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Adaptive Reconfiguration in Complex E-Commerce Systems: Flow and Stock Adjustment Under the COVID-19 Shock

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Abstract

E-commerce has reshaped short-term financial management by altering transaction speed, payment structures, and supply chain coordination. This study examines how large publicly listed e-commerce firms, viewed as complex digital business systems, adjusted their working capital policies during and after the COVID-19 shock. The sample is based on the 100 largest e-commerce companies worldwide by market capitalization, as reported by CompaniesMarketCap (February 2026), and is reduced to 76 firms from 23 countries due to data availability, yielding 802 firm-year observations. Firm-level data are obtained from LSEG Datastream, while macroeconomic variables are sourced from the World Bank. The analysis distinguishes between two dimensions of working capital: flow-based operational adjustment, measured by the cash conversion cycle (CCC), and stock-based balance-sheet adjustment, captured by net working capital relative to total assets (WC/TA). Fixed-effects models with firm-clustered standard errors are employed. The results indicate a substantial contraction of the CCC during the pandemic, followed by partial persistence of that contraction rather than a return to pre-pandemic norms. In contrast, WC/TA remains broadly stable during the crisis but declines in the post-pandemic period, suggesting a delayed balance-sheet adjustment. Business-model heterogeneity is not statistically significant, which may reflect a common system-level response across e-commerce firm types. Leverage and supply-chain pressures are associated with working capital intensity (WC/TA), while inflation shapes operate cycle duration (CCC). The findings are consistent with a two-stage adaptive response to systemic disruption.

Keywords: working capital dynamics; cash conversion cycle; complex digital business systems; e-commerce; COVID-19 shock; system adaptation; B2B; B2C; C2C

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1. Introduction

E-commerce has moved beyond its role as a supplementary distribution channel and now functions as a core organizational form in retail and platform-based intermediation. E-commerce firms operate as complex digital business systems, integrating digital payment infrastructures, logistics networks, supplier relationships, and customer flows into tightly coupled operating architectures [1]. These features reshape short-term financial management. Compared to traditional retail, e-commerce firms often operate with compressed operating cycles, supported by advanced customer payments and flexible supplier credit arrangements [1,2]. The same structural features, however, leave these firms exposed when transaction volumes fluctuate sharply, delivery networks slow down, or supplier relationships are stressed.

The expansion of e-commerce has therefore introduced a distinct configuration of working capital dynamics. High transaction frequency and digital payment systems tend to accelerate receivables collection, while platform-based models can redistribute financing needs across participants in the value chain. However, these mechanisms also rely on the smooth functioning of logistics networks and predictable demand patterns. When these conditions are disrupted, the effects propagate quickly through firms' operating cycles. The COVID-19 pandemic constituted a systemic shock that made these propagation dynamics visible across the e-commerce sector. Simulation-based analyses show that epidemic outbreaks generate rapid, nonlinear disruptions across global supply chain networks, with cascading effects on inventory availability, lead times, and operational flows [3]. In many e-commerce segments, demand increased sharply, yet this coincided with severe constraints in global supply chains, including delivery delays, inventory shortages, and increased transportation costs [4]. Under these conditions, working capital management shifted from routine optimization toward adaptive short-term adjustment under systemic constraint.

The empirical literature on working capital and firm performance is well-established in its broad outlines, but two issues remain insufficiently explored. First, existing empirical studies are predominantly sector-specific and structurally remote from digital commerce—examining financial firms [5], firms listed in single national markets [6], food manufacturers [7], automotive manufacturers [8], or traditional retailers [9]. Other studies restrict attention to specific industrial segments within a single emerging economy [10], or draw on broad multi-industry panels that pool firms whose working capital architectures differ fundamentally from those of e-commerce platforms [11,12]. The mechanisms through which e-commerce firms collect receivables, turn over inventory, and manage supplier credit are structurally distinct from those of manufacturers or traditional retailers, and evidence from these settings may not transfer cleanly to this context. COVID-19-related e-commerce research has focused mainly on digital transformation and logistics [13], leaving working capital adjustment under-examined. Second, the literature often treats working capital as a single construct, without distinguishing between the speed of the operating cycle and the level of short-term asset investment. In complex digital business systems, external disruption may simultaneously trigger flow-based operational adjustments—reflected in the cash conversion cycle (CCC)—and stock-based balance-sheet reconfigurations—reflected in net working capital relative to total assets (WC/TA).

Dynamic capabilities theory suggests that firms respond to external disruption through mechanisms operating at different timescales: sensing and seizing responses unfold rapidly, while structural reconfiguration occurs more slowly. These two timescales map directly onto the CCC and WC/TA distinction: fast-cycle operational adjustment versus slow-cycle balance-sheet reconfiguration. Under systemic disruption, the two mechanisms may activate at different intensities and with different timing lags—a split adjustment pattern that single-metric designs cannot detect.

This study addresses both gaps by examining how large listed e-commerce firms adjusted their working capital policies during and after the COVID-19 shock. The analysis also tests whether adjustment patterns differ across B2B, B2C, and C2C business models, and controls for macroeconomic conditions including global supply chain disruption. Unlike existing COVID-19 working capital studies—which examine structurally different industries, use a single metric, and rarely extend beyond 2021—this study focuses on e-commerce as a distinct digital business system, decomposes adjustment into two temporally separate mechanisms (CCC and WC/TA), and tracks whether pandemic-era changes persisted through 2024. The question is not whether working capital changed, but which adaptive mechanism activated, at what speed, and with what durability.

The sample comprises 76 listed e-commerce firms drawn from the top 100 largest companies by market capitalization, spanning 23 countries across five continents over the period 2010–2024. The fifteen-year observation window is designed to support a three-way comparison: baseline working capital behavior in the pre-pandemic years, the acute adjustment phase of 2020–2021, and the recovery period through 2024. This three-period structure enables assessment of adjustment durability, while the cross-country coverage supports country-level macroeconomic controls unavailable in single-market studies.

The results indicate a pronounced contraction of the cash conversion cycle during the pandemic, followed by partial persistence of that contraction in the post-pandemic period rather than a full reversion to pre-pandemic norms. Working capital intensity (WC/TA) did not respond significantly during the acute phase, but declined in the post-pandemic period, suggesting a delayed balance-sheet adjustment. The evidence also suggests that these adjustments are broadly similar across business models, while external constraints, particularly leverage and supply-chain pressures, are more significantly associated with WC/TA, and inflation shapes operating cycle duration.

Taken together, the findings contribute to the literature in four ways. First, the study adopts a complex digital business systems lens, linking payment, logistics, and supply-chain subsystems to working capital dynamics under external disruption. Second, the COVID-19 shock is associated with two temporally distinct adjustment forms—a flow-based CCC contraction during the pandemic and a delayed stock-based WC/TA decline afterward—a two-stage pattern undetectable with a single metric. Third, by extending the analysis through 2024, the study assesses whether pandemic-era adjustments persisted during the recovery period, offering insight into the adaptive capacity of large listed e-commerce firms. Fourth, the absence of statistically significant differences across B2B, B2C, and C2C business models suggests a possible common system-level response to the COVID-19 shock, pointing to shared structural properties of e-commerce platforms that may override model-specific differences under systemic disruption. To the best of the authors' knowledge, this study is among the first to examine whether the response of C2C marketplaces to the pandemic shock differs from that of B2B and B2C models within this working-capital adjustment framework.

The remainder of the paper is structured as follows. Section 2 outlines the relevant literature and positions the study within existing research. Section 3 describes the data, variables, and regression models. Section 4 presents empirical results in light of previous research. Section 5 concludes.

2. Literature Review and Development of Research Hypotheses

2.1. Theoretical Framework

The literature on working capital management (WCM) under crisis conditions explains firms' decisions through the lens of dynamic capabilities theory (DCT). These capabilities refer to a firm's ability to build, integrate, and reconfigure internal and external competences in order to survive and even prosper during periods of major turbulence [14], such as the COVID-19 pandemic, which profoundly affected the cash conversion cycle, supply chains, and access to sources of financing. The main pillars of DCT [15] are: the sensing of opportunities and threats in the business environment, the seizing of information whose proper interpretation enables decision-making regarding strategic investments and product architecture, and the transforming by coordinating resources and reconfiguring processes in order to generate competitive advantages. Applied to e-commerce firms, these three pillars map onto the capacity to detect external disruptions, process signals across interconnected subsystems, and reconfigure operational and financial parameters in response.

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These dynamic capabilities enable organizational learning and the selection of the most appropriate resources to respond quickly to dynamic market conditions, as well as to create and subsequently sustain competitive advantages [16]. In e-commerce systems, this adaptive capacity is embedded in the interdependencies connecting digital operations, payment processing, supply chain coordination, and short-term financial management. A disruption in one area—such as a logistics bottleneck, a demand surge, or a change in payment timing—may be transmitted across these operational and financial linkages, triggering adjustments in working capital parameters across the system. The COVID-19 pandemic significantly altered the business environment through shortages of goods, demand fluctuations, and panic-buying phenomena, which required rapid adaptations of commercial policies and adjustments in relationships with customers and suppliers, both of which represent key areas of WCM.

Some authors [15] argue that the pandemic created the need to extend DCT from the firm level to the macro level, as supply chains had to be reconfigured to ensure the viability of the commercial cycle. From a complex systems perspective, this extension reflects the fact that e-commerce firms do not adjust in isolation: their operational-financial reconfiguration is coupled with, and constrained by, broader supply chain and payment ecosystems. Supply networks exhibit complex adaptive system properties [14], meaning that disruptions propagate across interdependent nodes in nonlinear ways—a dynamic consistent with the COVID-19 shock, when simultaneous demand acceleration, logistics bottlenecks, and financing constraints coincided with adjustments across e-commerce operating cycles. The adaptation and transformation of supply chains entailed, among other things, the revision of inventory management policies, as firms were compelled to accept the tying up of capital in inventories, the renegotiation of payment terms and the adjustment of the entire financing structure of the operating cycle in order to protect liquidity and improve the efficiency of internal reserves [14]. According to Cheng et al. [17], dynamic capabilities explain the reduction in consumers' perceived risk, with beneficial effects on the stability of cash inflows, due to increasing customer loyalty. In addition, digital transformation acts as a driver of agility and resilience, which, according to Elnadi et al. [18], optimizes inventory levels within the supply chain. These adjustments correspond to two analytically distinct system responses: a flow-based operational reconfiguration, observable in the cash conversion cycle, and a stock-based balance-sheet reconfiguration, observable in net working capital relative to total assets. DCT is consistent with the possibility that these responses operate on different timescales, as firms may first adjust operational flows and only subsequently restructure balance-sheet positions—a sequencing consistent with a two-stage adaptive pattern.

Therefore, the challenges created by COVID-19 for firms' WCM, including in e-commerce, were not limited to liquidity alone, but also concerned dynamic capabilities, as they required control of working capital through a dynamic approach involving structural and technological adaptations within firms and across the entire commercial ecosystem. The systemic nature of the COVID-19 shock—simultaneously affecting demand, logistics, supply chains, and financing conditions—makes e-commerce firms a particularly relevant context for examining whether complex digital business systems exhibit common adaptive responses across different organizational configurations, or whether system architecture, as reflected in B2B, B2C, and C2C business models, produces differentiated reconfiguration patterns.

2.2. Working Capital Management and COVID-19 Pandemic Disruption

Working capital management (WCM) is a lever used by managers to influence firms' financial position through the management of cash, receivables, and inventories. The

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efficient WCM during periods of crisis has been the subject of considerable attention in the literature, and the COVID-19 systemic shock was no exception.

The related literature examines the effects of the pandemic through several distinct mechanisms, with impacts varying in both direction and magnitude depending on the sector, firm size, and institutional context, indicating substantial heterogeneity. One key mechanism concerns the liquidity shock, which affected operating cycle durations (CCC). Tarkom (2022) [4] examined US publicly traded companies between 2019 and 2021, showing that firms exposed to the shock generated by COVID-19 exhibited higher CCC. While the author found evidence that the pandemic negatively impacted WCM, they also documented the mitigating effect of investment opportunities and government support measures on the adverse effects of COVID-19 on liquidity. Hamshari et al. (2022) [5] observed similar deterioration among listed Jordanian financial firms. They also found that firms under analysis adopted more conservative approaches, involving longer CCC durations and stronger focus on receivables, which helped them outperform companies using alternative WCM approaches. Therefore, these studies indicate that firms adopted defensive WCM strategies, using receivables management as their primary adjustment mechanism.

A second mechanism concerns inventory adjustments following pressures emerging in the supply chain. Demiraj et al. (2022) [8], using data from the European automotive industry, showed that WCM was strongly affected by the dynamic adjustments made to the CCC in order to absorb the decline in sales, as well as by disruptions in the supply chain. Dodd and Liao (2025) [13] offer a more nuanced view, arguing that companies which maintained high inventory levels as part of their WCM strategy suffered during the first phase of the pandemic, but in its later stages outperformed their competitors because they used inventory as a hedge against supply chain disruptions. In other words, these studies highlight tensions in inventory management strategies: under normal conditions, high inventory levels negatively affect liquidity, but disruptions generated by crises make them strategic buffers.

A third stream of the literature focuses on the nature of the shock in the context of the institutional environment. Liu et al. (2024) [19], comparing the Chinese agri-food sector during COVID-19 with the 2008 financial crisis, highlighted that WCM was affected differently depending on the type of shock, with the impact of COVID-19 being stronger than that of the 2008 financial crisis. This finding is consistent with Dodd and Liao (2025) [13] who argue that the reason the shock created by the COVID-19 pandemic differed from other crises lies in the disruption of global supply chains, which compounded the decline in demand and the commodity price shocks that had also occurred during other periods of turbulence. Ahmad et al. (2022) [20], studying firms from three developing Asian economies, emphasized the essential role of flexibility in working capital policies in the face of prolonged health-related or financial shocks. In contrast, studies from Poland [21] and United Arab Emirates [22] found no significant changes in overall WCM efficiency during the pandemic due to proactive adjustments to inventory levels and collection/payment terms, and, for UAE firms, governmental financial support. In the same vein, Xu and Jin (2022) [23] did not detect a significant impact of the health crisis on the cash holdings of Chinese agri-food companies, despite a decline in the accounts receivable turnover ratio.

However, the studies cited above do not primarily examine firms in the e-commerce sector, whose structural and operational particularities, related to mechanisms such as platform business model, digital payment infrastructures and direct-to-consumer logistics, are expected to significantly shape, and potentially alter, the direction of the relationship between the pandemic and WCM. A first e-commerce specific mechanism concerns digital payment systems and the platform-mediated movement of cash flows. Electronic transactions reduced difficulties in collecting receivables and, through the creation of new payment methods [24], enabled greater payment flexibility. They also simplified the cash conversion cycle by enabling a better matching between expenses and revenues on electronic platforms, reducing the need for physical liquidity [25]. More recent studies [26] support this idea through findings showing that payment infrastructure has the highest marginal impact on the development of e-commerce platforms, as instant payments accelerate the CCC and reduce transaction costs [27]. Electronic payment infrastructure facilitates digital financial inclusion, which supports the generation and accessibility of working capital for online sellers by enabling access to liquidity without physical collateral and by allowing growth through e-commerce platforms [28]. According to Wei et al. [29], transaction histories and platform ratings can serve as data inputs for assessing firms' creditworthiness, enabling them to obtain working capital through channels that provide an alternative to traditional banking requirements.

A related mechanism involves digitalization of supply-chain processes. The logistical and financial disruptions generated by the pandemic accelerated the adoption of technology and digitalization among e-commerce firms, including SMEs, as a means of optimizing working capital positions through the reduction of operating costs and resource waste [30]. As observed by Gao et al. (2023) [31], digitalization of the supply chains increased transparency and enhanced the monitoring of operations, which reduced inventory levels and increased revenue, as well as customer satisfaction. Moreover, digitalization through investments made by participants in the supply chain enabled better coordination across the supply chain and stimulated demand, thereby extending the effects of digitalization on WCM from the individual firm level to the entire platform ecosystem [32,33]. However, the pandemic was also associated with an increase in working capital requirements for firms experiencing sales expansion and a lack of integration with suppliers across the supply chain, which limited real-time inventory control. This duality is discussed by Bravo et al. (2022) [30], who simultaneously document the flexibility of WCM allowed by instruments accessible mostly for e-commerce firms, alongside persistent vulnerabilities related to inventory replenishment difficulties. In the context of cross-border e-commerce, although digitalization has reduced financing constraints and information asymmetries, regulatory barriers and restricted access to platforms in certain markets have continued to affect WCM even after the pandemic [34,35].

Against this broader background, the present study seeks to examine whether the pandemic is associated with a shortening of the operating cycle and an increase in working capital intensity in e-commerce by testing the following hypotheses.

H1a. *The COVID-19 systemic shock is associated with a contraction in the flow-based operational adjustment of e-commerce firms, reflected in a shorter operating cycle duration.*

H1b. *The COVID-19 systemic shock is associated with an increase in the stock-based balance-sheet adjustment of e-commerce firms, reflected in higher working capital intensity.*

Hypotheses H1a and H1b are designed to capture firms' dual and sequential adaptive response to pandemic-induced disruptions, in line with the predictions of DCT. From a DCT perspective, adjustments in operational flows (reflecting the sensing and seizing capabilities, activated simultaneously by a systemic shock) are expected to precede inventory reconfigurations recorded in the balance sheet, which correspond to the transforming capability. This sequence arises because digital systems enable rapid adjustments in operational flows, whereas changes in firms' financial positions and stock structures typically materialize more gradually.

For the less extensively studied post-pandemic period, the present study examines whether the adjustments implemented during the pandemic were only temporary or became more permanent by testing the following hypotheses:

H2a. *The post-pandemic period is associated with a partial reversal in the flow-based operational adjustment of e-commerce firms, with operating cycle duration partially recovering toward pre-pandemic levels.*

H2b. *The post-pandemic period is associated with a partial reversal in the stock-based balance-sheet adjustment of e-commerce firms, with working capital intensity partially recovering toward pre-pandemic levels.*

The notion of partial reversion underlying these hypotheses stems from the assumption of irreversibility embedded in the transforming pillar of DCT. Dynamic capabilities are expected to generate resource reconfigurations that become semi-permanent and cannot be fully reversed once implemented. As a result, firms are expected to exhibit convergence toward pre-pandemic conditions, but not a complete return to pre-pandemic levels.

2.3. Working Capital Management and Business Models in E-Commerce

The severe liquidity disruptions and major shifts in consumer behavior triggered by the COVID-19 pandemic did not affect all firms equally, not even those operating within the same sector, such as e-commerce. Firms relying on different customer-serving models responded differently due to the specific features of their operational and financing structures.

According to Turban et al. (2018) [36], the business-to-business (B2B) model is characterized by longer payment cycles, negotiated inter-firm terms, and recurrent purchases; the business-to-consumer (B2C) model typically involves a high volume of transactions and a shorter commercial cycle; whereas customer-to-customer (C2C) models, enabled by platforms, tend to generate revenues primarily through commissions and listing fees rather than through direct product sales. B2B e-commerce refers to internet-based transactional platforms through which organizational buyers and sellers interact in order to satisfy their needs while also benefiting from complementary value-added services [37]. The quality of the services offered by platforms, such as logistics, payment systems, data analytics, and marketing support, leads B2B relationships to be perceived as strategic interdependencies [38]. B2C e-commerce is generally understood as a digital business model in which firms sell goods and services directly to final consumers through online platforms that enable personalized customer interaction [31]. C2C e-commerce, in turn, represents a digital exchange model, typically mediated by online marketplaces, that facilitates transactions between individual consumers in conditions of security and trust [39].

For the B2B model, which is characterized by trade credit and long-term relationships with business partners, the pandemic led to longer payment periods as a strategic measure to support sales [40], while also exacerbating liquidity shortages under conditions of restricted external financing. In the B2B environment, Mora Cortez and Johnston (2020) [32] show that the COVID-19 crisis differed from previous crises by creating a stronger need for technological transformation in order to maintain business relationships and transaction continuity. As a result, trade credit terms were renegotiated and payments were deferred, with direct effects on working capital. Along similar lines, Zahoor et al. (2022) [14] argue that the use of dynamic capabilities and strategic agility, through the reconfiguration of business models and a shift toward digital channels, enabled B2B firms to mitigate disruptions by adjusting payment terms, rebalancing inventory volumes between physical warehouses and digital channels, and increasing liquidity buffers in order to prevent or reduce the risk of non-payment specific to B2B transactions. Inter-firm collaboration, including the joint development of digital solutions, also made it possible to redistribute the working capital burden among supply chain partners [41]. Xiao et al. (2024) [42] explain the resilience of B2B firms, in the context of the disruptions caused by the simultaneous distortion of demand and supply and by logistical infrastructure problems, through the lens of Resource Dependence Theory, within which cash and trade receivables play a central role. Chytilová and Talír (2024) [39] statistically show that the intensity of coercive measures was positively associated with the level of disruption experienced by B2B firms (unlike B2C firms), highlighting the distinct way in which B2B firms adjusted internal resources during the pandemic. From a DCT perspective, the long-term contractual relationships characteristic of the B2B model tend to result in a slower activation of the sensing capability and a more extensive deployment of the transforming capability through structural supply chain adjustments.

While B2B transactions declined at the onset of the pandemic, B2C transactions surged dramatically [43], with this trend partially reverting toward the later stages of the pandemic. E-commerce platforms revolutionized market access in the B2C sector, enabling access to vast customer bases with minimal investment [29]. The strong increase in online demand, stimulated by virtual showrooms and personalized recommendations [33,38], enabled B2C firms to collect sales revenues more easily, thereby improving their working capital intensity despite broader economic turbulence [44]. The duration of the operating cycle also shortened for these firms, as digital payment systems accelerated cash collection and inventory turnover improved because of higher sales volume. Mancuso et al. (2023) [45] argue that these developments can be explained largely by the rise in contactless payments and the expansion of home delivery services. However, B2C firms that lacked an online presence were more vulnerable to the negative effects of the pandemic, as mobility restrictions forced them to simplify their organizational structures, diversify their product offerings [39], and undertake radical digital transformations. E-commerce B2C firms were therefore less affected than those in traditional retail, for which the impact of lockdowns and restrictions on the movement of people was particularly severe [46]. From a DCT perspective, the B2C model, through its direct exposure to demand fluctuations, appears to affect dynamic capabilities in a way that contrasts with the B2B model: the sensing capability tends to be activated more rapidly, the seizing capability more aggressively through inventory policies and volatile pricing strategies, while the transforming capability is engaged only superficially.

Only a limited number of studies examine the response of C2C businesses to the pandemic. Chytilová and Talír (2024) [39] show that the use of digital transaction platforms improved the speed of commercial exchanges and cash flows between users. From a DCT perspective, in the case of the C2C model, where intermediation is the dominant feature, dynamic capabilities appear to be partially delegated to users, with more limited direct exposure.

Given these inconclusive or incomplete findings and the theoretical framework that assumes heterogeneous responses across business architectures, the present study tests whether the business model type dampens or amplifies the pandemic effect by developing the following hypotheses.

H3a. *Business model type moderates the effect of the COVID-19 systemic shock on the flow-based operational adjustment of e-commerce firms.*

H3b. *Business model type moderates the effect of the COVID-19 systemic shock on the stock-based balance-sheet adjustment of e-commerce firms.*

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In the post-pandemic period, digital business has increasingly become the new normal, with customers growing more demanding in terms of response speed and the reliability of on-time delivery [37], thus requiring firms to strengthen their logistics and service capabilities. B2B firms adapted after the pandemic by diversifying their product portfolios, allowing declines in demand for some products to be offset by increased demand for others [47], while also reducing customer concentration [42]. However, broader business diversification may also prove detrimental, as global crises can disrupt multiple business segments simultaneously [42]. Moreover, the insufficient level of working capital required to sustain day-to-day operations, which was an issue that threatened business continuity in certain sectors during the pandemic, continued to persist in the post-pandemic period, as illustrated by the case of Indian manufacturers that remained financially vulnerable [48].

At the same time, the integration of digital and physical channels has become a permanent component of the new normal for many B2B and B2C firms, as such integration is increasingly regarded as necessary for ensuring the resilience of cash flows in future crises [46]. In this context, digitalization continues to serve as a mechanism for improving working capital efficiency [45], while maintaining a low cash conversion cycle remains essential for minimizing financing costs [12].

To examine the post-pandemic position of e-commerce firms, the following hypotheses are proposed.

H4a. *The post-pandemic reconfiguration of the operating cycle differs across e-commerce business model types, reflecting model-specific adaptive responses within a common digital infrastructure.*

H4b. *The post-pandemic reconfiguration of working capital intensity differs across e-commerce business model types, reflecting model-specific adaptive responses within a common digital infrastructure.*

Figure 1 summarizes the conceptual logic of the study. The COVID-19 shock is expected to affect e-commerce firms through demand, logistics and supply-chain, and digital payment channels. These pressures are reflected first in flow-based operational adjustment, measured by CCC, and subsequently in delayed stock-based balance-sheet adjustment, measured by WC/TA. B2B, B2C, and C2C models are included as a common business-model context. The next section translates these proposed links into the empirical design.

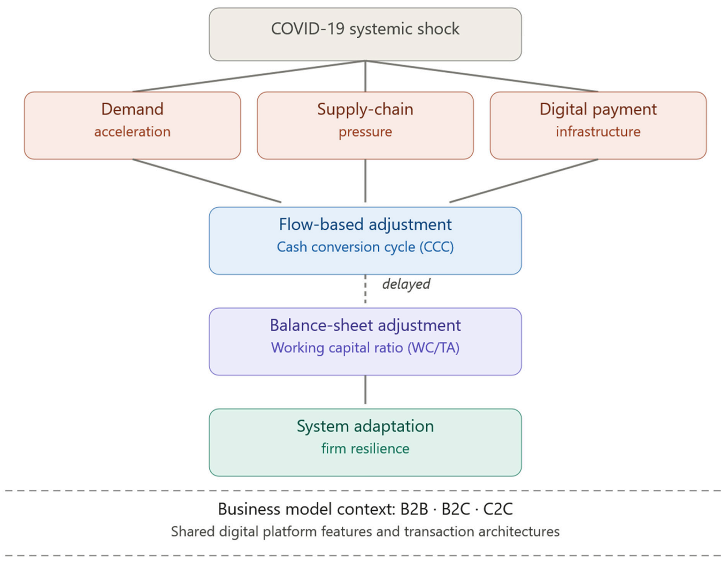

Figure 1. Conceptual model.

3. Research Methodology

3.1. Sample and Data

In selecting the firms included in the sample, the analysis initially relied on the top 100 largest e-commerce companies worldwide by market capitalization, as published by CompaniesMarketCap in February 2026. This approach may introduce survivorship and look-ahead bias, as firms that failed, delisted, or declined before 2026 are excluded by construction. Accordingly, the findings should be interpreted as evidence for large surviving listed e-commerce firms rather than the e-commerce sector as a whole. The severity of these biases is, however, partially mitigated by the unbalanced structure of the panel, which exhibits a progressive increase in the number of firms with available data, from 25 in 2010 to 39 in 2015 and 73 in 2019. This structure implies a reduced influence of selection based on 2026 market capitalization on the earlier years of the sample, as many firms contribute observations only for the more recent years of the study period. Depending on the availability of financial data for the selected variables, the final sample consisted of 76 firms from 23 countries and 5 continents (see Figure 2) and 802 annual observations, resulting in an unbalanced panel. However, the lack of data for certain macroeconomic variables further reduced the number of observations included in the models, which ranged from 648 to 722. Firm-level financial data were obtained from the LSEG Datastream database, while country-level and global macroeconomic data were primarily retrieved from the World Bank.

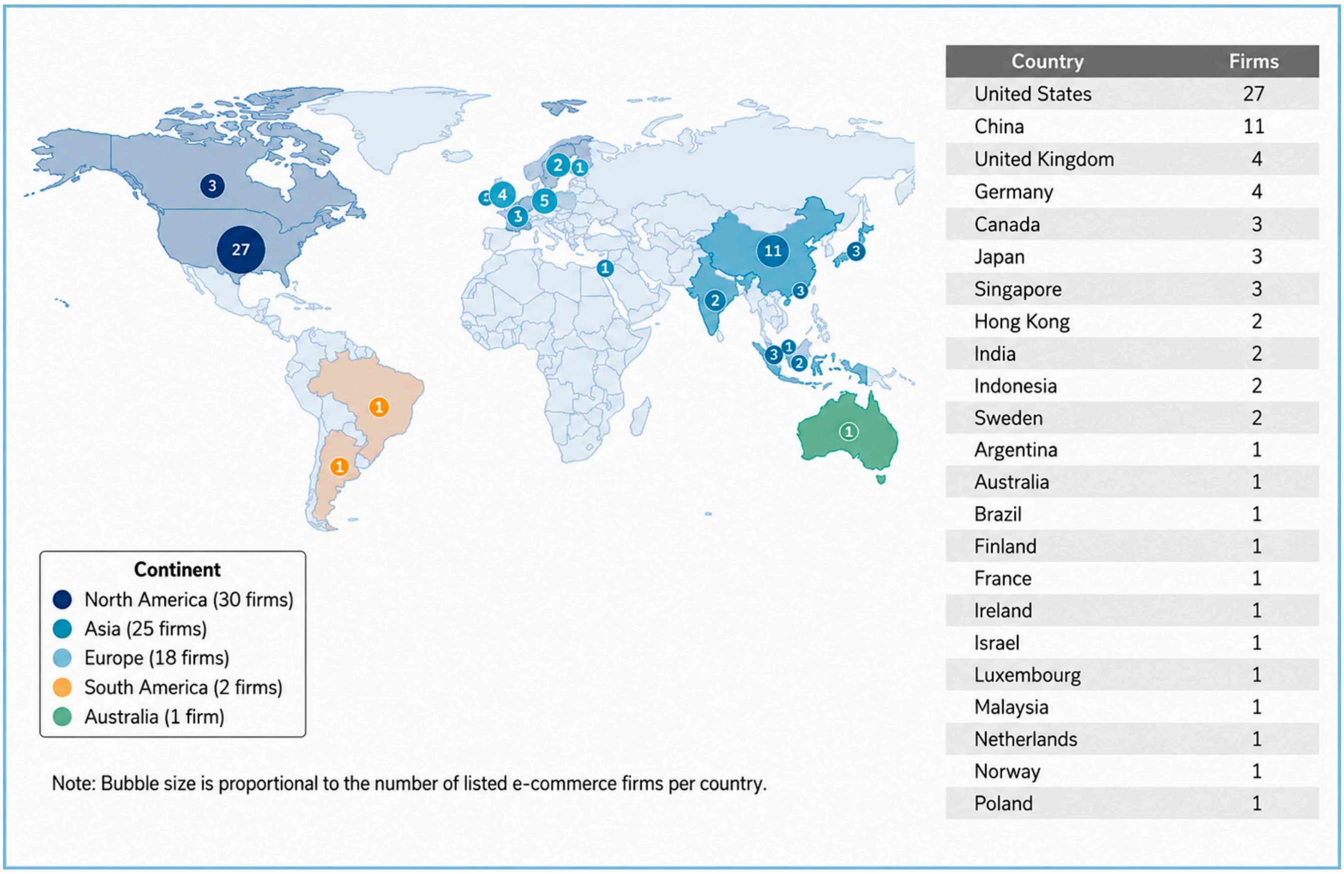

Figure 2. Structure of firms' countries by continent.

The period under analysis is 2010–2024. A time span of 15 years is sufficient to capture the maturation trajectory of global e-commerce. The period is structured into three distinct phases to reflect the heterogeneous impact of COVID-19 across e-commerce firms: a 10-year pre-pandemic period, a 2-year period marked by COVID-19-related disruptions, and a post-pandemic recovery period after those disruptions.

3.2. Dependent, Independent and Control Variables

To measure working capital management, two different indicators are employed as *dependent variables*. The first is the *cash conversion cycle* (CCC), defined as days inventory outstanding plus days sales outstanding minus days payable outstanding. This variable captures the net number of days during which a firm's cash is tied up in operating activities and is widely used in the literature in studies examining working capital efficiency [49,50] to measure *the operating cycle duration*.

The second dependent variable is the *net working capital* (WC/TA), used as a measure of *working capital intensity*, which relates the difference between current assets and current liabilities, interpreted as net current operating investment, to the firm's total assets [4,12,50]. This measure provides a balance-sheet perspective on how the firm's liquidity is utilized, thereby complementing the picture captured by the CCC.

The *independent variables* are represented by the *pandemic dummy variables, business model dummy variables* and their *interactions with the business models*. The impact of the external shocks triggered by the COVID-19 pandemic, which severely disrupted supply chains, payment flows, and short-term liquidity [4,20,48], is captured through three dummy variables, with the pre-pandemic period serving as the omitted reference category: the pre-treatment period (2010–2019); the acute pandemic phase (2020–2021)—DUR; and the post-pandemic recovery phase (2022–2024)—POST [12,20,40].

Firms' responses to these disruptions depended on several factors among which the business model employed shaped their working capital dynamics. Dummy variables for B2B (used as the reference category), B2C, and C2C capture the main transaction models in e-commerce, reflecting their distinct features in terms of revenue generation and value creation [14,32,36,39], as well as the extent to which these characteristics conditioned the impact of the pandemic on working capital efficiency (BM_B2C_DUR, BM_C2C_DUR, BM_B2C_POST, BM_C2C_POST). Firms were classified according to their *dominant* business model, based on firms' annual financial statements and other public reports. The main revenue-generating segment was identified, and, in cases where companies operated across multiple segments, the segment generating the majority of revenues was considered dominant. The reasoning was replicable and systematic, but it involved a certain degree of authors' judgment for firms that did not directly report this information or that operated highly integrated multi-segment activities. Table A1 in Appendix A shows the list of firms in the sample and their dominant business model. It also includes a grouping of firms based on a hybrid business model. These are firms that, in addition to a dominant model, engage in other secondary business model(s), combining two or all three models used in the paper. This classification is an alternative to the tripartite one, used to test the robustness of the results.

The firm-level, country-level and global macroeconomic *control variables* are presented in Table 1. Several control variables are conceptually related to working capital outcomes. Their inclusion is intended to reduce omitted-variable bias rather than to support causal identification and should be viewed as conditioning variables rather than strictly exogenous determinants.

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Table 1. Variables in the models and data source.

Variable	Definition and Measurement	Data Source	Citations
Dependent variables			
Cash conversion cycle (CCC)	Days inventory outstanding (DIO) + days sales outstanding (DSO) − days payable outstanding (DPO), in days DIO = (average inventory/COGS) × 365 DSO = (average receivables/revenue) × 365 DPO = (average payables/COGS) × 365	LSEG Datastream	[4,49,51]
Working capital intensity (WC/TA)	Net working capital = (Current assets-Current liabilities)/Total assets	LSEG Datastream	[4,50]
Variables of interest			
During-pandemic dummy (DUR)	Binary indicator equal to 1 for years 2020–2021, 0 otherwise Pre-pandemic period (2010–2019) is the omitted baseline	Authors' classification	[4,8,9,20,48]
Post-pandemic dummy (POST)	Binary indicator equal to 1 for years 2022–2024, 0 otherwise	Authors' classification	[4,8,9,20,48]
B2C dummy	Binary indicator equal to 1 if the firm primarily operates a business-to-consumer model, 0 otherwise B2B is the omitted baseline	Authors' classification based on firm reports, using the dominant BM	[39,45]
C2C dummy	Binary indicator equal to 1 if the firm primarily operates a consumer-to-consumer (platform) model, 0 otherwise	Authors' classification based on firm reports, using the dominant BM	[36,39]
Business-model interactions (BM_B2C_DUR, BM_C2C_DUR, BM_B2C_POST, BM_C2C_POST)	Interaction terms which capture the differential effect of during- and post-pandemic period on B2C or C2C firms relative to the B2B reference category	-	-
Firm-level control variables			
Firm size (SIZE)	Natural logarithms of total assets. Larger firms have a more complex WC structures	LSEG Datastream	[20,50,52]
Sales growth (SALES_GROWTH)	Year-on-year percentage change in sales revenue. Controls for demand-driven variations in WC requirements	LSEG Datastream	[20,48,50,53,54]
Debt-to-assets (DA)	Total debt divided by total assets (financial leverage). May limit WC structures and shorten CCC	LSEG Datastream	[51,53–56]
Intangible assets ratio (IAR)	Intangible assets divided by total assets Core source of competitive advantage affecting the WC structure	LSEG Datastream	[56,57]
Tobin's Q (TQ)	Ratio of market value of equity + total debt to total assets. The ratio is log-transformed. Proxy for growth opportunities and investment incentives	LSEG Datastream	[53,58]
Profit margin (PM)	Net income divided by net sales revenue Captures the trade-off between liquidity and profitability	LSEG Datastream	[23,59]
Operating cycle (OC)	Days inventory outstanding (DIO) + days sales outstanding (DSO) Directly impacts the time-to-cash gap	LSEG Datastream	[52,59]

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Table 1. *Cont.*

Variable	Definition and Measurement	Data Source	Citations
Country-level control variables			
GDP growth (GDP)	Annual real GDP growth rate (%) for each firm's country Controls for country-specific business cycle conditions	World Bank	[48,50,60]
Inflation (Infl)	Annual consumer price inflation rate (%) for each firm's country Higher inflation raises WC needs and lengthens the CCC	World Bank	[20,48,60]
Individuals using the internet (IUTI)	Percentage of the population in each firm's country that used the internet in the past three months Captures the digital market penetration of e-commerce, affecting the WC dynamic	World Bank	[61]
Global macro control variables			
Global Supply-Chain Pressure Index (GSCPI)	Single composite index that measures the overall stress or disruption in global supply chains Higher pressure increases WC needs and slows cash conversion	Federal Reserve Bank of New York	[62]

3.3. Econometric Specifications

To test the impact of the pandemic on WC management, the model from Equation (1) (M1) is estimated. This is the baseline model.

While the first model directly investigates the pandemic's effects on the firms in the sample, the second model (M2, Equation (2)) introduces interactions between pandemic period dummies and the firm's business model classification to test whether firms with a dominant B2C and C2C BM responded differently compared to the reference category B2B.

$$Y_{it} = \alpha_i + \beta_1 \times DUR_t + \beta_2 \times POST_t + \gamma \times Controls_{it} + \varepsilon_{it} \quad (1)$$

$$Y_{it} = \alpha_i + \beta_1 \times DUR_t + \beta_2 \times POST_t + \beta_3 \times (BM_i \times DUR_t) + \beta_4 \times (BM_i \times POST_t) + \gamma \times Controls_{it} + \varepsilon_{it} \quad (2)$$

where *i* denotes firm and *t* denotes year. Y_{it} are the dependent variables: CCC and WC/TA. DUR_t is a dummy variable equal to one for the acute phase of the COVID-19 pandemic (2020–2021). $POST_t$ equals one for the recovery period (2022–2024). Pre-pandemic years of 2010–2019 are the baseline. BM_i, namely B2C and C2C, are the business model dummies, with B2B as the omitted reference category. Controls is a vector of variables organized by three levels, firm, country, and global, as described in Table 1.

Both models include firm fixed effects (α_i) and period fixed effects to absorb unobserved time-invariant heterogeneity, as well as common shocks affecting firms during the pandemic and post-pandemic periods [4,63,64]. The time dimension is captured through two period indicators, DUR (2020–2021) and POST (2022–2024), with the pre-pandemic period (2010–2019) serving as the reference category. Because DUR and POST are period-level indicators, they represent the temporal fixed effects used in the analysis. Full calendar-year fixed effects were not included because they would be perfectly collinear with the period dummies. The specification therefore captures differences across the pre-pandemic, pandemic, and post-pandemic periods rather than year-specific effects. Systems-oriented econometric designs employing two-way fixed-effects models have been applied recently to examine how e-commerce systems respond to macroeconomic conditions and external shocks [65], confirming the appropriateness of this approach for panel studies of digital business systems.

Model 2 includes BM only as a moderator effect, since the inclusion of firm fixed effects makes it, as it is time-invariant, collinear with α_i and thus impossible to estimate independently. The interacted terms $BM_i \times DUR_t$ and $BM_i \times POST_t$ capture the differentiated response to the pandemic shock for each type of business model.

Standard errors are clustered at the firm level to allow for an arbitrary autocorrelation structure over the analyzed period [63], as required by the persistence of WC-related indicators and the unbalanced structure of the sample. Wald F-test is performed to evaluate the joint significance of the interaction coefficients in Model 2.

To reduce the influence of outliers, winsorization of firm-level continuous variables at the 5th and 95th percentiles was necessary, a common practice in the literature [4,53]. Winsorization was not needed for country- and global-level variables, as these are time series that do not contain extreme observations like those at the firm level.

The robustness of the results is verified by removing the interactions between BM and the acute pandemic period (DUR). In addition, inflation (Infl) is replaced with the interest rate variable (IR), and interactions between the macro variable GSCPI and BM are added. A further robustness check addresses the concern that results may be sensitive to sample composition differences across models.

To complement the panel regressions with an exploratory nonlinear perspective, we estimate four regression trees. Trees were grown with a maximum depth of three levels (maxdepth = 3), a minimum of 20 observations required to attempt a split (minsplit = 20), a minimum terminal-node size of 10 observations (minbucket = 10), and a complexity parameter of 0.02 (cp = 0.02). Each tree was validated using 10-fold cross-validation and subsequently pruned using cost-complexity pruning based on the minimum cross-validation error. The trees are intended for exploratory analysis and do not substitute for the fixed-effects models.

4. Results and Discussion

4.1. Summary Statistics

Table 2 reports the descriptive statistics for the 802 firm-year observations drawn from 76 listed e-commerce firms. The mean cash conversion cycle (CCC) of −5.497 days (SD = 102.117) is consistent with the operational profile of e-commerce platforms, where digital payment processing and supplier-extended trade credit tend to compress the operating cycle relative to traditional retail [49,51]. The wide standard deviation—and a range from −322.8 to 152.2 days—points to substantial heterogeneity in working capital structures across firms, business models, and institutional environments, in line with evidence that working capital policies are jointly shaped by firm-specific factors and external conditions [53]. The net working capital ratio (WC/TA) averages 0.218 (SD = 0.252), with most firms maintaining a positive net current asset position.

Among firm-level controls, the mean debt-to-assets ratio (DA) of 0.194 indicates moderate leverage, while the intangible assets ratio (IAR) of 0.147 reflects the role of non-physical resources as competitive assets in e-commerce [56]. Log-transformed Tobin's Q (L_TQ) averages 0.225, consistent with above-book-value market valuations and the growth expectations embedded in listed digital platforms [58]. A mean sales growth of 31.3% and a negative average profit margin (PM = −0.108) are typical of high-growth e-commerce firms in their investment-heavy expansion phases. The pandemic-period distribution is adequate: 18.7% of observations fall in the during-pandemic window (2020–2021), 28.3% in the post-pandemic recovery (2022–2024), and 53% in the pre-pandemic baseline. The GSCPI averages 0.531 with peak values concentrated in 2021–2022, capturing the supply chain stress of that period [62].

Table 2. Descriptive statistics.

Variable	Mean	SD	Min	Max	N
CCC (days)	−5.497	102.117	−322.753	152.154	722
WC/TA	0.218	0.252	−0.231	0.702	802
SIZE (log assets)	14.412	2.770	10.259	20.423	802
SALES_GROWTH (%)	31.319	44.948	−29.330	156.369	726
DA	0.194	0.235	0.000	0.870	802
IAR	0.147	0.191	0.000	0.660	802
L_TQ (log Tobin's Q)	0.225	0.251	0.001	0.924	659
PM	−0.108	0.316	−1.153	0.243	802
OC (days)	82.666	67.428	10.000	277.000	739
IUTI (%)	82.631	13.967	47.900	96.300	802
GDP growth (%)	2.888	3.067	−6.540	10.110	802
Inflation (%)	3.404	10.009	−1.139	219.884	794
GSCPI	0.531	1.209	−0.678	3.101	802
DUR (dummy)	0.187	0.390	0.000	1.000	802
POST (dummy)	0.283	0.451	0.000	1.000	802
BM_B2C (dummy)	0.683	0.465	0.000	1.000	802
BM_C2C (dummy)	0.110	0.313	0.000	1.000	802

Notes: Firm-level variables winsorized at 5th/95th percentiles. Macro variables not winsorized. CCC = cash conversion cycle; WC/TA = net working capital/total assets; SIZE = log total assets; DA = debt-to-assets; IAR = intangible assets ratio; L_TQ = log Tobin's Q; PM = profit margin; OC = operating cycle; IUTI = internet usage (% population); GSCPI = Global Supply-Chain Pressure Index; DUR = during-pandemic dummy (2020–2021); POST = post-pandemic dummy (2022–2024); N = number of observation; SD = standard deviation.

4.2. Correlation Analysis

The VIF diagnostics confirm the absence of problematic multicollinearity (Table 3—Panel C). Mean VIF values of 2.34 (M1) and 2.29 (M2) are well below the conventional threshold of 10 [63,64], and all individual VIFs remain below 5.6.

Several pairwise correlations align with prior evidence (Table 3). Leverage (DA) is negatively associated with the working capital ratio ($r = -0.331$, $p < 0.001$), consistent with the argument that more indebted firms operate with tighter liquidity buffers [11,53]. The GSCPI is strongly correlated with the during-pandemic dummy ($r = 0.729$, $p < 0.001$), confirming that the period of greatest supply chain stress overlapped almost entirely with 2020–2021 [62]; both variables are retained separately as they capture distinct constructs. IUTI is positively correlated with the post-pandemic dummy ($r = 0.344$, $p < 0.001$), consistent with the documented acceleration of digital adoption during the recovery period [61], while inflation is positively associated with the post-pandemic dummy ($r = 0.157$, $p < 0.001$), capturing the inflationary surge of 2022–2023.

4.3. Regression Results

The regression results indicate a clear temporal pattern in working capital adjustment. During the pandemic, CCC compressed sharply, whereas the contemporaneous effect on working capital intensity (WC/TA) was not statistically distinguishable from zero. In the post-pandemic period, CCC remained below its pre-pandemic level and WC/TA declined, which suggests that the changes associated with the shock were not fully temporary. Across both outcomes, the interaction terms with business model remained insignificant, indicating a broadly common response across B2B, B2C, and C2C firms. The sections below discuss these patterns.

Table 3. Correlation matrix and variance inflation factor diagnostics.

Panel A. M1 (CCC)—Pairwise Correlations												
Variable	**DUR**	**POST**	**SIZE**	**SALES_GROWTH**	**DA**	**IAR**	**L_TQ**	**WC/TA**	**GDP Growth**	**Inflation**	**IUTI**	**GSCPI**
DUR	1	—	—	—	—	—	—	—	—	—	—	—
POST	−0.356 ***	1	—	—	—	—	—	—	—	—	—	—
SIZE	0.038	0.032	1	—	—	—	—	—	—	—	—	—
SALES_GROWTH	0.152 ***	−0.217 ***	0.104 **	1	—	—	—	—	—	—	—	—
DA	0.053	0.044	−0.003	0.008	1	—	—	—	—	—	—	—
IAR	−0.017	0.004	−0.008	−0.004	0.152 ***	1	—	—	—	—	—	—
L_TQ	0.095 *	0.071	−0.066	0.074	0.735 ***	0.130 ***	1	—	—	—	—	—
WC/TA	0.072	−0.052	−0.098 *	0.039	−0.331 ***	−0.318 ***	−0.164 ***	1	—	—	—	—
GDP growth	−0.058	−0.012	0.105 **	0.073	0.003	−0.056	−0.042	−0.036	1	—	—	—
Inflation	−0.033	0.157 ***	0.151 ***	0.221 ***	0.039	−0.039	0.040	−0.007	−0.058	1	—	—
IUTI	0.089 *	0.344 ***	−0.264 ***	−0.123 **	0.087 *	0.175 ***	0.119 **	−0.068	−0.376 ***	0.032	1	—
GSCPI	0.729 ***	−0.097 *	0.053	0.157 ***	0.075	−0.010	0.089 *	0.061	0.148 ***	0.039	0.125 **	1
Panel B. M2 (WC/TA)—Pairwise Correlations												
Variable	**DUR**	**POST**	**SIZE**	**SALES_GROWTH**	**DA**	**L_TQ**	**PM**	**OC**	**GDP Growth**	**Inflation**	**IUTI**	**GSCPI**
DUR	1	—	—	—	—	—	—	—	—	—	—	—
POST	−0.358 ***	1	—	—	—	—	—	—	—	—	—	—
SIZE	0.039	0.028	1	—	—	—	—	—	—	—	—	—
SALES_GROWTH	0.156 ***	−0.212 ***	0.112 **	1	—	—	—	—	—	—	—	—
DA	0.056	0.046	0.001	0.010	1	—	—	—	—	—	—	—
L_TQ	0.096 *	0.073	−0.061	0.076	0.731 ***	1	—	—	—	—	—	—
PM	−0.060	0.013	0.138 ***	−0.127 **	−0.146 ***	−0.139 ***	1	—	—	—	—	—
OC	−0.031	−0.030	−0.024	−0.122 **	−0.030	−0.100 *	−0.161 ***	1	—	—	—	—
GDP growth	−0.051	−0.011	0.104 **	0.070	0.006	−0.039	0.019	−0.077	1	—	—	—
Inflation	−0.033	0.156 ***	0.152 ***	0.223 ***	0.040	0.042	0.029	0.117 **	−0.059	1	—	—
IUTI	0.086 *	0.344 ***	−0.263 ***	−0.119 **	0.081 *	0.113 **	−0.032	−0.151 ***	−0.370 ***	0.033	1	—
GSCPI	0.729 ***	−0.098 *	0.054	0.161 ***	0.076	0.089 *	−0.078 *	−0.045	0.153 ***	0.039	0.123 **	1

Table 3. *Cont.*

Panel C. VIF Diagnostics			
Variable	**M1 (CCC)**	**Variable**	**M2 (WC/TA)**
DUR	2.87	DUR	2.85
POST	5.56	POST	5.55
BM_B2C	2.22	BM_B2C	2.09
BM_C2C	2.23	BM_C2C	2.20
BM_B2C_POST	5.33	BM_B2C_POST	5.32
BM_C2C_POST	2.51	BM_C2C_POST	2.50
SIZE	1.22	SIZE	1.21
SALES_GROWTH	1.21	SALES_GROWTH	1.26
DA	2.47	DA	2.23
IAR	1.29	L_TQ	2.28
L_TQ	2.33	PM	1.15
WC/TA	1.34	OC	1.18
GDP growth	1.34	GDP growth	1.37
Inflation	1.24	Inflation	1.27
IUTI	1.66	IUTI	1.68
GSCPI	2.60	GSCPI	2.59
Mean VIF	2.34	Mean VIF	2.29

Note: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

4.3.1. Operating Cycle Duration

Table 4 reports the baseline results for cash conversion cycle (CCC).

Table 4. Regression results with CCC as the dependent variable.

Variable	(1) Model 1	(2) Model 2
DUR	−128.361 ** (57.785)	−134.799 ** (60.649)
POST	−64.132 ** (31.829)	−80.297 * (43.258)
BM_B2C_DUR	—	8.862 (23.326)
BM_C2C_DUR	—	17.438 (25.673)
BM_B2C_POST	—	18.510 (35.660)
BM_C2C_POST	—	40.580 (38.068)
SIZE	24.246 * (13.127)	24.269 * (13.019)
SALES_GROWTH	−0.076 (0.104)	−0.069 (0.106)
DA	30.031 (19.494)	29.479 (19.131)
IAR	−39.018 (39.883)	−39.213 (43.540)
L_TQ	−0.967 (14.115)	−1.702 (14.304)
WC/TA	24.387 (33.103)	23.636 (33.629)
GDP growth	−1.992 (1.746)	−2.152 (1.741)
Inflation	0.501 *** (0.139)	0.378 ** (0.151)
IUTI	−0.585 (0.582)	−0.584 (0.650)
GSCPI	18.252 (13.272)	18.213 (13.213)
Constant	−252.035 (178.230)	−252.055 (177.343)
N	648	648
R^2	0.137	0.144

Notes: All models include firm fixed effects and period fixed effects. Standard errors clustered at the firm level in parentheses. All firm-level variables winsorized at the 5th–95th percentile. Macro variables not winsorized. B2B is the omitted business model category. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. As BM dummy coefficients (BM_B2C, BM_C2C) are 0.000 (.) due to their perfect collinearity with firm fixed effects (as time-invariant variables), they cannot be estimated independently and are not retained in the table. Column (1): no business model variables. Column (2): BM dummies + BM × POST interactions.

The during-pandemic dummy (DUR) carries a large, negative, and statistically significant coefficient in the baseline CCC model without business-model interactions: $\beta_1 = -128.361$ (SE = 57.785, $p < 0.05$). The estimate is stable when business-model interaction terms are added ($\beta_1 = -134.799$, SE = 60.649, $p < 0.05$), confirming that the pandemic effect on the operating cycle does not vary appreciably with model specification. The negative coefficient implies a shortening of CCC, which may be favorable in efficiency terms because less capital is tied up in operations. Relative to the pre-pandemic baseline, large listed e-commerce firms cycled through their operating activities approximately 128 days faster during 2020–2021, after absorbing firm and period fixed effects. Given the sample mean CCC of −5.5 days, this is a shift in substantial magnitude, and it suggests that the adjustment likely reflects a broad-based reconfiguration of operational flows spanning multiple components of the operating cycle simultaneously—receivables collection, inventory management, and payables timing—rather than originating from a single source [48,51,52].

The DUR coefficient provides empirical support for H1a. The estimates are consistent with a demand-acceleration channel specific to e-commerce as a digital business system: platforms operating in a sector where the COVID-19 period coincided with a structural demand surge faced operational pressure to accelerate order fulfillment, compress payment cycles, and clear inventories faster rather than allow them to accumulate. Tarkom [4], studying US publicly traded firms on a quarterly basis during 2019Q1–2021Q2, finds that COVID-19 exposure is associated with a higher CCC. That result captures the supply-side disruption channel dominant in lockdown-sensitive sectors. Our sample is restricted to the largest listed e-commerce companies globally, where pandemic-period demand surged rather than contracted. Hamshari et al. [5], studying Jordanian listed companies, document a significant negative effect of COVID-19 on the CCC, directionally consistent with our result. The divergence from Tarkom [4] thus likely reflects sectoral composition: demand-accelerating sectors experienced CCC compression while supply-constrained or demand-disrupted sectors experienced elongation. The efficient working capital management literature, from Shin (1998) [66] onward, establishes that a shorter CCC reduces the time capital is tied up in operations and lowers exposure to liquidity shortfalls; the pandemic-period compression, while externally driven, is associated with an outcome structurally consistent with that framework in terms of operational flow efficiency.

The post-pandemic coefficient (POST) is the central test of whether the pandemic-era contraction was transitory or durable. In the baseline model (no business-model interactions), $\beta_2 = -64.132$ (SE = 31.829, $p < 0.05$); in the specification with business-model interactions, $\beta_2 = -80.297$ (SE = 43.258, $p < 0.10$). The operating cycle during 2022–2024 remained roughly 64–80 days shorter than the pre-pandemic baseline—a substantial contraction that persisted well after the acute phase of the crisis. H2a is therefore partially supported: the POST coefficient does not indicate a full return toward pre-pandemic norms but rather the continuation, at around 50–60% magnitude, of the pandemic-era compression. Relative to the acute phase, some normalization did occur—POST (−64 to −80 days) is roughly 40–50% the magnitude of DUR (−128 days to −134 days)—indicating partial reversal relative to 2020–2021. The absence of full reversion is consistent with the possibility that pandemic-era adjustments—accelerated payment infrastructure, leaner inventory norms, restructured supplier relationships—became embedded in firms' operational routines rather than being unwound once demand conditions normalized. Valiña-Sotelo and Iglesias (2026) [12], studying G-7 and E-7 firms over 2010–2023, document that the post-pandemic period left lasting structural imprints on firms' financial management across both developed and emerging economies. Elfeituri and Alfitouri (2025) [9] similarly find that COVID-19-era liquidity management practices shaped post-crisis balance-sheet outcomes in UK retail firms.

The business-model interaction terms are positive in sign but statistically insignificant throughout, suggesting a possible common response across e-commerce business models. This indicates that neither the pandemic compression of CCC nor its post-pandemic partial persistence differed systematically across B2B, B2C, and C2C firms. H3a and H4a are therefore not supported for operating cycle duration (CCC). This result is substantively informative rather than merely null. Platform architecture shapes operational interdependencies and governs how subsystems coevolve under external pressure [67]; when the underlying architecture is common across platform types, as in e-commerce, system-level responses to disruption tend to converge regardless of the specific transaction model. This convergence is further explained through the DCT lens: systemic shocks affecting shared digital infrastructures reduce the relevance of model-specific dynamic capabilities, which become subordinate to the platform's collective response. Consistent with Volz et al. (2025) [68], under systemic shocks, platform logic is the primary determinant of firm survival, overshadowing the internal adaptive capabilities of B2B, B2C, or C2C models and reducing them to execution tools operating within a broader platform ecosystem. This suppression of model-specific heterogeneity is a pattern of complex systems under severe exogenous stress.

The existence of a common system-level response across different business models should nevertheless be interpreted with some caution, as it may be partially influenced by the unequal distribution of the three groups in the sample, with the relatively small share of the C2C group potentially limiting the ability to identify heterogeneous effects. More specifically, out of the 76 firms in the sample, B2C firms account for 72.4% (55 firms), B2B firms account for 17.1% (13 firms), and C2C firms account for 10.5% (8 firms). However, robustness checks using an alternative classification scheme based on a hybrid business model (detailed in the following section) indicate that the main findings are not necessarily driven by the classification scheme.

Among the control variables, two warrant brief attention. Firm size (SIZE) has a positive and marginally significant coefficient (β = 24.246–24.269, SE ≈ 13.1, $p < 0.10$), indicating that larger e-commerce firms operate with longer CCCs. This diverges from Chang et al. (2025) [11], who document a negative size–CCC relationship in a broad cross-country panel and attribute it to bargaining power advantages. The divergence may reflect a sector-specific dynamic: large e-commerce platform operators often deliberately extend payment terms to seller networks as a commercial strategy, lengthening the CCC despite high bargaining power. Zhang and Yu (2025) [69], studying Chinese e-commerce firms, find that a longer CCC significantly attenuates the profitability benefits of supply chain resilience investments, underscoring the strategic cost of extended operating cycles in this sector. Inflation (Infl) is positive and significant (β ≈ 0.38–0.50, $p < 0.05$ to $p < 0.01$ depending on specification), consistent with the macroeconomic working capital literature [6,60]. The result may help explain the incomplete CCC recovery in the POST period: the inflationary surge of 2022–2023 introduced additional macroeconomic pressure that offset part of the structural efficiency gains from pandemic-era operational reconfiguration.

4.3.2. Working Capital Intensity

Table 5 reports the baseline results for WC/TA.

Table 5. Regression results with WC/TA as the dependent variable.

Variable	(1) Model 1	(2) Model 2
DUR	0.267 (0.170)	0.252 (0.171)
POST	−0.164 (0.099)	−0.186 * (0.107)
BM_B2C_DUR	—	0.022 (0.055)
BM_C2C_DUR	—	0.034 (0.092)
BM_B2C_POST	—	0.049 (0.065)
BM_C2C_POST	—	−0.014 (0.120)
SIZE	0.033 * (0.018)	0.032 * (0.019)
SALES_GROWTH	−0.000 (0.000)	−0.000 (0.000)
DA	−0.386 *** (0.071)	−0.390 *** (0.072)
IAR	—	—
L_TQ	0.132 ** (0.060)	0.126 ** (0.058)
PM	0.003 (0.056)	0.005 (0.057)
OC	0.001 (0.000)	0.001 (0.000)
GDP growth	0.003 (0.004)	0.003 (0.004)
Inflation	−0.001 (0.000)	−0.000 (0.001)
IUTI	−0.002 (0.002)	−0.002 (0.002)
GSCPI	−0.103 * (0.054)	−0.102 * (0.054)
Constant	−0.031 (0.284)	−0.011 (0.288)
N	647	647
R^2	0.185	0.190

Notes: All models include firm fixed effects and period fixed effects. Standard errors clustered at the firm level in parentheses. All firm-level variables winsorized at the 5th–95th percentile. Macro variables not winsorized. B2B is the omitted business model category. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. IAR is not included in the WC/TA specification (collinear with other intangible proxies). As BM dummy coefficients (BM_B2C, BM_C2C) are 0.000 (.) due to their perfect collinearity with firm fixed effects (as time-invariant variables), they cannot be estimated independently and are not retained in the table. Column (1): no business model variables. Column (2): BM dummies + BM × DUR/POST interactions.

The during-pandemic dummy (DUR) in the WC/TA models is positive but statistically insignificant: $\beta_1 = 0.267$ (SE = 0.170) in the no-interaction baseline and $\beta_1 = 0.252$ (SE = 0.171) in the interaction specification. H1b is therefore not supported, although the sign of the coefficient is directionally consistent with the hypothesis. This result is not inconsistent with the CCC finding and is coherent with a two-stage adaptive response framework. The flow/stock distinction is relevant here: a firm can accelerate its operating cycle while holding balance-sheet positions stable, consistent with the precautionary liquidity literature [4,53].

The post-pandemic coefficient is the central result for WC/TA. In the no-interaction baseline, $\beta_2 = -0.164$ (SE = 0.099); in the interaction specification, $\beta_2 = -0.186$ (SE = 0.107, $p < 0.10$). It should be noted that the $p < 0.10$ significance threshold for the POST coefficient is reached only in Model 2 (with business-model interactions); in the baseline Model 1, $\beta_2 = -0.164$ (SE = 0.099) falls short of conventional significance levels. The conclusion for H2b therefore rests on the Model 2 estimate, and should be interpreted with corresponding caution. The insignificant DUR coefficient for WC/TA, combined with the large DUR effect on CCC, is consistent with a first-stage adaptive response operating through operational flow velocity rather than balance-sheet restructuring. For WC/TA, this pattern is better interpreted as a delayed balance-sheet reconfiguration than as reversal in the strict sense. DUR did not produce a statistically significant increase in WC/TA to begin with, so the negative POST coefficient cannot be read as a partial reversal of a significant pandemic rise. H2b is therefore not supported. The structural operational efficiency gains achieved during the pandemic—leaner inventory management, accelerated digital payment cycles, reorganized supplier relationships—appear to have translated, with a lag, into lower balance-sheet investment in net current assets, suggesting that reconfiguration of stock-based working capital intensity followed, rather than accompanied, the initial flow-based operational adjustment. This pattern is consistent with Pant et al. (2024) [48] and Elfeituri and Alfitouri (2025) [9], who document post-crisis WCM rebalancing in COVID-19-exposed firms, and with Valiña-Sotelo and Iglesias (2026) [12], who find that post-pandemic structural shifts in WCM persisted across both developed and emerging economies through 2023.

Taken together, the CCC and WC/TA estimates are consistent with a two-stage adaptive response. The sequencing: flow-based operational adjustment first and stock-based balance-sheet reconfiguration second is consistent with the DCT framework applied in this paper: sensing and seizing capabilities were deployed rapidly during the acute shock, while the transforming dimension materialized with a lag during the recovery period [14,15].

All business-model interaction terms in the WC/TA models are likewise statistically insignificant and small in magnitude. H3b and H4b are therefore not supported for working capital intensity (WC/TA). As in the CCC models, the absence of significant interaction effects is consistent with a possible common response across e-commerce business models, rather than with systematically differentiated balance-sheet adjustments by business model type. This is consistent with evidence from Markovic et al. (2021) [41] and Xiao et al. (2024) [42], who find that the pandemic compressed the strategic space available to firms, making common sector-level responses more prevalent than firm- or model-specific adaptation. Therefore, the lack of statistical significance of the interactions with the business model, although partially misaligned with hypotheses H3b and H4b, falls within the logic of the DCT lens, the architectural-platform logic, as theorized by Volz et al. (2025) [68] and the heterogeneity suppression under severe crises.

As in the case of operating cycle duration, this interpretation of the results must take into account that the three business model groups are unevenly distributed, particularly the C2C group, which may limit the ability to detect interaction effects for each group. To reduce the risk of exclusively linking the lack of significance in the moderation results to the firms' classification by business model, an alternative classification scheme based on a dummy variable for the hybrid model (1 if present, 0 otherwise) was used (see Table A1 in Appendix A for details). The sample comprised a total of 42 firms with hybrid activity (55.3%). The baseline models in Tables 4 and 5 (col. 2) were re-estimated to include interactions between the pandemic-related variables (DUR and POST) and the hybrid model (hybrid_DUR, hybrid_POST). Due to space constraints, these results were not tabulated (though available on request), but they remained unchanged in terms of sign, magnitude, and statistical significance, confirming that the main findings do not appear to be driven by the business model classification scheme.

Four controls are statistically significant in the WC/TA models. The debt-to-assets ratio (DA) has a strongly negative and highly significant coefficient ($\beta = -0.386$ to -0.390, SE = 0.071–0.072, $p < 0.001$), consistent with the financing hierarchy implied by pecking order theory [70,71]: more leveraged firms operate with tighter net current asset positions, consistent with leverage acting as a constraint on balance-sheet working capital. A 10-percentage-point increase in DA is associated with approximately a 3.9-percentage-point reduction in WC/TA, an economically substantial effect corroborated by Baños-Caballero et al. (2014) [53] and Chang et al. (2025) [11]. Tobin's Q (L_TQ) is positive and significant (β = 0.126–0.132, SE $\approx$ 0.058–0.060, $p < 0.05$): firms with higher market-to-book valuations maintain larger working capital positions relative to total assets, consistent with q-theory and with evidence that working capital investment responds positively to growth opportunities [6,53,58]. Firm size (SIZE) is positive and marginally significant ($\beta \approx$ 0.032–0.033, SE ≈ 0.018, $p < 0.10$), consistent with the CCC result and with the view that larger e-commerce platforms sustain higher WC/TA ratios due to broader product assortments and more complex logistics [52]. The GSCPI has a negative and marginally significant coefficient ($\beta \approx -0.102$ to -0.103, SE ≈ 0.054, $p < 0.10$), consistent with supply-chain pressure operating as an external operating constraint: disruptions may constrain inventory replenishment while accelerating supplier payment demands, which may contribute to lower WC/TA in downstream e-commerce aggregators [62,70]. The operating cycle (OC) is included as a control to absorb variation attributable to gross operating cycle length; its coefficient is small in magnitude and is not a focal variable of this analysis.

In summary, the status of hypothesis validation is as follows: H1a is fully supported, as CCC was significantly compressed during the acute pandemic period due to the rapid increase in demand in e-commerce; H2a is partially supported, as the compression of CCC persisted in the post-pandemic period, suggesting structural operational reconfigurations; H1b and H2b are not supported, as WC/TA did not increase during the acute period, while its post-pandemic decline suggests a delayed balance-sheet adjustment rather than a return to pre-pandemic levels. None of the H3 and H4 hypotheses, which concern interactions with the business model, are supported. The two-stage adaptive pattern hypothesized through the DCT lens is supported by the temporal ordering of the results rather than by the sign of the coefficients associated with the variables of interest. Furthermore, the findings regarding working capital intensity are consistent with a delayed activation of the transforming capability, which can be explained through DCT's distinction between the seizing and transforming pillars. The non-significant moderation results (H3a, H3b, H4a, and H4b) may likewise be reinterpreted through the platform logic perspective, whereby platform-level dynamics appear to prevail over business-model-specific dynamic capabilities, thereby reducing the heterogeneity anticipated by the original hypotheses.

4.4. Additional Nonlinear Check—Regression Trees

The following results are exploratory. Regression trees do not control for firm fixed effects and are not designed to recover the period coefficients estimated in the panel regressions. Regression trees were estimated for CCC and WC/TA under both specifications (Appendix B, Figure A1). The trees do not incorporate firm fixed effects and are not designed to replicate the panel estimates; their purpose is to assess whether the variable importance and partitioning structure suggested by the data remain broadly consistent with the fixed-effects results outside the linear additive framework.

For CCC, the primary split in both specifications separates observations with WC/TA below versus above 0.023, producing a marked divergence in leaf means: the lower-WC/TA branch (23% of observations) has a mean CCC of −44 days, while the upper branch (77%) averages +9.5 days, against a full-sample mean of −5.5 days. Within the lower-WC/TA branch, further splits on SIZE (threshold: log assets $\geq$ 17) and IAR ($\geq$0.13) identify a small subset of large, high-intangible firms with exceptionally compressed CCCs—the deepest leaf averages −269 days for 2% of observations. Within the higher-WC/TA branch, DA (<0.076) and L_TQ ($\geq$0.7) further partition observations, with the most negative leaf averaging −229 days for 2% of observations, corresponding to low-leverage, high-growth-opportunity firms. Exploratorily, this partitioning suggests that firm size and financial structure occupy the highest levels of the nonlinear decision hierarchy for CCC—a pattern that aligns descriptively with their prominence in the fixed-effects specifications, though the two methods are not directly comparable. The pandemic dummies (DUR and POST) do not emerge as splitting variables, which reflects their time-series nature: tree-based methods without fixed effects are poorly suited to detecting period effects that are collinear with time, and their absence from the tree does not contradict the fixed-effects estimates. The tree structure is identical under Equations (1) and (2); business-model dummies (BM_B2C, BM_C2C) do not appear as splitting variables in either specification. This is noted descriptively and is broadly aligned with the pattern observed for the BM interaction terms in the panel models, though no causal inference is drawn from this convergence.

For WC/TA, the dominant first split is on DA at a threshold of 0.032, separating low-leverage firms (29% of observations, mean WC/TA = 0.37) from the higher-leverage majority (71%, mean WC/TA = 0.15). Within the low-leverage branch, the operating cycle (OC) and profit margin (PM) identify further heterogeneity: firms with OC $\geq$ 76 days and PM $\geq$ 0.074 reach a leaf mean of 0.51 (6% of observations), while those with OC < 41 days average 0.21. Exploratorily, DA occupies the highest node in the decision hierarchy, suggesting that leverage is the dominant source of unconditional heterogeneity in WC/TA within this sample. The secondary role of OC and PM is descriptively consistent with the interpretation that more profitable firms with longer operating cycles tend to maintain larger net current asset buffers. As with CCC, the tree structure is unchanged between Equations (1) and (2); business-model dummies do not emerge as splitting variables in either specification, a pattern noted descriptively. Taken together, the regression tree results are presented as exploratory evidence on nonlinear predictor hierarchy. They indicate that financial structure—particularly leverage—is a prominent source of within-sample heterogeneity in WC/TA under a nonlinear, assumption-free method. The pandemic-period dynamics identified in the panel models operate through a time dimension that tree-based methods without fixed effects are not designed to recover, and the absence of DUR and POST from the tree structure should not be interpreted as evidence against those effects.

4.5. Robustness Check

Table 6 reports the robustness checks.

Three robustness specifications are estimated for each dependent variable. The first replaces the inflation variable with the interest rate (IR), addressing the possibility that the monetary policy transmission channel is more relevant than price-level dynamics. The second removes business-model × DUR interaction terms from the baseline specification, allowing assessment of whether post-pandemic effects are independent of those during the pandemic. The third adds business-model × GSCPI interaction terms, examining whether firms' exposure to global supply-chain pressure differs by transaction model.

Table 6. Robustness checks for CCC and WC/TA.

Variable	CCC			WC/TA		
	(1) IR Macro	(2) −POST Ints	(3) +GSCPI Ints	(1) IR Macro	(2) −POST Ints	(3) +GSCPI Ints
DUR	−134.630 ** (55.381)	−127.731 ** (57.507)	−126.921 ** (57.745)	0.266 (0.169)	0.268 (0.169)	0.271 (0.169)
POST	−84.269 ** (37.793)	−78.379 * (41.188)	−78.554 * (41.251)	−0.183 * (0.107)	−0.182 * (0.107)	−0.182 * (0.107)
BM_B2C_POST	14.495 (28.648)	15.735 (29.092)	16.357 (30.675)	0.042 (0.053)	0.042 (0.053)	0.042 (0.056)
BM_C2C_POST	28.993 (29.608)	34.056 (30.445)	35.984 (32.479)	−0.025 (0.093)	−0.026 (0.095)	−0.016 (0.097)
SIZE	27.922 ** (12.333)	24.319 * (13.098)	24.288 * (13.053)	0.033 * (0.017)	0.032 * (0.018)	0.032 * (0.019)
SALES_GROWTH	−0.041 (0.101)	−0.067 (0.106)	−0.069 (0.106)	−0.000 (0.000)	−0.000 (0.000)	−0.000 (0.000)
DA	39.719 * (22.194)	29.453 (19.225)	29.501 (19.259)	−0.385 *** (0.071)	−0.390 *** (0.072)	−0.388 *** (0.071)
IAR	−48.570 (41.914)	−38.804 (41.494)	−39.152 (42.489)	—	—	—
L_TQ	−0.629 (14.031)	−0.694 (14.247)	−1.298 (14.238)	0.127 ** (0.058)	0.128 ** (0.058)	0.126 ** (0.057)
WC/TA	24.348 (33.169)	24.166 (33.430)	23.603 (33.542)	—	—	—
PM	—	—	—	0.003 (0.056)	0.004 (0.056)	0.005 (0.056)
OC	—	—	—	0.001 (0.000)	0.001 (0.000)	0.001 (0.000)
GDP growth	−2.304 (1.611)	−2.098 (1.677)	−2.138 (1.719)	0.003 (0.004)	0.003 (0.004)	0.003 (0.004)
Inflation	—	0.376 ** (0.151)	0.393 ** (0.153)	—	−0.000 (0.001)	−0.000 (0.000)
IR	2.411 *** (0.659)	—	—	−0.001 (0.001)	—	—
IUTI	−0.250 (0.648)	−0.568 (0.619)	−0.586 (0.638)	−0.002 (0.002)	−0.002 (0.002)	−0.002 (0.002)
GSCPI	20.684 (12.895)	18.243 (13.173)	16.211 (14.322)	−0.101 * (0.053)	−0.102 * (0.054)	−0.106 ** (0.052)
BM_B2C × GSCPI	—	—	2.130 (5.585)	—	—	0.003 (0.018)
BM_C2C × GSCPI	—	—	4.499 (6.670)	—	—	0.019 (0.023)
N	655	648	648	654	647	647
R^2	0.202	0.143	0.144	0.188	0.190	0.191

Notes: All models include firm fixed effects and period fixed effects. Standard errors clustered at the firm level in parentheses. All firm-level variables winsorized at the 5th–95th percentile. Macro variables not winsorized. B2B is the omitted business model category. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. As BM dummy coefficients (BM_B2C, BM_C2C) are 0.000 (.) due to their perfect collinearity with firm fixed effects (as time-invariant variables), they cannot be estimated independently and are not retained in the table. For each dependent variable, column (1) replaces inflation with interest rate (IR), column (2) removes BM × DUR interactions, and column (3) adds BM × GSCPI interactions. IAR is not included in the WC/TA models. WC/TA is a control only in the CCC specifications, while PM and OC are controls only in the WC/TA specifications. Ints = interactions.

Across all three robustness specifications, the CCC pandemic effect remains large, negative, and statistically significant: DUR ranges from −126.9 to −134.6 days, always significant at the 5% level. The POST coefficient ranges from −78.4 to −84.3 days, remaining significant at the 5–10% level depending on specification. When IR replaces inflation (column 1), the R^2 rises to 0.202 from 0.137 to 0.144, and the IR coefficient is positive and highly significant ($\beta = 2.411$, $p < 0.01$), confirming that monetary tightening is an additional driver of CCC elongation and offering a complementary explanation for the partial compression in the POST period. For WC/TA, the robustness specifications yield fully consistent results. The DUR coefficient remains positive and insignificant across all three variants (range: 0.266–0.271), the POST coefficient remains negative and significant at the 10% level in all specifications (range: −0.182 to −0.183), and all business-model interaction terms—for POST, and also for the GSCPI variant—remain insignificant.

Because the models use partially different regressors, their estimation samples differ slightly—648 and 647 observations, respectively—due to variable-specific missingness. To verify that this difference does not drive the main findings, both models are re-estimated on a common sample of 643 firm-year observations for which all variables used in either model are simultaneously non-missing, covering 75 of 76 firms. Results are reported in Table 7.

The common sample preserves the period distribution of the original samples: 294 pre-pandemic observations (45.7%), 129 during-pandemic observations (20.1%), and 220 post-pandemic observations (34.2%). The DUR coefficient for CCC changes from −127.7 to −133.1 days (−4.2%), and the POST coefficient from −78.4 to −79.6 days (−1.5%). For WC/TA, the DUR coefficient changes from 0.268 to 0.264 (−1.6%) and the POST coefficient from −0.182 to −0.196 (−7.7%). In all cases, the sign, magnitude, and statistical significance of the period coefficients are preserved. These results confirm that the main findings are not an artifact of sample composition differences across models.

Table 7. Robustness: common-sample estimation.

Variable	(1)	(2)
	Dependent Variable: CCC	**Dependent Variable: WC/TA**
DUR	−133.065 ** (58.610)	0.264 (0.169)
POST	−79.560 * (41.553)	−0.196 * (0.105)
BM_B2C_POST	15.496 (29.117)	0.063 (0.049)
BM_C2C_POST	35.044 (30.697)	−0.006 (0.092)
SIZE	24.573 * (13.325)	0.026 (0.017)
SALES_GROWTH	−0.036 (0.107)	−0.000 (0.000)
DA	28.364 (19.766)	−0.363 *** (0.076)
IAR	−39.899 (41.882)	—
L_TQ	−1.125 (14.378)	0.108 * (0.062)
WC/TA	25.501 (33.550)	—
PM	—	−0.007 (0.057)
OC	—	0.001 (0.000)
GDP growth	−1.938 (1.683)	0.004 (0.004)
Inflation	0.361 ** (0.152)	−0.000 (0.001)
IUTI	−0.567 (0.620)	−0.002 (0.002)
GSCPI	18.872 (13.221)	−0.100 * (0.053)
Constant	−257.575 (182.017)	0.057 (0.273)
Fixed effects	Firm + Period FE	Firm + Period FE
Clustered SE	Firm	Firm
Winsorization	5–95	5–95
N	643	643
R^2 within	0.149	0.174

Notes: Common sample comprises firm-years with non-missing values across both specifications simultaneously (N = 643). Both models include firm fixed effects and period fixed effects. Standard errors clustered at the firm level in parentheses. All firm-level variables winsorized at the 5th–95th percentile. Macro variables not winsorized. B2B is the omitted business model category. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

The robustness check results confirm the core findings. The similarity of the estimates across baseline and alternative specifications suggests that the observed associations between the pandemic-period indicators and working capital measures, as well as the absence of significant business-model differences, are not sensitive to reasonable changes in model specification.

5. Conclusions

This study examines how large, publicly listed e-commerce firms, understood as complex digital business systems embedded in global supply chains and international capital markets, adjusted their working capital in response to the COVID-19 pandemic and its aftermath. Drawing on a panel of 76 firms from 23 countries across five continents, selected from the largest e-commerce companies worldwide by market capitalization, the analysis tracks two distinct dimensions of working capital adjustment: the cash conversion cycle (CCC) and net working capital relative to total assets (WC/TA). The study compares pre-pandemic, acute pandemic, and post-pandemic periods and tests whether adjustment patterns differed across B2B, B2C, and C2C business models.

The two measures reveal different adjustment timings. During 2020–2021, the CCC contracted sharply in a pattern consistent with accelerated payment processing, faster inventory clearance, and restructured supplier terms—operational adjustments whose incidence may be related to exceptional pandemic-period demand, though the panel design does not permit a causal attribution to COVID-19 specifically. WC/TA, by contrast, did not respond significantly during the acute phase; its decline emerged only in the post-pandemic period. The evidence therefore is consistent with a two-stage adaptive response: rapid reconfiguration of operational flows came first, while delayed balance-sheet stock adjustment followed later. For CCC, H2a is only partially supported: the post-pandemic period brought partial normalization relative to the acute phase but not a return toward pre-pandemic norms. For WC/TA, H2b is not supported in its original form: the adjustment was delayed rather than reversed, as no significant pandemic-period increase preceded the post-pandemic decline. Among the control variables, leverage (DA) and global supply-chain pressure (GSCPI) are the main significant determinants of WC/TA, operating as financial and supply-chain constraints, while inflation is the primary significant macroeconomic driver of CCC.

This two-stage adaptive response is the study's central empirical contribution and has implications for how working capital research approaches systemic shocks in digital business contexts. Single-metric frameworks applied only to the pandemic window may misread the adjustment process, because operating-cycle dynamics and balance-sheet positions moved at different speeds and in different phases. The post-pandemic period is therefore not simply a recovery window; it is the stage in which the second phase of adjustment becomes observable. For researchers and practitioners, the distinction between flow-based operating-cycle dynamics and stock-based balance-sheet positioning is more informative than treating working capital as a single composite construct. Interpreted through the dynamic capabilities framework, the acute phase is consistent with rapid sensing and seizing capabilities reflected in operational adjustment, while the post-pandemic decline in WC/TA suggests a slower transforming stage in which pandemic-era operational adjustments may have gradually propagated into firms' balance-sheet positions, though this interpretation remains speculative within the present design.

Business-model interaction terms are uniformly insignificant: B2C and C2C firms are adjusted in ways statistically indistinguishable from the B2B reference category. While this result does not allow strong causal claims, it is consistent with a possible common response across e-commerce business models under platform logic and the DCT lens, which seem to override model-specific dynamic capabilities, subordinating firm-level capabilities to ecosystem-level constraints and producing crisis homogenization. The practical implications concern managers, investors, and decision-makers. Managers should not interpret CCC compression in isolation, because a shorter operating cycle may reflect operational flow reconfiguration rather than a simple deterioration or improvement in liquidity conditions. At the same time, they should monitor balance-sheet working capital intensity, leverage constraints, inflation exposure, and supply-chain pressures, since these factors shape the delayed adjustment of net working capital. The absence of significant business-model differences in this sample does not support the assumption that B2B, B2C, and C2C firms necessarily require fundamentally different working capital responses, though this finding should be interpreted cautiously given sample composition. Also, future research could examine whether moderation effects might emerge under conditions of less severe disruptions than those generated by the COVID-19 pandemic.

The contribution of this study does not lie in the confirmation of the hypotheses, but rather in the empirical identification of two complementary patterns: on the one hand, a sequential and asymmetric working capital adjustment process; on the other hand, a convergence of adaptive responses across different business models as a result of the systemic constraints generated by the pandemic crisis. These patterns offer more nuanced theoretical implications for future research than those originally articulated in the hypotheses.

Several limitations should be acknowledged. Because the sample is based on a 2026 ranking, survivorship and look-ahead bias cannot be fully excluded. Firms that failed, delisted, or experienced substantial decline prior to 2026 are not represented. Consequently, the findings are most applicable to large, publicly listed e-commerce firms and should not be generalized to the broader e-commerce sector without caution. The study relies on an observational panel design and does not employ a strong causal identification strategy, such as instrumental variables or a natural experiment with a clean control group; the

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estimates therefore capture associations rather than confirmed causal effects. As in much of the corporate finance literature, some explanatory variables may be jointly determined with working capital outcomes. Although firm fixed effects address time-invariant unobserved heterogeneity, potential simultaneity between working capital, leverage, profitability, and growth opportunities cannot be fully excluded. Results should therefore be interpreted as conditional associations rather than causal effects.

A further limitation concerns temporal identification. The period dummies DUR and POST aggregate multiple concurrent phenomena—demand acceleration, fiscal stimulus, supply chain disruption, inflationary pressures, monetary tightening, and post-crisis normalization—that cannot be disentangled within the present design. Although the models control for major macroeconomic factors on a calendar-year basis, the period coefficients may therefore capture developments beyond the COVID-19 shock itself, and should be interpreted as associations with the pandemic and post-pandemic periods rather than as strictly causal effects. The design also cannot absorb firm-specific secular trends, such as platform maturation trajectories that may coincide temporally with these periods, as isolating COVID-specific variation from such trends would require either firm-specific time trends or a non-e-commerce control group, neither of which is available in the current dataset. The analysis also does not incorporate formal system dynamics simulation or agent-based modeling, which would be required to trace feedback mechanisms and nonlinear adjustment paths within e-commerce systems. Regression trees do not control for firm fixed effects, cannot recover within-firm period estimates, and should be interpreted as descriptive rather than causal evidence.

Future research could extend the observation window beyond 2024 to determine whether the incomplete CCC reversion represents a permanent structural shift or a slowly closing gap. Further disaggregation by firm size, geography, ownership structure, or platform architecture could reveal heterogeneity in adaptive responses that the current sample cannot fully detect. Formal dynamic modeling approaches, including system dynamics simulation or agent-based frameworks, could complement the empirical findings by tracing how operational flow adjustments propagate into balance-sheet stock positions over time.

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Appendix A

Table A1. Classification by dominant business model of sampled e-commerce firms.

No.	Company	Dominant Segment	Hybrid Activity
1	1-800-PetMeds	B2C	No
2	1stdibs.com	B2C	Yes—professional dealers sell to some B2B seller services
3	a.k.a. Brands	B2C	No
4	Alibaba	B2C	Yes—B2B wholesale and C2C
5	Alibaba Health Information Technology	B2C	Yes—B2B pharma services
6	Allegro.eu	B2C	Yes—includes C2C marketplace
7	Amazon	B2C	Yes—B2C + C2C + B2B
8	Americanas	B2C	Yes—retail + marketplace
9	ASOS	B2C	No
10	Auction Technology Group	C2C	Yes—B2B auction services
11	Baozun	B2B	Yes—B2B services + B2C operations
12	BHG Group AB	B2C	Yes—marketplace elements
13	Bike24 Holding	B2C	No
14	Bukalapak.com	B2C	Yes—C2C marketplace
15	CarParts.com	B2C	No
16	Carvana	B2C	No
17	Cettire Limited	B2C	No
18	Chewy	B2C	No
19	Cimpress	B2B	Yes—some B2C brands
20	Copart	B2B	Yes—B2C public buyers (minority)
21	Coupang	B2C	Yes—marketplace sellers
22	Dingdong Maicai	B2C	No
23	eBay	C2C	Yes—B2C sellers
24	Global Fashion Group	B2C	Yes—marketplace elements
25	Global-e	B2B	No
26	GoTo	B2C	Yes—fintech + B2B services
27	Groupon	B2C	Yes—B2B merchant services
28	Grove Collaborative	B2C	No
29	Hong Kong Technology Venture Company (HKTV)	B2C	Yes—marketplace
30	Hour Loop	B2C	No
31	IndiaMART	B2B	No
32	Instacart (Maplebear Inc.)	B2C	Yes—B2B retailer services
33	JD Health	B2C	Yes—B2B pharma
34	JD.com	B2C	Yes—B2B + marketplace
35	Jumia	B2C	Yes—marketplace C2C
36	Katapult Holdings	B2B	Yes—B2C fintech
37	Kits Eyecare	B2C	No
38	LightInTheBox Holding	B2C	No
39	Lightspeed POS	B2B	No

Table A1. *Cont.*

No.	Company	Dominant Segment	Hybrid Activity
40	Liquidity Services	B2B	No
41	Lulu's Fashion Lounge	B2C	No
42	Meds Apotek AB	B2C	No
43	Meituan	B2C	Yes—B2B merchant services
44	MercadoLibre	C2C	Yes—B2C + fintech
45	Mercari	C2C	Yes—B2C sellers
46	momo.com Inc.	B2C	No
47	Monotaro	B2B	No
48	MSTC Limited	B2B	Yes—auction platform
49	Natural Health Trends	B2C	Yes—distributor network
50	Newegg	B2C	Yes—marketplace sellers
51	Ocado	B2C	Yes—B2B logistics tech
52	PDD Holdings (Pinduoduo)	B2C	Yes—C2C + marketplace
53	Rakuten	B2C	Yes—marketplace + fintech
54	Redcare Pharmacy	B2C	No
55	Rent the Runway	B2C	No
56	Revolve	B2C	No
57	Sea Limited	B2C	Yes—fintech + B2B
58	Shopify	B2B	Yes—B2C tools
59	The Original BARK Company	B2C	No
60	The RealReal	C2C	Yes—B2C luxury resale
61	THG (The Hut Group)	B2C	Yes—B2B services
62	ThredUp	C2C	Yes—B2C resale
63	Treasure Global	B2C	Yes—fintech elements
64	Upexi	B2C	No
65	Uxin Limited	B2C	Yes—C2C auto marketplace
66	Vend Marketplaces	C2C	No
67	Vente-Unique.com	B2B	No
68	Verkkokauppa.com	B2C	No
69	Vipshop	B2C	No
70	Vivid Seats	C2C	Yes—B2C ticket resale
71	VTEX	B2B	No
72	Wayfair	B2C	No
73	Webuy Global	B2C	No
74	Westwing Group	B2C	No
75	Yunji	B2C	Yes—social C2C elements
76	Zalando	B2C	Yes—marketplace model

Note: Dominant segment classification is based on the majority revenue segment as disclosed in each firm's available annual reports.

Appendix B

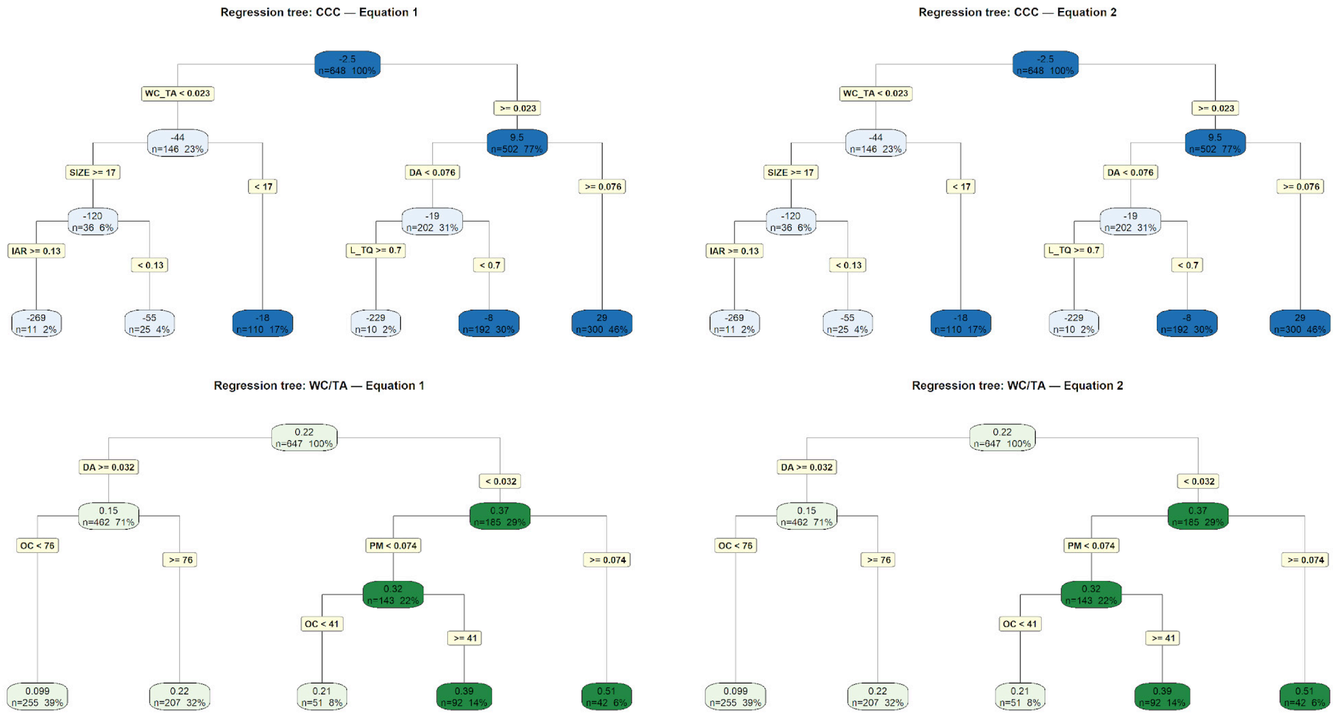

Figure A1. Regression trees. Note: Blue-colored nodes correspond to the regression trees estimated for the CCC models (Equations (1) and (2)), whereas green-colored nodes correspond to the regression trees estimated for the WC/TA models (Equations (1) and (2)). Darker shades indicate terminal nodes with higher predicted values within each tree.

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