory Turnover.

No metric measuring payables performance provides significance. This contrasts the strategies outlined in Frieske and Stieler (2022), where firms in the automotive sector, impacted by the shortage, adapted their purchasing strategies. It may also be possible that changes in purchasing are not captured by working capital metrics, for instance by quickly shifting to backup suppliers as suggested in Simchi-Levi et al. (2022). The increase in DPO that can be observed relative to the period before the shock, shows that both treated and counterfactual industries increased the time to make due payments, but no inference can be made attributable to the chip shortage. This might be a strategy pursued particularly in light of the pandemic-induced crisis (Demiraj et al. (2022)), as many studies suggest this to have negative impacts on profitability (Deloof (2003), Lazaridis and Tryfonidis (2006)). These results also deny the third hypothesis, which expected a statistically significant increase in DPO of affected firms as a consequence of term renegotiation with suppliers.

Lastly, both samples show non-significant results for CCC. This suggests that despite facing unprecedented challenges, treated firms might have managed to shield themselves from any larger increases induced by the shortage. Meanwhile, both samples find themselves with increasing days for CCC, aligned with the descriptive statistics. While the CCC levels between the control and treatment group show deviation in the fourth panel of Figure 4, it is possible to visualize that CCC is maintained at a relatively stable level throughout the sampled period, supporting the optimum argument made by Altaf and Shah (2018). Moreover, in the larger sample, both groups present a spike at the moment of the shock, most likely induced as a general pandemic effect, followed by a timely reduction and steady increase until the end of the period of the event study.

For the presented results, some coefficients may be driven by firms of different sizes, as found by Moussawi et al. (2006), revealing a significant relationship between WCM and firm size. These should influence their capability in negotiating with suppliers or in handling a longer time to convert its sales to cash, enabling a competitive advantage for firms that need to immediately implement policies to ensure short-term liquidity (Zimon and Tarighi (2021)).

Considering the difference in results presented through different firm sizes in Section 5.1, the next segment will follow the setup and break down the regression analysis following the approach presented in Section 4.3.3. Each analysis will be broken down for each working capital metric based on firm size to form a robustness test. This will be done both for the median-based sample, as well as for the sample split by quartiles. The goal is to gauge if these influence the policies developed to the introduced shock and to assess the robustness of the obtained results from the methodology.

Table 14, in the Appendix, displays the Average Treatment Effect on Treated of each metric across the firm size quintile for the median-based sample, Table 15, also in the Appendix, displays the treatment effect for each quintile within the quartile-based sample. Figures 5 to 11 display the plots for each quintile per item, showing the Average Treatment Effect per period for both the treatment group and counterfactual group developed through the median-based sample's GSCM.

In analyzing the impact of the semiconductor shortage across different firm sizes, it is possible to understand some of the drivers of the results across the median and quartile-based samples. Moreover, it's possible to gauge how different firm size groups react to the induced supply chain shortage. It is expected to find some degree of influence driven by firm size, as shielded by Moussawi et al. (2006) and Lazaridis and Tryfonidis (2006). The first size quintile includes 59 treated firms, the second 83 treated firms, the third 91 treated firms, the fourth 81 treated firms and the fifth gathers 96 treated firms. For the quintiles within the quartile-based sample, 13, 31, 44, 40 and 44 firms respectively.

For metrics evaluating the efficiency of receivables, the quintile representing the largest firms shows an average decrease of 5.1 days compared to the counterfactual group, significant at the 1% level. For the quartile-based sample, the largest firms decrease DSO by 11 days in comparison to the control group - also significant at 1%. The quartile-based sample's largest firms also present an average 17% increase in Receivable Turnover in comparison to the counterfactual group (significant at 1%). These results indicate that larger firms may have needed to use their higher control over their credit policies to achieve a timely reaction to the chip shortage. It also suggests that they are seeking to ensure profitability (Deloof (2003), Altaf and Shah (2018), Ren et al. (2019)), by being able to increase efficiency and maintain high-quality clients with creditworthiness. The results further support H1 and H4, aligning with Zimon and Tarighi (2021) and Frieske and Stieler (2022). Considering that larger firms may also have higher bargaining power, they can seek external financing more easily and are less reliant on short-term solvency provided by strong working capital management (Baños-Caballero et al. (2014)), it could be argued that an aggressive approach to DSO would be expected, instead of the obtained results.

However, it may also be likely that these larger firms benefit from controlling market positions and can impose changes to their collection policies without losing their customer base, which would otherwise seek products from firms with less conservative credit policies. Perhaps, due to an effect of the overall shortage (Helper and Soltas (2021)), customers were also tied to these companies as smaller firms may have struggled to keep up with increased demand.

Besides the results for the top quintile, the second quintile (Q2) presents an average increase of Receivable Turnover of 8.5% compared to the counterfactual group, as well as 11.6% for the same quintile in the quartile sample, both significant at 5%. When the results are observed in Figure 9, it may be said that they are driven by the sharp decreasing trends in turnover by the control group, leading to a gap in comparison to the treated firms. The results obtained from the firm size breakdown provide mixed findings relative to Moussawi et al. (2006), suggesting that WCM inefficiencies are correlated with larger firm size, while the counterfactual group suffers from a steep downward trend in Receivable Turnover. On the other hand, small chip-reliant firms do manage to improve their ratios - supporting their findings.

By evaluating the Inventory Days metric, it's possible to observe mostly no significant results, contrary to the previously presented observations. This suggests that firm size does not greatly affect inventory management policies after the introduction of the semiconductor shortage. From Figure 6, it's possible to observe that increasing trends in DIO are mostly similar and potentially attributable to a greater pandemic effect. Yet, in the quintiles of the quartile-based sample (Table 15), it's possible to observe an increase of DIO on average by 24 days in Q2 relative to the counterfactual group, significant at the 10%-level. Following the rationale of strategic inventory increases, this would further give support to the firm-size assessment made by Moussawi et al. (2006) and the overall trend of affected industries of anticipating the shortage and building up inventories for higher demand. Furthermore, these findings add to the confirmation of the second hypothesis, but not to the validation of the fourth hypothesis.

As with previous findings, payable metrics display almost no significant differences between the observed treated and counterfactual groups across the quintiles, as seen in Figures 7 and 11. However, the Payable Turnover for middle-sized firms decreases on average by 10% for treated companies, in comparison to middle-sized counterfactual firms after the shock - significant at 10%. This suggests that medium enterprises suffered from higher difficulty in making timely payments to their suppliers after the chip shortage (Frieske and Stieler (2022)) and could worsen relationships with suppliers, ultimately reducing profitability (Deloof (2003)). Conversely, the study conducted by Zimon and Tarighi (2021), focusing on Polish SMEs, suggests that firms of this size trying to maximize ROA may benefit from negotiating longer periods to make payments, supporting these findings. Nevertheless, the results may reveal some intricate nuances in the supply chain management of middle-sized firms. For instance, they could be ordering high levels of supplies for inventory in advance due to uncertainty in the supply chain. For this argument to be made, a more cautious study of affected middle-sized firms outside of this study would be needed.

Most results to CCC in the quintiles point to little change between treated and control groups, suggesting that most of the impact was due to overall pandemic effects, as shown in the descriptive statistics in Table 7. Significant changes at the 10% and 1% level can be identified in the third quintile for the median-split and quartile-based samples, respectively. Treated firms have an 8.89-day and 25.33-day longer cash conversion period after the shock, compared to the counterfactual groups, indicating a more prolonged cycle of converting resources into cash in mid-sized firms. These point towards difficulties faced by the middle market amidst the semiconductor shortage, and provide further clarity to the results previously seen to the small and middle-sized firms. It could also reflect the points made in Zimon and Tarighi (2021), where higher CCC may be due to a focus on increasing sales instead of improving liquidity through payment collection.

When comparing these findings with the results from the median and quartile-based, it's evident that firm size plays an important role when shaping a firm's credit policy, allowing larger firms (Q5) to increase Receivable Turnover. The small to middle-sized firms segment also provides results that provide some support to the patterns observed in the analysis of the full median and quartile split samples. For instance, SMEs may be pursuing an extension of capacity (Lind et al. (2012)) and introducing more conservative credit policies (Deloof (2003) Ren et al. (2019)). Moreover, middle-sized firms suffer from increased CCC, which could be a reflection of a sales-focused strategy, or difficulty implementing an effective strategy to circumvent shortages. Nevertheless, they do not benefit firm profitability in the short-term (Richards and Laughlin (1980), Deloof (2003), Baños-Caballero et al. (2014), García-Teruel and Martínez-Solano (2007)). A greater deep-dive into the economic segment of small to medium-sized companies is needed, to make more robust conclusions about the impacts obtained. Furthermore, the main analysis of the entire median and quartile-split samples may provide more conclusive results, as each counterfactual is generated considering the firm size.

The next section will conclude the paper, by summarising the methodology and the results obtained. In addition, it will review its implications and compare them to the hypotheses made in Section 2.5. Also, limitations to this study will be addressed, as well as suggestions on further research that could be conducted in this particular field.

6 Conclusion

This event study attempted to gauge the impact of the chip shortage, induced by the COVID-19 pandemic, on the working capital management of U.S. industries. To assess this, the sensitivity of U.S. industries to semiconductors was measured and split into low and high-sensitivity groups. To best isolate the effect of the chip shortage from the overall effects of the pandemic, the methodology of this study used the established control group to create a counterfactual scenario through a GSCM (Xu (2017)), based on firm-specific characteristics of the treated group. DSO, DIO, DPO, and CCC, as well as turnover ratios for receivables, inventory, and payables, were assessed in this paper (Deloof (2003), Lazaridis and Tryfonidis (2006), Baños-Caballero et al. (2014)).

The following hypotheses were developed with expectations of the shortage's impact on treated firms in comparison to the counterfactual groups:
H1: a reduction in the collection period of receivables, along with increased efficiency in receivables turnover; H2: an increase in DIO along with a decrease of the respective turnover; H3: an increase in DPO due to renegotiation of contracts with suppliers, followed by a decrease in Payable Turnover; H4: an expectation for larger firms to be prompt in ensuring implementing new working capital policies.

Through the methodology implemented, the following results and implications were made:

The first hypothesis was confirmed through decreases in DSO for industries sensitive to the semiconductor shortage (Table 3) in both created samples. These findings, show that changes in credit policies by affected firms were made, and are further supported by increases in Receivable Turnover. It may be argued that these firms are focusing on increasing liquidity and profitability. With the timing of changes being recognized as soon as in the first quarter of 2021, they also point toward firms quickly adjusting their working capital management towards a new equilibrium level to not induce high costs (Ramani et al. (2022), Lind et al. (2012), Lazaridis and Tryfonidis (2006), Gill et al. (2010), Baños-Caballero et al. (2014)).

The second hypothesis is confirmed through inventory turnover, with significant decreases in affected firms' ratios when compared to the generated control group. A statement made by the White House addresses inventory constraints across all of the U.S. but at the same time, record demand (Helper and Soltas (2021)). The results from the study thus suggest that the decrease in this ratio is due to firms expanding capacity and stockpiling in anticipation of the increased demand and uncertain length of the shortage. Additionally, the timing of the reduction in inventory turnover (Q2 2021), as well as the model of Frieske and Stieler (2022), support this inference (Demiraj et al. (2022), Ramani et al. (2022)).

The third hypothesis found no support in the results of this study. It was expected that affected firms would negotiate terms with suppliers to extend their due payments and thus, additionally ensure liquidity. However, it is possible that affected firms mainly addressed liquidity through their policies to receivables. Additionally, increases in DPO may be a general effect of the pandemic and its consequential disruptions. Further effects were found only for middle-sized firms, reducing turnover relative to the control group, but these results were not enough to support H3 (Zimon and Tarighi (2021)).

Lastly, the fourth hypothesis found some evidence for larger firms decreasing DSO and increasing RT, indicating that they may have more control over their credit policies, with a quicker reaction to the chip shortage. It could also be said that larger firms are, thus, to some extent more efficient in imposing profitability-seeking strategies, because of their stronger market position. Meanwhile, DIO displayed increases in SMEs, supporting the findings of the second hypothesis, but not the fourth. Similarly, middle-sized firms decrease PT relative to their counterfactuals, potentially attempting to maximize ROA (Zimon and Tarighi (2021). Further studies detailed to the middle market would need to be made to make proper inferences, as other factors could be driving the results. The same segment presented significant results for increases in the Cash Conversion Cycle, indicating a focus on increasing sales in the long run instead of improving liquidity (Zimon and Tarighi (2021)). Other quartiles displayed similar trends between the treated and counterfactual groups. Additionally, the generated counterfactual group in the firm size test may be of lesser quality, as firm size is removed as a predictor.

The main findings from this study are the differences originating from the semiconductor shortage observable in the management of accounts receivables of chip-reliant firms, intended to increase liquidity and profitability. Additionally, an expansive strategy for inventories after the shortage seeks to increase inventories to attend to the demand surge followed by savings made from the U.S. population. Furthermore, the middle market drove some intriguing results, opposing some of the intuition presented in WCM literature, most likely due to the particular effects of the semiconductor shortage.

There are also some limitations to this study. Over the next few years, it may be possible to better assess the long-term impacts of the introduced shortage, beyond a nearly 3-year post-shock period. It would also be an interesting exercise to analyze in more detail, within the U.S., the efficiency of policies implemented by the government to avert the chip crisis - like the facilitation of diversifying suppliers and the shift of chip production to the U.S. (Helper and Soltas (2021)), to obtain a nuanced understanding of its effects. The restricted amount of high-quality data caused some limitations to the GSCM approach in attempting to construct the best possible counterfactual group. Data quality and availability are higher at the annual level - over more time, it may be possible to use annual data to construct further predictors of working capital metrics that may increase the robustness of the SCM. In this study, they were limited to revenue growth, firm size, and leverage ratio. Lastly, the findings apply mostly to a pandemic scenario or a situation with similar effects. Such a health crisis is a rare event, which may require caution in generalizing the findings of this paper to other crises.

This study attempted to assess the impacts of the semiconductor shortage in the U.S., but the disruption had worldwide effects. An interesting field of further research would include conducting this study in different regions. Additionally, breaking down certain industries' value chains and observing the effect of working capital management between different levels of the supply chain could be of relevancy for robust policy recommendations. Similarly, a detailed breakdown focussing on larger firms or SMEs could also be of interest. Amidst supply chain disruptions, research on the relationship between working capital management and profitability could be extended by focusing on periods of distress. As a chip shortage can have such a broad impact, understanding how to maintain liquidity and profitability during such an event could be of importance to many industries.

A Appendix

Table 4: 3-Digit NAICS Codes and Corresponding Industries

NAICS Code	Industry
111	Crop Production
112	Animal Production and Aquaculture
113	Forestry and Logging
114	Fishing, Hunting and Trapping
115	Support Activities for Agriculture and Forestry
211	Oil and Gas Extraction
212	Mining (except Oil and Gas)
213	Support Activities for Mining
221	Utilities
236	Construction of Buildings
237	Heavy and Civil Engineering Construction
238	Specialty Trade Contractors
311	Food Manufacturing
312	Beverage and Tobacco Product Manufacturing
313	Textile Mills
314	Textile Product Mills
315	Apparel Manufacturing
316	Leather and Allied Product Manufacturing
321	Wood Product Manufacturing
322	Paper Manufacturing
323	Printing and Related Support Activities
324	Petroleum and Coal Products Manufacturing
325	Chemical Manufacturing
326	Plastics and Rubber Products Manufacturing
327	Nonmetallic Mineral Product Manufacturing
331	Primary Metal Manufacturing
332	Fabricated Metal Product Manufacturing
333	Machinery Manufacturing
334	Computer and Electronic Product Manufacturing
335	Electrical Equipment, Appliance, and Component Manufacturing
336	Transportation Equipment Manufacturing
337	Furniture and Related Product Manufacturing
339	Miscellaneous Manufacturing

Table 4 – *Continued from previous page*

NAICS Code	Industry
423	Merchant Wholesalers, Durable Goods
424	Merchant Wholesalers, Nondurable Goods
425	Wholesale Electronic Markets and Agents and Brokers
441	Motor Vehicle and Parts Dealers
442	Furniture and Home Furnishings Stores
443	Electronics and Appliance Stores
444	Building Material and Garden Equipment and Supplies Dealers
445	Food and Beverage Stores
446	Health and Personal Care Stores
447	Gasoline Stations
448	Clothing and Clothing Accessories Stores
451	Sporting Goods, Hobby, Musical Instrument, and Book Stores
452	General Merchandise Stores
453	Miscellaneous Store Retailers
454	Nonstore Retailers
481	Air Transportation
482	Rail Transportation
483	Water Transportation
484	Truck Transportation
485	Transit and Ground Passenger Transportation
486	Pipeline Transportation
487	Scenic and Sightseeing Transportation
488	Support Activities for Transportation
492	Couriers and Messengers
493	Warehousing and Storage
511	Publishing Industries (except Internet)
512	Motion Picture and Sound Recording Industries
515	Broadcasting (except Internet)
517	Telecommunications
518	Data Processing, Hosting, and Related Services
519	Other Information Services
531	Real Estate
532	Rental and Leasing Services
533	Lessors of Nonfinancial Intangible Assets
541	Professional, Scientific, and Technical Services
551	Management of Companies and Enterprises

Table 4 – *Continued from previous page*

NAICS Code	**Industry**
561	Administrative and Support Services
562	Waste Management and Remediation Services
611	Educational Services
621	Ambulatory Health Care Services
622	Hospitals
623	Nursing and Residential Care Facilities
624	Social Assistance
711	Performing Arts, Spectator Sports, and Related Industries
713	Amusement, Gambling, and Recreation Industries
721	Accommodation
722	Food Services and Drinking Places
811	Repair and Maintenance
812	Personal and Laundry Services
813	Religious, Grantmaking, Civic, Professional, and Similar Organizations
921	Executive, Legislative, and Other General Government Support
924	Administration of Environmental Quality Programs
926	Regulation and Administration of Transportation Programs
928	National Security and International Affairs

Table 5: Average Betas for 3-digit NAICS Codes

NAICS Code	β_{NAICS}
111	0.50
112	0.54
113	0.32
114	0.30
115	0.65
211	0.68
212	0.59
213	0.88
221	0.50
236	-0.26
237	0.53

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Table 5 continued from previous page

NAICS Code	β_{NAICS}
238	0.93
311	0.74
312	0.32
313	-0.63
314	0.51
315	0.60
316	0.31
321	0.50
322	0.50
323	0.49
324	0.52
325	0.34
326	0.51
327	0.51
331	0.54
332	0.44
333	0.50
334	0.46
335	0.50
336	0.72
337	0.58
339	0.37
423	-0.38
424	0.54
425	0.58
441	1.01
442	0.65
443	0.48
444	0.40
445	0.34
446	0.53
447	0.28
448	0.53
451	0.83
452	0.19

Continued on next page

Table 5 continued from previous page

NAICS Code	β_{NAICS}
453	0.45
454	0.62
481	0.31
482	0.29
483	0.45
484	0.41
485	0.51
486	0.49
487	0.11
488	0.28
492	0.52
493	0.63
511	0.55
512	1.59
515	0.40
517	-0.10
518	0.43
519	0.40
531	0.28
532	0.57
533	0.49
541	0.50
551	0.39
561	0.45
562	0.74
611	0.63
621	0.42
622	0.47
623	1.11
624	0.56
711	0.45
713	0.78
721	0.37
722	0.67
811	0.35

Continued on next page

Table 5 continued from previous page

NAICS Code	β_{NAICS}
812	0.50
813	1.54
921	0.23
924	0.23
926	0.35
928	0.13

	Mean	Median	Max	Min
Days Inventory Outstanding				
Pre Q2 2020	104.86	85.90	651.14	3.15
Post Q2 2020	114.99	94.97	677.59	2.89
Days Sales Outstanding				
Pre Q2 2020	57.38	55.45	269.75	2.63
Post Q2 2020	58.45	55.97	338.52	3.08
Days Payables Outstanding				
Pre Q2 2020	49.90	46.18	197.62	6.40
Post Q2 2020	52.40	49.32	205.02	5.96
Cash Conversion Cycle				
Pre Q2 2020	112.34	95.06	626.27	7.23
Post Q2 2020	121.03	101.73	726.58	7.49

Table 6: Descriptive Working Capital Metrics - Quartile-based

	Q1	Q2	Q3	Q4	Q5
Days Inventory Outstanding					
Pre Q2 2020	135.47	108.88	91.85	93.15	80.90
Post Q2 2020	149.11	120.18	100.97	102.76	87.92
Days Sales Outstanding					
Pre Q2 2020	60.43	61.27	55.26	55.23	58.22
Post Q2 2020	63.78	63.11	55.78	55.66	57.98
Days Payables Outstanding					
Pre Q2 2020	49.08	45.95	44.45	49.97	56.23
Post Q2 2020	47.51	48.29	47.37	54.89	59.22
Cash Conversion Cycle					
Pre Q2 2020	146.83	124.20	102.66	98.41	82.88
Post Q2 2020	165.38	135.00	109.38	103.53	86.68

Table 7: Descriptive Working Capital Metrics - Firm Size Quintiles

	Mean	Median	Max	Min
Receivables Turnover				
Pre Q2 2020	2.09	1.61	34.20	0.33
Post Q2 2020	2.09	1.60	29.26	0.27
Inventory Turnover				
Pre Q2 2020	1.65	1.07	28.57	0.14
Post Q2 2020	1.57	0.96	37.25	0.13
Payables Turnover				
Pre Q2 2020	2.39	1.98	15.19	0.46
Post Q2 2020	2.28	1.86	16.46	0.44

Table 8: Descriptive Turnover Metrics - Median-based Sample

	Mean	Median	Max	Min
Receivables Turnover				
Pre Q2 2020	2.13	1.62	34.20	0.33
Post Q2 2020	2.15	1.61	29.26	0.27
Inventory Turnover				
Pre Q2 2020	1.64	1.05	28.57	0.14
Post Q2 2020	1.51	0.95	31.17	0.13
Payables Turnover				
Pre Q2 2020	2.34	1.95	14.07	0.46
Post Q2 2020	2.25	1.82	15.10	0.44

Table 9: Descriptive Turnover Metrics - Quartile-based Sample

Metric	Q1	Q2	Q3	Q4	Q5
Receivables Turnover					
Pre Q2 2023	1.99	2.03	2.07	2.32	2.03
Post Q2 2023	1.96	1.99	2.08	2.33	2.09
Inventory Turnover					
Pre Q2 2023	1.28	1.44	1.79	1.57	2.15
Post Q2 2023	1.28	1.36	1.66	1.43	2.12
Payables Turnover					
Pre Q2 2023	2.56	2.46	2.55	2.28	2.07
Post Q2 2023	2.56	2.33	2.42	2.08	2.01

Table 10: Descriptive Turnover Metrics - Firm Size Quintiles

Table 11: GSCM Result Over Time - Median-based

10% significance level (*); 5% significance level (**); 1% significance level (***).
Standard Errors in Parentheses.

Time	Metrics						
	DSO	DIO	DPO	CCC	RT	IT	PT
-12	-0.017	0.644	-0.384	0.353	0.005	-0.006	0.011
	(0.378)	(1.147)	(0.701)	(1.216)	(0.007)	(0.008)	(0.012)
-11	0.324	-0.511	-0.134	-1.247	-0.013	0.009	0.006
	(0.438)	(1.016)	(0.567)	(1.070)	(0.007)	(0.008)	(0.010)
-10	-0.123	-1.169	-0.682	0.236	0.008	0.002	0.014
	(0.427)	(1.186)	(0.694)	(1.213)	(0.008)	(0.008)	(0.012)
-9	0.622	-1.470	0.269	-1.444	-0.015	-0.012	-0.015
	(0.441)	(1.305)	(0.613)	(1.247)	(0.008)	(0.009)	(0.011)
-8	0.079	2.085	0.163	1.574	0.004	-0.003	-0.003
	(0.436)	(1.042)	(0.596)	(0.922)	(0.008)	(0.008)	(0.011)
-7	-0.071	-1.680	0.090	-1.022	-0.001	0.013	-0.014
	(0.507)	(1.284)	(0.613)	(1.459)	(0.008)	(0.009)	(0.012)
-6	-1.003	0.274	-0.135	1.596	0.017	0.007	0.011
	(0.491)	(1.071)	(0.649)	(1.343)	(0.009)	(0.008)	(0.012)
-5	-0.145	-0.042	0.757	0.114	0.001	-0.014	-0.013
	(0.555)	(1.294)	(0.776)	(1.336)	(0.008)	(0.009)	(0.012)
-4	-0.494	2.653	0.006	1.780	0.000	-0.006	-0.006
	(0.440)	(0.996)	(0.666)	(1.089)	(0.007)	(0.007)	(0.012)
-3	0.002	3.802	0.790	1.144	-0.004	0.000	-0.018
	(0.472)	(1.221)	(0.656)	(1.115)	(0.009)	(0.008)	(0.011)
-2	-1.132	-0.301	-1.130	0.571	0.019	0.007	0.023
	(0.480)	(1.298)	(0.570)	(1.361)	(0.008)	(0.009)	(0.012)
-1	0.212	-1.385	0.752	-1.701	0.000	-0.008	-0.010
	(0.445)	(1.099)	(0.624)	(1.192)	(0.008)	(0.007)	(0.010)
0	1.747***	-2.897**	-0.362	-1.955	-0.022**	0.011	0.015
	(0.556)	(1.302)	(0.786)	(2.087)	(0.010)	(0.009)	(0.013)
1	-1.141	-0.018	1.266	-1.818	0.008	-0.011	-0.017
	(0.864)	(1.855)	(0.878)	(1.756)	(0.012)	(0.024)	(0.017)
2	-2.174*	-2.856	0.101	-2.439	0.030*	-0.055	0.013
	(1.226)	(2.611)	(1.078)	(2.515)	(0.018)	(0.046)	(0.020)
3	-0.927	-4.289	1.512	-1.730	0.003	-0.105	-0.020

Continued on next page

Table 11 – continued from previous page

Time	Metrics						
	DSO	DIO	DPO	CCC	RT	IT	PT
	(1.291)	(3.364)	(1.293)	(2.985)	(0.018)	(0.068)	(0.021)
4	-3.258*	-3.221	1.577	1.259	0.026	-0.162*	-0.024
	(1.670)	(4.773)	(1.528)	(3.442)	(0.021)	(0.087)	(0.025)
5	-3.582**	-7.080	1.183	0.871	0.031	-0.191*	-0.021
	(1.800)	(6.060)	(1.529)	(3.856)	(0.023)	(0.104)	(0.025)
6	-5.550***	-12.114	-1.029	1.409	0.063**	-0.234**	0.019
	(1.814)	(8.368)	(1.660)	(5.004)	(0.025)	(0.114)	(0.029)
7	-4.401	-15.653	0.494	-0.302	0.040*	-0.270**	-0.009
	(1.775)	(9.978)	(1.834)	(5.432)	(0.024)	(0.126)	(0.028)
8	-6.479***	-18.668	-0.908	-0.053	0.056**	-0.272**	0.015
	(2.450)	(11.559)	(1.974)	(5.899)	(0.025)	(0.138)	(0.031)
9	-5.882**	-22.293*	-0.122	-1.811	0.060**	-0.257*	-0.001
	(2.441)	(12.441)	(1.959)	(6.300)	(0.028)	(0.140)	(0.032)
10	-6.613***	-24.569*	-1.569	-2.222	0.079***	-0.256*	0.018
	(2.357)	(12.788)	(1.858)	(6.492)	(0.030)	(0.141)	(0.033)
11	-4.918**	-30.092**	-0.114	-3.759	0.049*	-0.255*	-0.001
	(2.289)	(15.320)	(2.283)	(7.100)	(0.029)	(0.147)	(0.036)
12	-5.600**	-27.467*	-0.407	-2.486	0.058**	-0.240*	0.000
	(2.525)	(15.099)	(2.228)	(7.337)	(0.029)	(0.145)	(0.036)

Table 12: GSCM Result Over Time - Quartile-based

10% significance level (*); 5% significance level (**); 1% significance level (***).

Standard Errors in Parentheses.

Time	Metrics						
	DSO	DIO	DPO	CCC	RT	IT	PT
-12	-0.259	1.706	0.516	0.660	0.009	-0.011	0.007
	(0.551)	(1.473)	(0.842)	(1.459)	(0.010)	(0.010)	(0.016)
-11	0.999	-0.222	-0.330	-0.204	-0.025	0.010	-0.002
	(0.590)	(1.434)	(0.723)	(1.348)	(0.010)	(0.010)	(0.014)
-10	-0.656	-0.927	0.089	-0.124	0.030	0.002	0.021
	(0.585)	(1.641)	(0.738)	(1.718)	(0.012)	(0.010)	(0.015)

Continued on next page

Table 12 – continued from previous page

Time	Metrics						
	DSO	DIO	DPO	CCC	RT	IT	PT
-9	1.206	-1.981	-0.200	-1.581	-0.026	-0.001	-0.012
	(0.595)	(1.605)	(0.766)	(1.522)	(0.011)	(0.012)	(0.016)
-8	0.043	2.858	-0.653	2.353	0.003	-0.007	-0.004
	(0.572)	(1.329)	(0.788)	(1.303)	(0.011)	(0.010)	(0.014)
-7	-0.030	-3.381	-0.031	-2.239	-0.009	0.012	-0.017
	(0.698)	(1.893)	(0.770)	(2.045)	(0.011)	(0.010)	(0.016)
-6	-0.947	-0.129	0.290	1.372	0.019	0.008	0.033
	(0.674)	(1.411)	(0.831)	(1.423)	(0.012)	(0.008)	(0.016)
-5	0.159	0.139	0.607	-0.493	-0.010	-0.020	-0.014
	(0.727)	(1.749)	(0.682)	(1.527)	(0.011)	(0.009)	(0.017)
-4	-1.184	2.526	-0.461	0.538	0.007	-0.006	-0.015
	(0.618)	(1.387)	(0.838)	(1.406)	(0.010)	(0.008)	(0.014)
-3	-0.273	2.526	0.893	0.492	-0.003	-0.002	-0.037
	(0.572)	(1.587)	(0.732)	(1.797)	(0.011)	(0.009)	(0.014)
-2	-2.311	-0.301	-1.130	0.571	0.040	0.013	0.046
	(0.644)	(1.298)	(0.570)	(1.361)	(0.012)	(0.010)	(0.014)
-1	-0.206	-1.385	0.752	-1.701	-0.000	-0.007	0.003
	(0.590)	(1.099)	(0.624)	(1.192)	(0.011)	(0.009)	(0.014)
0	3.459***	-2.689	0.191	-0.069	-0.034	0.009	-0.010
	(0.754)	(1.652)	(0.586)	(1.403)	(0.013)	(0.010)	(0.017)
1	-1.141	-0.018	1.266	-1.818	0.006	0.005	-0.037
	(0.864)	(1.855)	(0.878)	(1.756)	(0.016)	(0.029)	(0.024)
2	-3.207*	0.394	0.965	-0.535	0.057**	-0.021	0.036
	(1.681)	(3.169)	(4.040)	(4.323)	(0.025)	(0.055)	(0.027)
3	-2.699	-1.250	1.502	-1.724	0.019	-0.049	0.012
	(1.791)	(4.397)	(5.405)	(5.746)	(0.026)	(0.079)	(0.027)
4	-5.489**	2.203	3.062	0.018	0.053*	-0.128	0.016
	(2.370)	(6.568)	(6.869)	(7.361)	(0.030)	(0.105)	(0.032)
5	-5.500**	-1.795	2.873	-2.558	0.057*	-0.163	0.023
	(2.553)	(8.665)	(7.140)	(9.253)	(0.032)	(0.127)	(0.035)
6	-7.619***	-3.261	1.491	-2.758	0.102***	-0.233	0.090**
	(2.571)	(12.272)	(7.155)	(13.266)	(0.036)	(0.144)	(0.040)
7	-6.775***	-7.751	2.869	-7.859	0.072**	-0.281*	0.061
	(2.456)	(14.637)	(8.311)	(15.619)	(0.035)	(0.159)	(0.040)

Continued on next page

Table 12 – continued from previous page

Time	Metrics						
	DSO	DIO	DPO	CCC	RT	IT	PT
8	-10.041***	-8.094	3.120	-9.285	0.097***	-0.334*	0.078*
	(3.426)	(17.205)	(8.882)	(17.789)	(0.036)	(0.176)	(0.043)
9	-9.078***	-12.224	5.515	-13.778	0.096**	-0.351*	0.034
	(3.457)	(18.552)	(8.869)	(19.413)	(0.040)	(0.182)	(0.042)
10	-10.983***	-11.539	3.981	-13.381	0.140***	-0.388**	0.067
	(3.276)	(18.887)	(8.129)	(20.914)	(0.044)	(0.185)	(0.044)
11	-9.124***	-17.078	5.081	-17.643	0.096**	-0.409**	0.059
	(3.297)	(22.611)	(10.655)	(23.166)	(0.041)	(0.192)	(0.049)
12	-10.659***	-12.783	5.626	-15.720	0.125***	-0.408**	0.039
	(3.571)	(22.344)	(10.696)	(24.010)	(0.041)	(0.187)	(0.050)

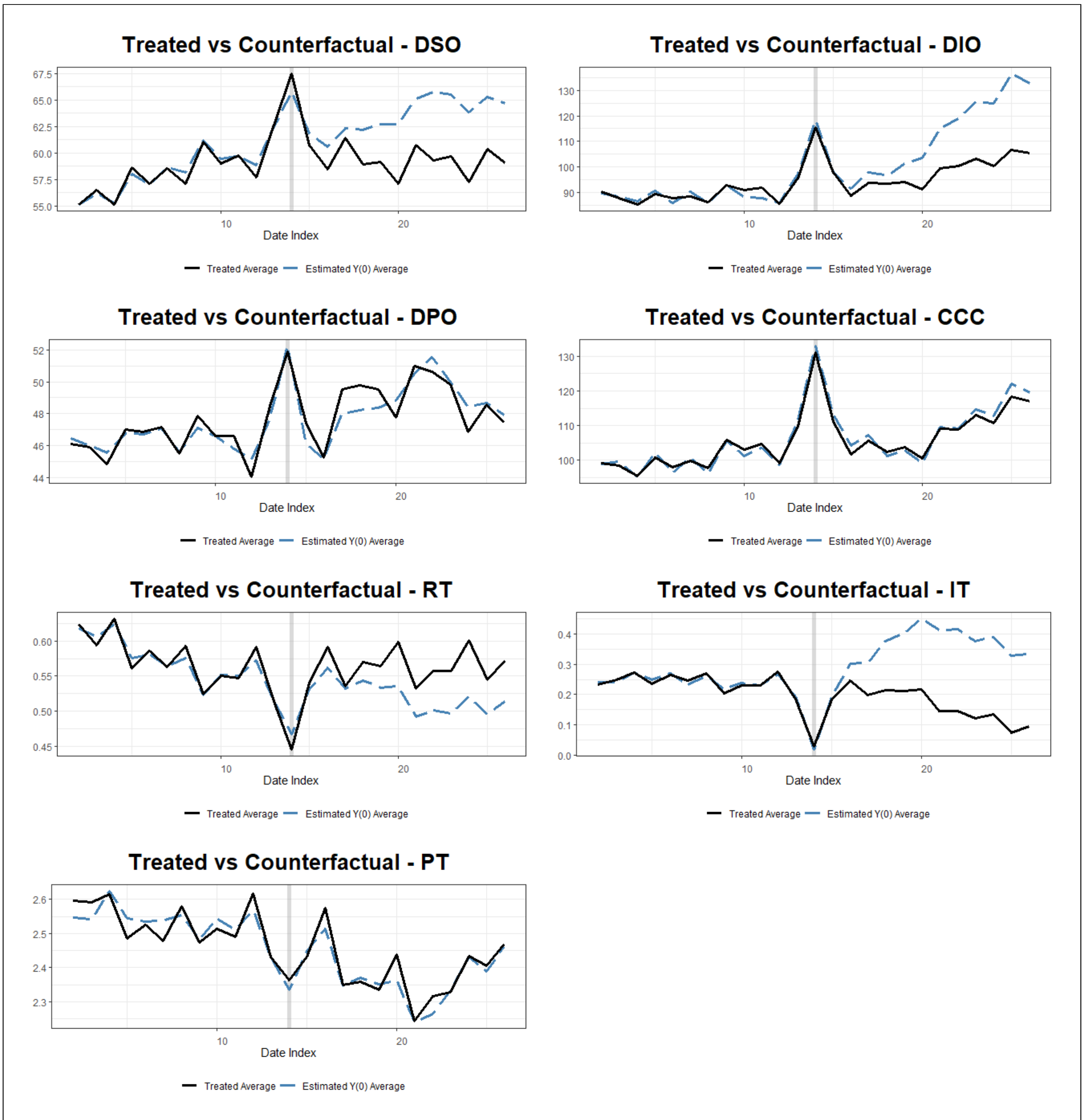

Figure 3: Generalized Synthetic Control Method Results - Median-based

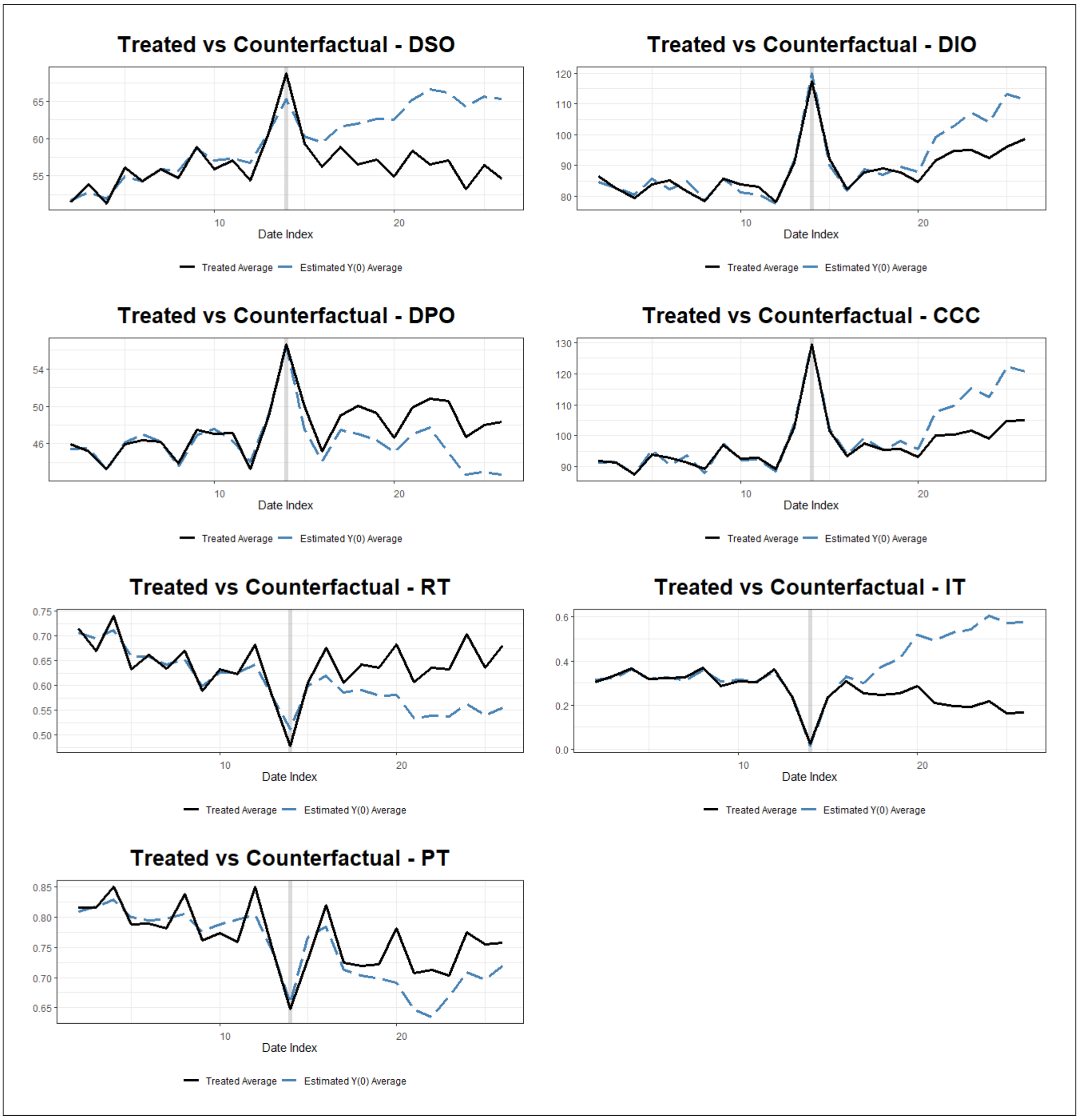

Figure 4: Generalized Synthetic Control Method Results - Quartile-based

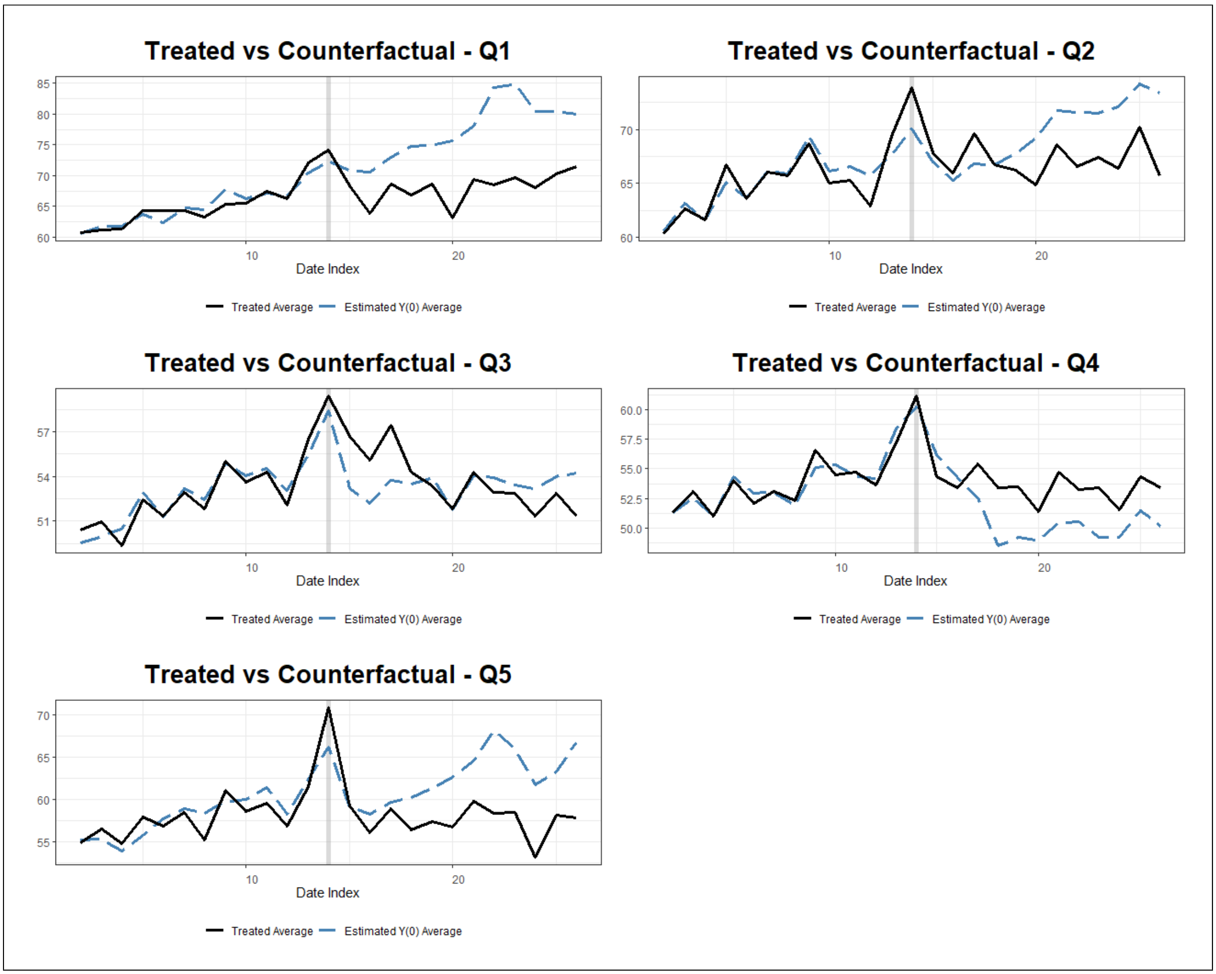

Figure 5: Days Sales Outstanding - Quintiles by Firm Size

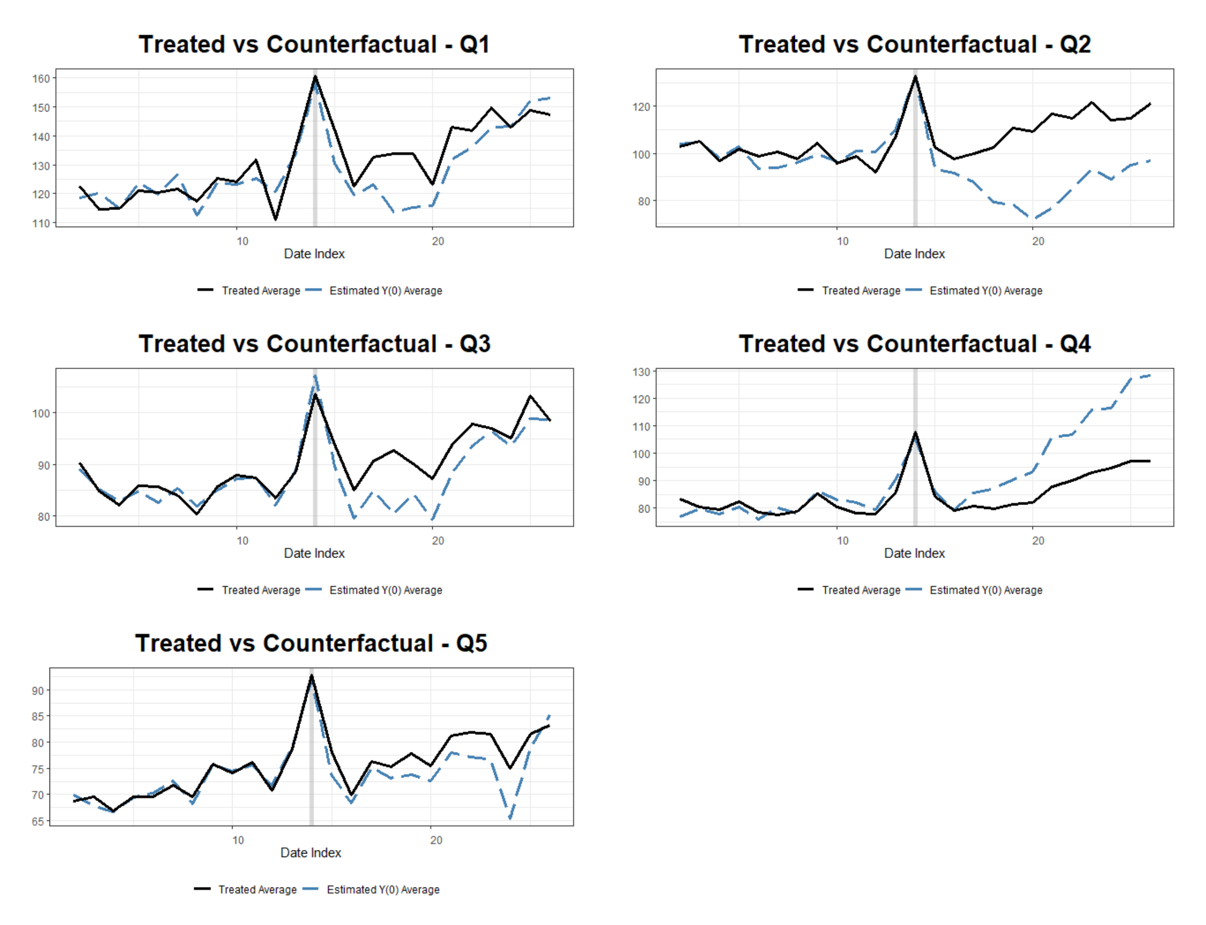

Figure 6: Days Inventory Outstanding - Quintile by Firm Size

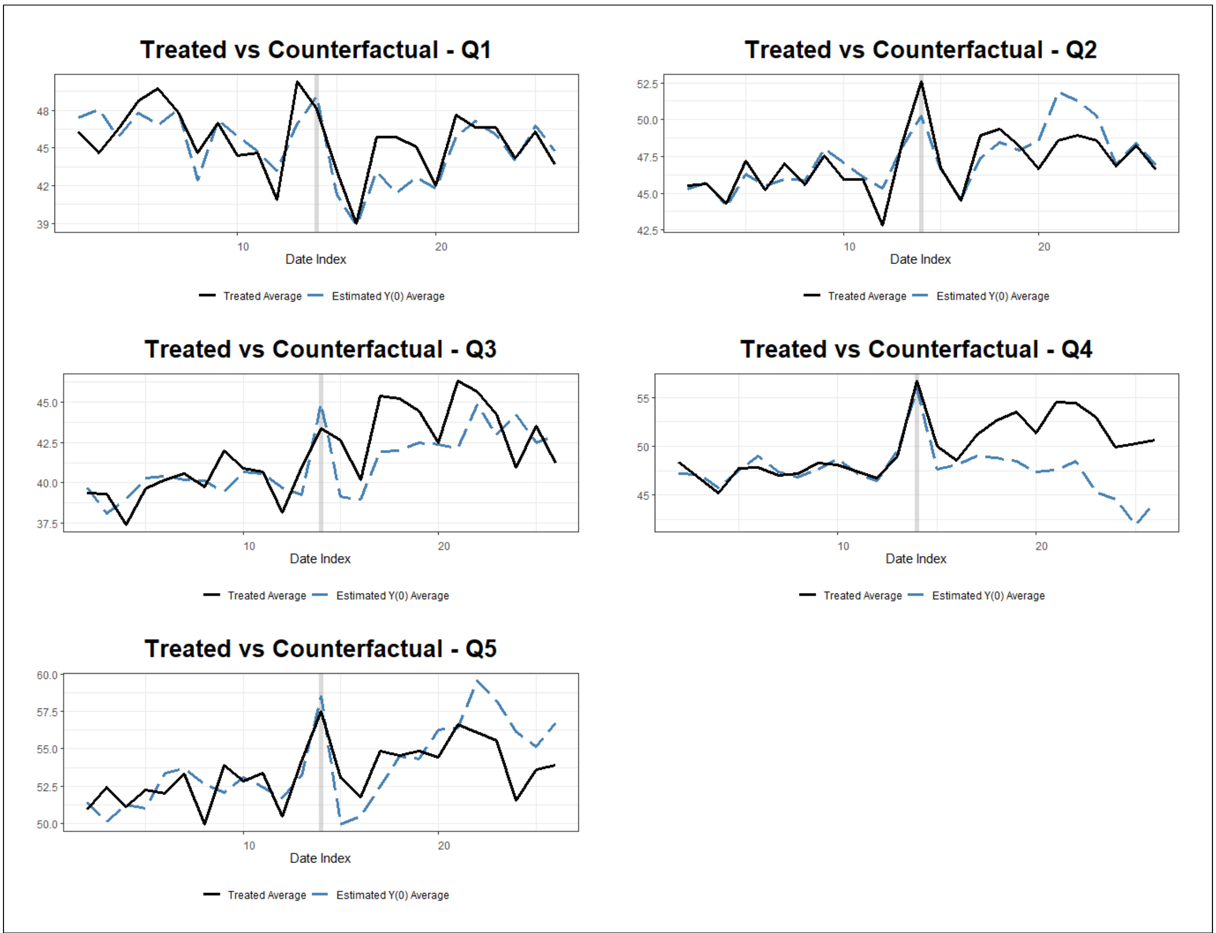

Figure 7: Days Payables Outstanding - Quintile by Firm Size

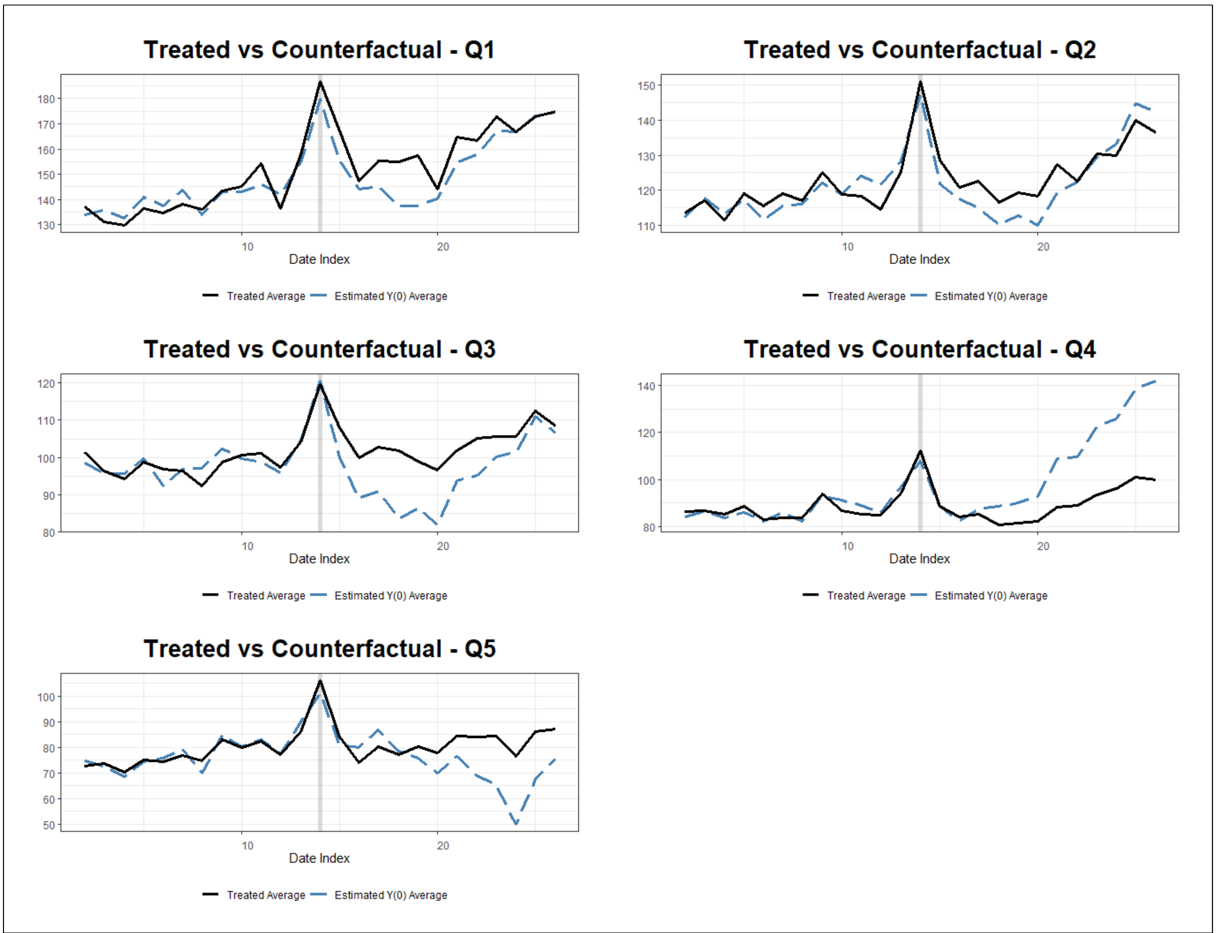

Figure 8: Cash Conversion Cycle - Quintile by Firm Size

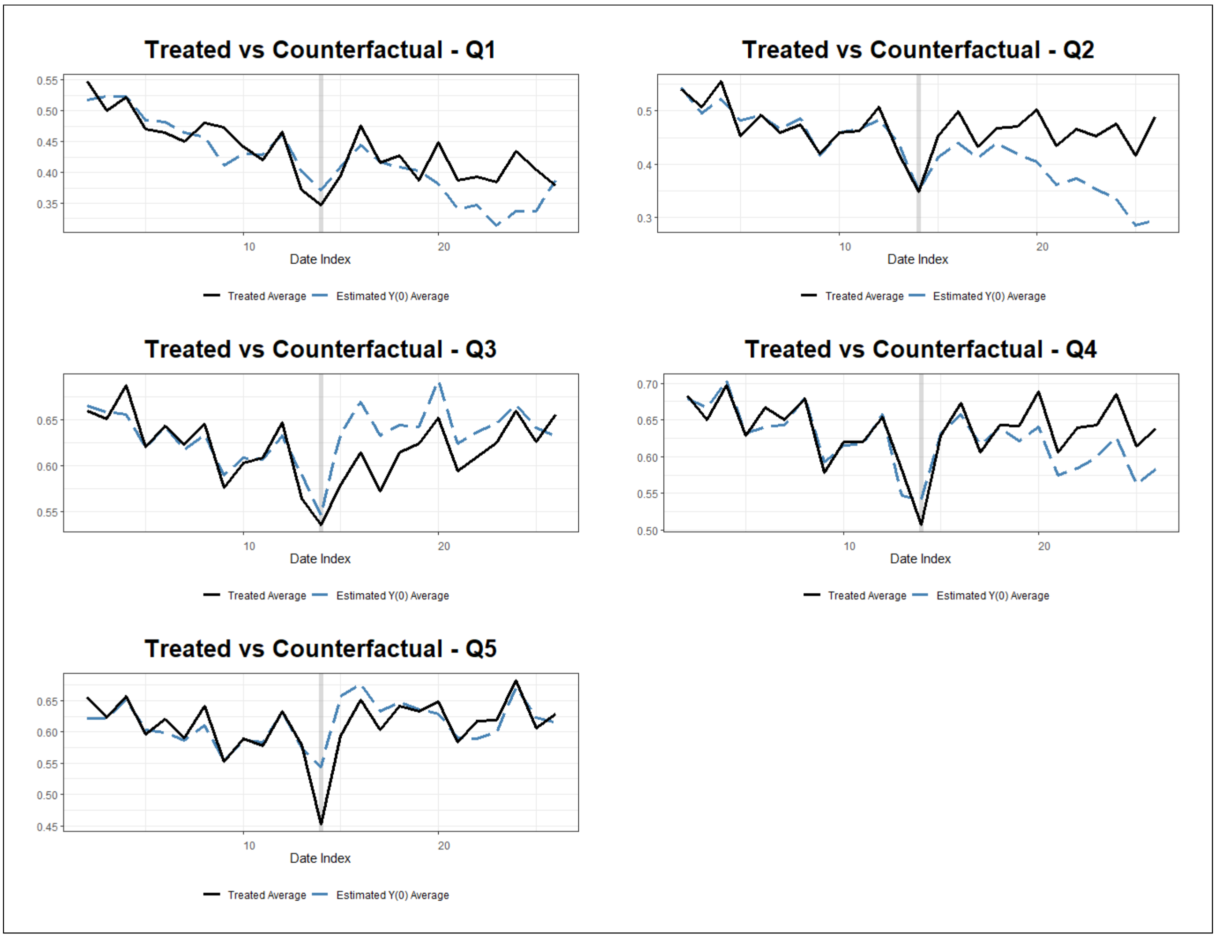

Figure 9: Receivables Turnover - Quintile by Firm Size

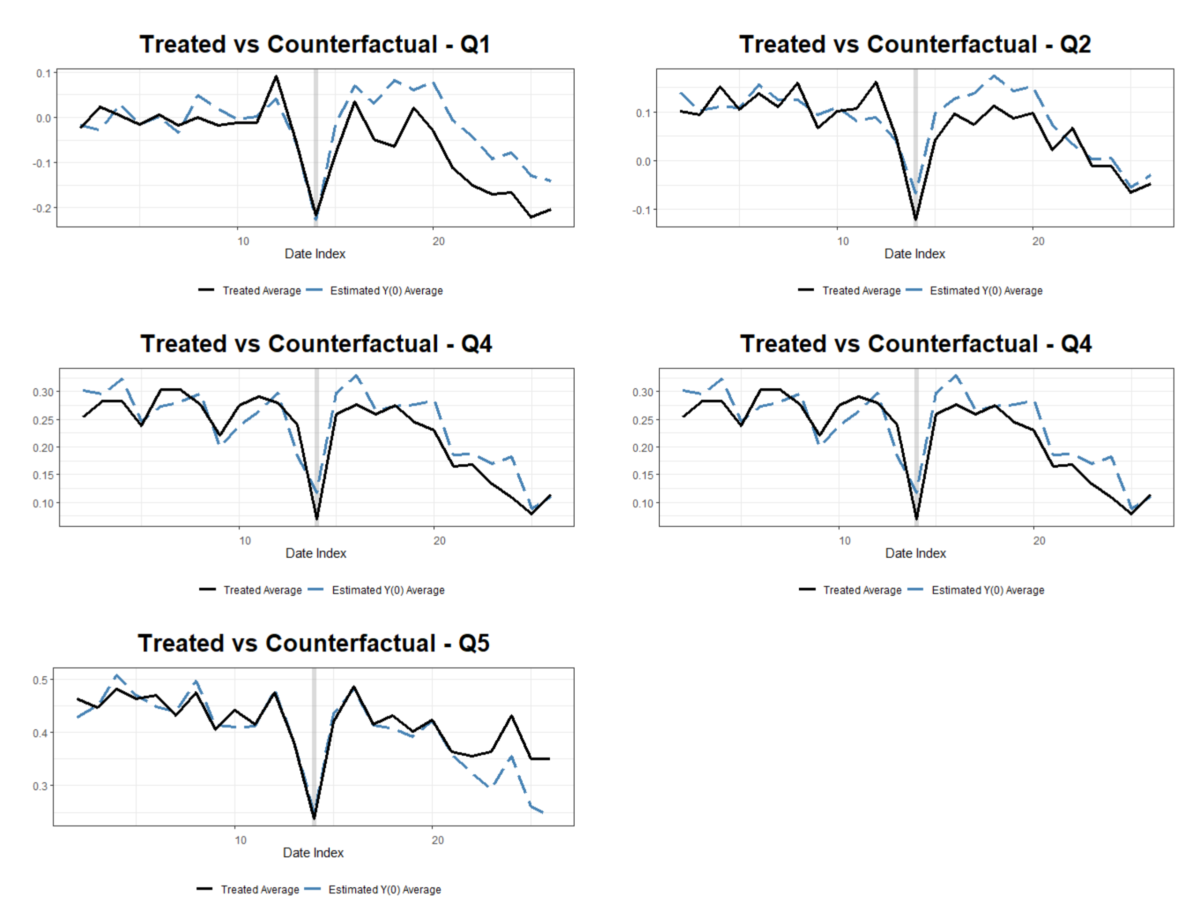

Figure 10: Inventory Turnover - Quintile by Firm Size

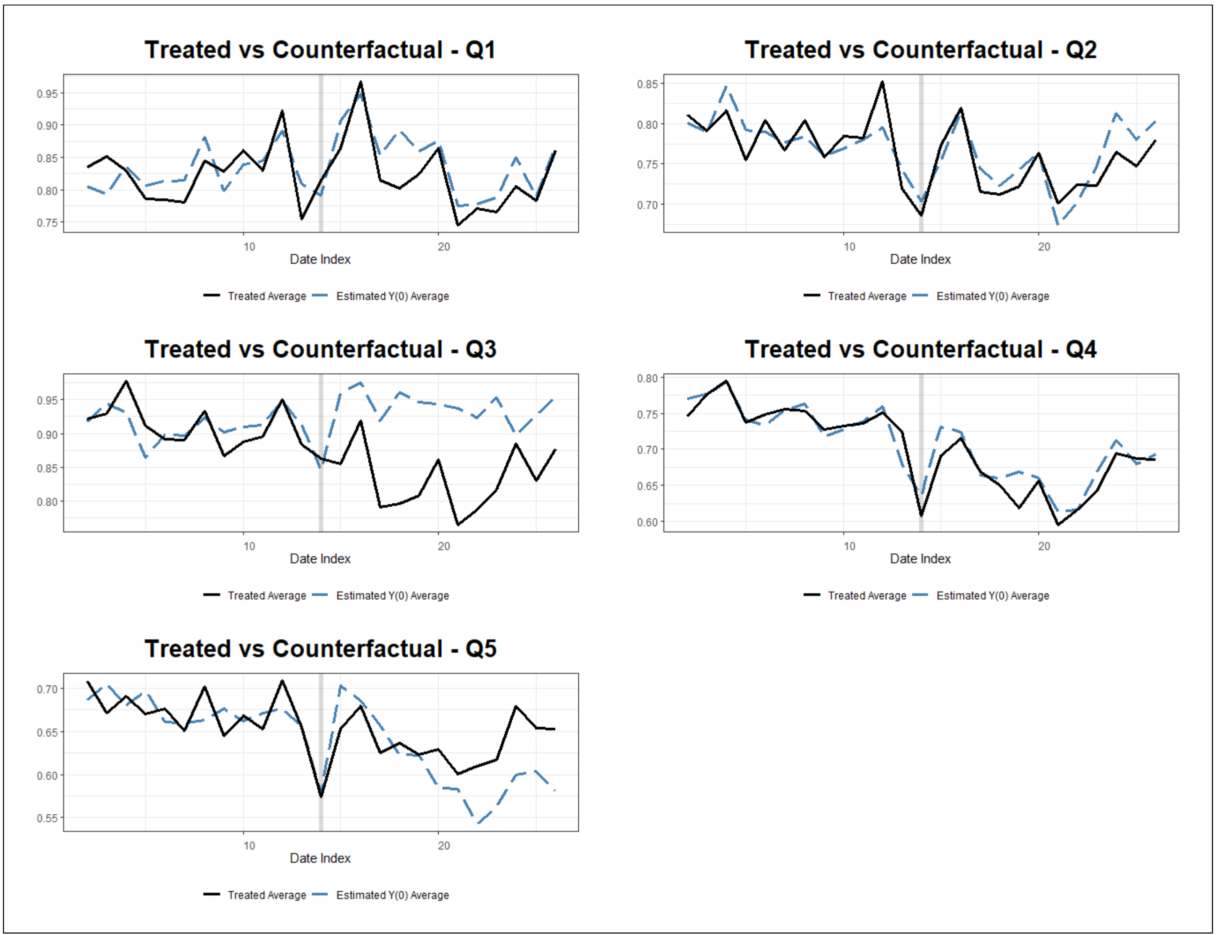

Figure 11: Payable Turnover - Quintile by Firm Size

	Median-based		Quartile-based	
	ATT	S.E.	ATT	S.E.
Days Sales Outstanding (DSO)	-4.21** (0.01696)	1.763	-6.843*** (0.005814)	2.481
Days Inventory Outstanding (DIO)	-14.03 (0.1078)	8.101	-5.924 (0.6195)	11.93
Days Payables Outstanding (DPO)	0.1653 (0.9105)	1.471	3.218 (0.6334)	6.747
Cash Conversion Cycle (CCC)	-1.09 (0.8052)	4.421	-7.175 (0.582)	13.04
Receivables Turnover	0.03766 (0.4707)	0.0522	0.1308 (0.1273)	0.08578
Inventory Turnover	0.08901** (0.04824)	0.04506	0.001991 (0.972)	0.0568
Payables Turnover	0.01408 (0.8504)	0.07465	0.1352 (0.1867)	0.1024

10% significance level (*); 5% significance level (**); 1% significance level (***)
p-Values in Parenthesis

Table 13: GSCM - Turnover Ratios in Absolute Value

	Quintiles				
	Q1 ATT	Q2 ATT	Q3 ATT	Q4 ATT	Q5 ATT
DSO	-9.297 (7.724)	-2.581 (3.47)	0.2704 (2.283)	2.613 (3.625)	-5.097*** (1.443)
DIO	7.014 (7.109)	10.97 (9.601)	4.789 (6.011)	-14.54* (8.388)	3.244 (5.834)
DPO	1.018 (3.81)	-0.5839 (1.562)	1.314 (1.771)	4.863 (4.233)	-0.7684 (3.018)
CCC	7.321 (7.54)	2.852 (7.979)	8.89* (5.271)	-17.26 (11.07)	8.416 (9.285)
RT	0.0335 (0.0853)	0.0855** 0.0422)	-0.0279 (0.0356)	0.0309 (0.03697)	-0.0048 (0.02033)
IT	-0.0838 (0.09721)	-0.0334 (0.0604)	-0.02908 (0.1116)	-0.02835 (0.0830)	0.03384 (0.0332)
PT	-0.02637 (0.0797)	-0.0096 (0.0622)	-0.1083* (0.05811)	-0.0142 (0.05657)	0.02605 (0.0501)

10% significance level (*); 5% significance level (**); 1% significance level (***)
Standard Errors in parenthesis

Table 14: GSCM - Median-based sample by Firm Size Quintile

	Quintiles				
	Q1 ATT	Q2 ATT	Q3 ATT	Q4 ATT	Q5 ATT
DSO	-9.961 (12.030)	2.302 (2.455)	2.409 (1.804)	5.024 (4.991)	-11.03*** (2.170)
DIO	34.090 (50.460)	24.160* (13.880)	11.990 (8.545)	-10.600 (15.360)	-0.544 (8.135)
DPO	-0.399 (8.021)	-0.665 (6.176)	-0.004 (2.248)	2.748 (5.907)	-7.053 (4.404)
CCC	4.550 (41.810)	10.410 (11.290)	25.330** (10.500)	-4.850 (3.774)	3.251 (15.520)
RT	-0.076 (0.1549)	0.1161** (0.0537)	-0.0113 (0.0487)	0.061 (0.0473)	0.1701*** (0.0420)
IT	0.0417 (0.0994)	-0.1056 (0.0863)	-0.1188 (0.1641)	0.0731 (0.121)	0.0803 (0.0495)
PT	-0.0167 (0.0957)	0.0716 (0.1286)	-0.0794 (0.0693)	0.1164 (0.0811)	0.0091 (0.0273)

10% significance level (*); 5% significance level (**); 1% significance level (***)
Standard Errors in parenthesis

Table 15: GSCM - Quartile-based sample By Firm Size Quintile

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