DELAY UNDER DURESS? REAL OPTIONS, FINANCIAL CONSTRAINTS AND FIRM RESPONSES TO THE COVID-19 PANDEMIC

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ABSTRACT

Real options theory predicts that firms preserve strategic flexibility by initially exercising reversible actions and delaying irreversible commitments until uncertainty subsides. Yet, this logic presupposes that firms have the financial flexibility to wait. Using the COVID-19 aviation crisis, a sudden global shock triggering unprecedented demand collapse, and subsequent recovery, we examine how financial constraints shape the sequencing and timing of reversible versus irreversible asset disinvestments and investments. Analyzing monthly data for 83 global airlines shows that while carriers generally followed real-options logic, storing aircraft before retiring or selling them and reactivating stored aircraft before new investments, financial constraints significantly moderated these patterns. Specifically, constrained airlines delayed reversible disinvestments and accelerated irreversible ones, diverging from canonical predictions. On the other hand, financial constraints reinforced real option theory predictions for investments, accelerating reversible investments and delaying irreversible ones. Our findings refine real options theory by highlighting financial constraints as a critical boundary condition, demonstrating that strategic flexibility during heightened uncertainty depends fundamentally on firms' ability to finance the act of waiting.

INTRODUCTION

Real Options Theory (ROT) has significantly influenced strategic management by highlighting how firms strategically manage uncertainty through managerial flexibility and staged investment decisions (Adner & Levinthal, 2004; Trigeorgis & Reuer, 2017). At its core, ROT underscores a critical trade-off between commitment and flexibility, suggesting that firms can preserve strategic flexibility by delaying irreversible commitments until uncertainty resolves (Dixit & Pindyck, 1994). This logic becomes especially pertinent when firms face a severe crisis where flexibility and future decision rights become critical as the resources, capabilities, and strategies differ fundamentally from those likely to succeed in stable settings (Kogut & Kulatilaka, 2001). In a crisis, the right, but not the obligation, to scale back, defer, abandon, and sequence investments is especially valuable (Lee & Makhija, 2009). However, ROT's assumption of frictionless capital markets critically neglects the reality of financial constraints, which tighten precisely during crises (Bolton, Wang, & Yang, 2019) and limit the very ability to wait.

Crises, such as severe financial downturns and global pandemics, dramatically heighten uncertainty, magnifying the complexity and consequences of asset decisions (Baker et al., 2020). During these periods, the timing and nature of such decisions can fundamentally determine firm survival (Bartik et al., 2020). Given ROT's explicit focus on flexibility under uncertainty, it is particularly suited to providing insights during crisis scenarios when strategic decision-making carries substantial risks and survival implications. Yet, to date, ROT scholarship has inadequately integrated the impact of severe financial constraints, precisely when these constraints become critical determinants of managerial flexibility and strategic action. Real options theory relies on a set of assumptions, including that firms can maintain options to disinvest or invest later, which is questionable when firms face financial constraints that become more binding during a crisis. Therefore, understanding how ROT logic interacts with financial constraints during crises can reveal essential insights into firm asset investment and disinvestment decisions under heightened uncertainty.

While extensive strategic research using ROT has addressed diverse investment scenarios such as market entry timing, alliances, R&D investments, and multinational network flexibility (see Trigeorgis & Reuer, 2017 for a review), applications of ROT to disinvestment decisions remain comparatively underexplored, with most existing studies narrowly focused on binary abandon-or-retain decisions. Yet, disinvestments, central to firm strategic adaptation, are rarely binary (Damaraju, Barney, & Makhija, 2015). Like investments, disinvestments vary in their degrees of reversibility and commitment. Investments and disinvestments are also usually considered mutually exclusively in the literature, even though, from a firm's perspective, holding the right amount of assets is crucial for firm survival and profitability. Again, this is especially salient in a crisis where firms must consider a portfolio of real options that span both investments and disinvestments (Vassolo, Anand, & Folta, 2004).

This paper directly addresses these critical oversights by theoretically integrating financial constraints into ROT and empirically examining how these constraints influence firms' timing and sequencing of reversible vs. irreversible investment and disinvestment decisions. We posit that integrating financial constraints fundamentally alters classical ROT predictions. In particular, ROT suggests that firms should sequence actions by first undertaking reversible decisions that preserve flexibility, such as temporarily mothballing assets, while deferring irreversible actions, such as asset sales, until uncertainty diminishes. Financial constraints, however, reduce firms' ability to wait, prompting earlier irreversible decisions in some cases and delaying reversible decisions in others to generate immediate liquidity (Bolton et al., 2019). Thus, financial constraints can shift the balance from preserving strategic flexibility to addressing immediate liquidity pressures, resulting in managerial decisions that diverge significantly from ROT's predictions.

To empirically explore these dynamics, we focus on the airline industry during the COVID-19 pandemic—an acute and prolonged crisis featuring substantial uncertainty and severe financial disruptions. This context offers distinct advantages for testing ROT predictions, as asset decisions regarding aircraft differentiate between reversible actions (such as temporary storage and reactivation) and irreversible ones (sales, retirements, and purchases). Airlines also experienced explicit and observable financial constraints shaped by factors like access to external finance and government bailouts. By studying their asset divestment and investment choices, we can systematically evaluate how financial constraints modify managerial responses predicted by ROT under extreme uncertainty.

Our findings significantly deviate from classic ROT predictions due to financial constraints. Overall, airlines broadly follow ROT logic by undertaking reversible asset divestments, such as temporary aircraft storage, while delaying irreversible actions. However, financially constrained airlines diverge from this pattern by delaying reversible divestments and undertaking irreversible asset disinvestments relatively faster to alleviate immediate liquidity pressures. Constrained firms also notably accelerate reversible investment actions, such as reactivating previously stored aircraft, while simultaneously delaying irreversible investments, notably new aircraft purchases and leases. These findings underscore that financial constraints fundamentally alter ROT logic, reshaping firms' sequencing of investment and divestment decisions during severe crises.

Our paper makes the following contributions. Theoretically, we extend ROT by explicitly incorporating financial constraints, revealing how constraints reshape managerial decision-making under heightened uncertainty. This integration clarifies conditions under which ROT predictions are significantly modified, providing a richer and more nuanced understanding of organizational flexibility and strategic decision-making. We also compare ex-ante (better access to external finance) and ex-post (government bailouts) reductions in constraint. Empirically, we consider a portfolio of options, analyzing both disinvestment and investment decisions in the context of a single shock, the uncertainty of which only gradually resolves over time. We exploit differences in the irreversibility of asset disinvestment and investment decisions and how firms stage these choices depending on the degree of irreversibility and financial constraints they face. A final, albeit secondary, contribution is methodological. Recent work has shown that the standard event study specification with two-way firm and time-fixed effects (TWFE) has multiple sources of bias (Roth et al., 2023), and we instead use an estimator specified to avoid these (Sun & Abraham, 2021). We exploit the staggered imposition of COVID-19 restrictions to define our treated and control groups and to identify our effects.

To connect our theory development to the literature, we first develop the theory and hypothesis, ignoring financial constraints. Subsequently, we argue how these predictions would change under financial constraints. We describe the data, variable construction, and methodology before reporting the findings and discussing their implications. We close with some robustness checks, limitations, practical relevance of our findings, and implications for future work.

THEORY AND HYPOTHESES

Real options theory (ROT) has long been a foundational framework for understanding how firms navigate uncertainty in investment and disinvestment decisions (Dixit, 1989; Dixit &

Pindyck, 1994). ROT suggests that firms retain flexibility by delaying irreversible actions when faced with uncertainty, preserving the right but not the obligation to commit resources until conditions become clearer (Dixit & Pindyck, 1994; Trigeorgis & Reuer, 2017). This logic applies to both investment (e.g., market-entry, R&D, alliances) and disinvestment (e.g., facility shutdowns, asset sales, divestitures) decisions (Folta & O'Brien, 2004). By waiting to invest, the firm has a call option – the right but not the obligation to invest in the future. Pindyck (1988) shows that the project must have a strictly positive net present value before it is optimal to invest. When a firm acquires assets that it may later retire or resell, it has a put option (Abel et al., 1996).

The literature on real options recognizes that firms face a portfolio of options, some that are substitutes for one another, some that are staggered in timing, and some that are complementary (Trigeorgis & Reuer, 2017). At the same time, most empirical work has examined simpler binary options such as market entry (Campa, 1994), acquisitions (Kogut, 1991), entering into alliances (Miller & Folta, 2002), exits (Efenbein and Knott, 2015), and closures (Moel and Tufano, 2002). Exceptions include the staged divestments examined in Damaraju et al. (2015), the choice between acquisitions and corporate venture capital (Tong & Li, 2011), and entry in the presence of dueling options (Folta & O'Brien, 2004). We will jointly analyze firms' decisions to disinvest and invest, consider a portfolio of options in investment and disinvestment decisions, and the staggered and differential exercise of these options. More importantly, we will focus on the interplay of real options logic and financial constraints to hypothesize how financial constraints reshape standard real options predictions.

Reversible and Irreversible Disinvestments

Within the ROT framework, disinvestment decisions can be categorized into reversible and irreversible choices. Reversible disinvestments allow firms to scale operations back up as conditions improve. Irreversible disinvestments eliminate future strategic flexibility and involve a loss of potential upside. Under standard ROT logic, firms should prioritize reversible adjustments first since this facilitates uncertainty resolution by gathering more information about the environment (McGrath, 1997). Such actions allow managers to gather information on whether demand will recover and does not foreclose future opportunities, ensuring they do not overcommit to permanent capacity reductions. Irreversible disinvestments, on the other hand, mean that re-entry requires substantial reinvestments that can lead to competitive disadvantages in the long run (Damaraju et al., 2015; McGrath, 1999). Irreversible disinvestments also have higher sunk costs, so uncertainty dissuades firms from choosing irreversible disinvestments relative to reversible ones because firms would have to incur those sunk costs again to re-enter if conditions improve (O'Brien & Folta, 2009). If conditions worsen, firms can continue disinvestment further in stages or engage in complete disinvestment that best fits their requirements. Hence, reversible disinvestments create future strategic options for a firm. Therefore, our first baseline hypothesis is[1]

> ***Hypothesis 1a****: In a crisis, when faced with demand loss of uncertain duration and magnitude, firms will undertake relatively reversible disinvestments sooner and relatively irreversible ones later.*

Reversible and Irreversible Investments

Investments with higher sunk costs are more irreversible because the initial capital outlay cannot be easily recouped if the investment turns out to be unfavorable. This lack of reversibility means a firm cannot simply sell off the asset or redeploy it to another use without incurring

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[1] Even though we refer to this as the baseline hypotheses, to the best of our knowledge it has not been tested empirically with continuous measures of disinvestment that vary in their degree of irreversibility.

significant losses. Instead, opting for smaller investments with lower sunk costs keeps open the upside potential while truncating downside losses (Dixit & Pindyck, 1994; Trigeorgis, 1996). Therefore, instead of making a single, large-scale investment decision, firms can break the decision into multiple stages, ensuring reversible investments precede irreversible ones. Tong and Li (2011) use an ROT lens to show that under high uncertainty, firms are more likely to undertake staged CVC investments that can be reversed or stopped instead of acquisitions that entail higher sunk costs and are more irreversible. Kogut (1991), Folta (1998), and Alfaro, Bloom, and Lin (2024) apply the real options logic to show how uncertainty, especially exogenous uncertainty, can lead to staged investments in a joint venture, which captures the potential upside of buying out the partner at a later stage when uncertainty is resolved. In a crisis, exogenous uncertainty is especially high (Alfaro et al., 2024), reinforcing the delaying of irreversible investments that entail higher sunk costs and higher commitment**.** Therefore, our second baseline hypothesis is:

> ***Hypothesis 1b:*** *In a crisis, when faced with demand loss of uncertain duration and magnitude, firms will undertake relatively reversible investments sooner and relatively irreversible ones later.*

Financial Constraints

The strategic management literature has largely overlooked the role of financial constraints in modifying real options decision-making. Not only is this a key source of heterogeneity across firms, but it is also likely to be especially salient in a crisis (Flammer & Ioannou, 2021). In the presence of financial constraints, firms need to worry about *both* real options and financial options, where they hoard liquidity to preserve financial flexibility, creating an interaction and potential trade-off between real and financial options.

The classic Dixit–Pindyck model assumes frictionless capital markets, where firms can always finance ongoing operations or future reinvestments. More precisely, firms can afford to wait for the optimal timing and staging of options. In reality, firms may be financially constrained – they either have restricted access to liquidity or face high external costs of financing. These constraints are most likely to bind during times of heightened uncertainty, such as a crisis (Bruton, Ahlstrom, & Wan, 2003).

Because financial constraints alter firms' ability to manage uncertainty, there will be systematically different responses in the timing and sequencing of disinvestment and investment choices. This argument has not been tested before. Prior work has emphasized how firms balance commitment versus flexibility when exercising real options (Ghemawat, 1991; Smit & Trigeorgis, 2004). However, it does not fully explore how financial distress forces firms to make trade-offs between reversible and irreversible divestments. We argue that constrained firms faced with uncertainty will depart from the traditional real option theory predictions in systematic ways: they *exercise some options earlier* (often out of necessity) and *hold onto others longer* (out of caution or inability to re-engage later). This results in a mix of more irreversible options and slower, staggered implementation of reversible ones for financially constrained firms relative to unconstrained firms.

Disinvestments Under Financial Constraints

Financial constraints can fundamentally alter the real options calculus. Under ROT, waiting to disinvest allows firms to resolve uncertainty and avoid the irreversible costs of liquidating assets prematurely. This option value is high when firms are unconstrained because they can afford to absorb short-term losses to preserve future flexibility. For financially constrained firms, however, this option value diminishes significantly. The immediate need for liquidity outweighs the benefits of waiting, forcing firms to prioritize short-term solvency over long-term strategic value. Therefore, a priori, we would expect that financially constrained firms are more likely to disinvest than financially unconstrained firms. Unconstrained firms, on the other hand, are not forced to prioritize liquidity over strategic flexibility.

Research that has embedded financial constraints into real options models finds that the optimal disinvestment (and investment) decision shifts (Boyle & Guthrie, 2003). A constrained firm disinvests sooner if the immediate need for liquidity outweighs the benefits of waiting. Moreover, delaying disinvestments could result in worse outcomes, such as bankruptcy or a forced fire sale at distressed prices. Bolton et al. (2019) demonstrate that financial constraints reduce the real option value of delay with firms "forced into inefficiently liquidating their valuable operating assets" – disinvesting too early relative to the first-best optimal timing. Essentially, current and the prospect of future cash shortages reduce the real option value of delay, leading to earlier disinvestment. Pulvino (1998) provides empirical support for this in the airline industry, showing that financially weaker airlines were forced to sell aircraft at a discount during industry downturns.[2]

When financially constrained, however, firms choose between disinvestment options that vary not just in their degrees of irreversibility but also in the extent to which they ease liquidity constraints. These choices require trade-offs between preserving financial vs. real flexibility (Alfaro et al., 2024; Caggese, 2007). Disinvestments that are relatively reversible (e.g., idling an asset) do not ease financial constraints. In fact, they may drain resources (mothballing an asset incurs maintenance or storage costs) and foreclose immediate cash inflows. To the extent constrained firms value financial flexibility and even meager cash flows, they will postpone

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[2] In extreme cases, the disinvestment decision is no longer an optimization of a going concern or chosen by the firm. Rather, binding financing constraints force fire sale and/or bankruptcy, so the abandonment option value vanishes and the firm is forced into liquidation to satisfy creditors. We do not analyze such a situation in our context.

reversible disinvestment or at least disinvest at a slower rate than unconstrained firms.[3] In contrast, more irreversible disinvestments (e.g., selling the asset) have a higher option real value in terms of waiting to disinvest. However, when a firm lacks liquidity, the financial option is more valuable to meet short-term obligations (e.g., debt payments and operational expenses). Therefore, constrained firms are more likely to choose irreversible disinvestments and more quickly generate cash, even if this sacrifices long-term flexibility and yields a lower asset price (compared to a potentially higher future price). Thus, financial constraints create a bifurcated response to disinvestment decisions: constrained firms are likely to prolong the process of reversible disinvestment while accelerating irreversible disinvestment. Unconstrained firms with financial flexibility are more likely to opt for quick reversible disinvestments while postponing and even eschewing irreversible disinvestments. Therefore:

> ***Hypothesis 2:*** *In a crisis, when faced with demand loss of uncertain duration and magnitude, financially constrained firms will undertake reversible disinvestment more slowly and irreversible disinvestments more rapidly compared to unconstrained firms.*

Investments Under Financial Constraints

In the case of investments, financially constrained firms face a trade-off. On the one hand, to avoid paying the high cost of raising outside funds, the firm delays committing to new investments until it has saved enough internally. Following a crisis, such firms are also in repair mode, seeking to build financial flexibility. On the other hand, once it invests, the investments potentially generate valuable higher cash flows, easing financial constraints. Therefore, in some situations, a constrained firm may invest faster (Bolton et al., 2019; Smit & Trigeorgis, 2004).

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[3] Empirical evidence from corporate finance suggests that financially constrained firms frequently opt to “ride out” downturns longer than their unconstrained counterparts, particularly when reversible adjustments (e.g., temporary shutdowns) are expensive (Campello et al., 2010).

Boyle and Guthrie (2003) show that a binding funding constraint lowers the investment threshold – firms invest sooner (at a lower project value) than the unconstrained Dixit–Pindyck benchmark. We resolve this contradiction through the optimal choice and sequencing of reversible vs. irreversible investments.

Irreversible investments tend to incur higher sunk costs. For constrained firms who value financial flexibility, such investments are not only difficult or infeasible due to limited access to external financing but also reduce financial flexibility. Additionally, constrained firms delay irreversible investments even in the recovery stage because they worry about finding themselves "stuck" with assets should future conditions worsen (Amran and Kulatilaka, 1999). The financial flexibility logic reinforces the real options logic for constrained firms. Therefore, despite the reduction or even evaporation of the real option of waiting to invest, as highlighted in Bolton et al. (2019), we hypothesize that constrained firms are more likely to delay irreversible investments.[4]

For reversible investments, such as restarting a plant or bringing mothballed assets back into operation, constrained firms are more likely to opt for faster reversible investments for two reasons. First, they have a stronger need for cash flows. Second, since the costs of bringing reversible investments online are lower, it is more likely that they can be financed by internal funding. Thus, the preference for immediate front-loaded cash flows (Bolton et al., 2019) may induce them to "over-invest" by opting for reversible investments sooner. The financial flexibility logic opposes the real options logic in constrained firms contemplating reversible

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[4] The literature recognized that faster investments may confer a strategic advantage in terms of larger market share and higher profits if the firm benefits from first mover advantages (Folta and O'Brien, 2004; Kulatilaka and Perotti, 1998). This option to grow should be valuable to constrained firms. However, this should accelerate both reversible and irreversible investments.

investments. Meanwhile, unconstrained firms, facing no pressing liquidity shortfalls, can adhere more closely to canonical real options prescriptions. They can afford to wait until uncertainty resolves further, treating even seemingly “smaller” or more reversible additions with caution.

Therefore, constrained firms valuing the financial flexibility provided by even small cash flows combined with an inability to make large outlays opt for smaller, more reversible investments while delaying or even eschewing bigger, irreversible ones. Unconstrained firms can schedule all projects according to classic real options thresholds.

> ***Hypothesis 3****: In a crisis, when faced with demand loss of uncertain duration and magnitude, financially constrained firms will undertake reversible investments more rapidly and irreversible investments more slowly compared to unconstrained firms.*

Table 1 summarizes our hypotheses, showing the baseline predictions H1a and H1b and how the predictions change when firms are financially constrained (H2 and H3).

CONTEXT, DATA, VARIABLES AND METHODOLOGY

From the earliest detection in Wuhan, China, in December 2019, the COVID-19 virus quickly showed its infectiousness and lethality through epidemics in China, Italy, Iran, and Latin America. The World Health Organization (WHO) declared COVID-19 a pandemic on March 11, 2020. As the pandemic unfolded, countries worldwide implemented stringent mobility restrictions, including the suspension of air traffic, to contain the contagion. This was the fastest and most significant demand reduction ever for the airline industry, with global passenger air traffic demand in 2020 60.1% below that of 2019 (ICAO, 2023). Mobility restrictions imposed by states largely explained the immediate demand loss but also introduced significant uncertainty for the airlines. How long would the mobility restrictions last? How reluctant would individuals be to travel once mobility restrictions were loosened? How much would business travel be curtailed for economic or safety reasons? Unlike past negative demand shocks like 9-11 or the Global Financial Crisis, airlines had little or no experience of a global pandemic and the subsequent sharp increase in uncertainty generated by the COVID-19 shock.

Matching of assets to demand and financing assets are familiar problems for asset-heavy firms. Airlines are especially proficient in the underlying economic calculations over boom-bust cycles. However, few had experience with such a seismic shock. They faced problems in estimating the duration of the crisis, the magnitude of the demand shock, the speed of recovery, and potential post-crisis changes in the competitive landscape. Moreover, even as demand collapsed, firms faced additional uncertainty in the form of a liquidity crunch, financial sector stress, and heightened bankruptcy risks.

Data Sources

Our empirical estimates are based on monthly data for an unbalanced panel of 83 airlines spanning December 2016 to January 2021. The start date is determined by the lead and lag structure of the methodology, while the end date is when all airlines are treated. Airlines in our sample account for more than 85% of worldwide revenues, none fly purely domestic routes, and 78% fly trans-continental routes. Data on aircraft asset decisions and their timing were obtained from AeroTransport Data Bank, which maintains a global database of all aircraft that can hold 30 or more passengers and their operators, owners, and use. Accounting data was obtained from Compustat. Data on the presence and timing of government airline bailouts is obtained using a variety of sources. For US airlines, the Treasure Department's website for COVID-19 relief lists by airline the date when they received a bailout in the form of the payroll support program under the CARES Act, the Consolidated Appropriations Act of 2021, and the American Rescue Plan Act of 2021. For European airlines, Greenpeace's Bailout tracker and the website Transportation & Environment have a comprehensive list of bailouts that we combine with newspaper searches and the European Commission's website to identify the exact date of each bailout. For Chinese airlines, we used the Ministry of Finance website; for Australian airlines, the government's GrantConnect database has the data. For all other airlines, we used newspaper searches. In most cases, the data simply lists the airlines that received a bailout, so we lack data on the exact magnitude of the bailouts.

To measure the COVID-19 shock, we used data on mobility restrictions from the Oxford COVID-19 Government Response Tracker (Hale et al., 2021), which tracks a comprehensive range of governmental mobility restrictions and other responses to the pandemic and uses it to produce a policy stringency measure.

Variables

Dependent variables. The dependent variables are monthly counts of aircraft that each airline (1) placed into *storage*, (2) *retired* from service (scrapped), (3) *sale* (to another airline or to a leasing company), (4) *returned to service* after storage, and (5) *purchase/new leases* of new aircraft. (1) – (3) measure disinvestment decisions, of which the last two are more irreversible, while (4) and (5) are investment decisions, with the last being more irreversible.

Aircraft can be placed into storage to avoid operational expenses incurred during flying for the duration of the storage. Stored aircraft are typically turned over to a storage firm for relocation to a dry-climate location and preparation for storage. For safety reasons, aircraft must also be prepared for return to service (Careless, 2021). Storage incurs costs (ongoing parking and maintenance costs and one-time costs related to safety precautions, removal of engines and auxiliary power units). Airlines also bear the risk of being unable to return aircraft into service as quickly as optimal. The risk of delays in returning is especially high because there could be insufficient capacity to prepare aircraft for service if multiple airlines simultaneously request returns from the storage sites. Retirement and sale are long-term actions that remove the aircraft from the airline fleet. They differ in that retirements can be done unilaterally, and there is a window where retired aircraft can be brought back into service or used for pilot training. Retired aircraft are stripped of all valuable components, either used or sold as spare components for existing aircraft. Sales, by contrast, while generating more revenues, are irreversible. Similarly, purchases require finding a seller (airline manufacturers, leasing companies, other airlines) and agreeing on a price, while returning airplanes to service is a unilateral decision affording more flexibility. Moreover, purchases entail significant sunk capital expenditure, while reactivating a stored aircraft requires comparatively minimal investment, primarily in maintenance and compliance checks, making it a more reversible decision.[5] Purchases are recorded at the time of agreement rather than delivery.

Treatment variable. Although the COVID-19 shock is exogenous to airline asset decisions, comparing groups of "treated" (affected by travel restrictions) and "control" (not affected) airlines to identify its impact is not straightforward for two reasons. First, given the global nature of the shock, there is no "clean" control group of airlines not buffeted by the pandemic. Eventually, COVID-19 hit all countries, and they converged on similar approaches (lockdowns, travel restrictions, closures), so all countries experienced the treatment. More accurately, there is no "never-treated" group. Second, starting in February or March 2020, there was a significant slowdown in passenger traffic even in the absence of travel restrictions, as fear amongst passengers led to a significant curtailment of travel. However, a simple before-after

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[5] While a new aircraft can also be stored so buying/leasing an aircraft may seem to offer equivalent flexibility, the reversibility is lower than reactivating stored aircraft. First, leases stipulate specific maintenance standards and return conditions. Storing a newly leased aircraft often necessitate additional maintenance costs compared to existing aircraft to meet these requirements upon return. Second, terminating an aircraft lease before its agreed term can result in substantial penalties, including remaining lease payments and early termination fees, reducing the reversibility of the investment. In contrast, reactivating an owned, stored aircraft allows the airline to adjust its fleet size without these contractual constraints, offering greater flexibility.

comparison does not permit a causal interpretation and leads to biased estimates in the presence of dynamic treatment effects (Goodman-Bacon, 2021). Therefore, we exploit the staggered imposition of restrictions on international travel by different countries and the intensity of these restrictions to compare "treated" airlines with those that are "last-treated." This allows us to isolate and identify the COVID-19 effect as a regulatory shock beyond any common time-varying shocks that affected all airlines through a decline in worldwide demand for travel.

Our treatment variable is from the Oxford COVID-19 Government Response Tracker. The index has nine sub-indices measuring school closures, workplace closures, cancellation of public events, restrictions on public gatherings, closures of public transport, stay-at-home requirements, public information campaigns, restrictions on internal movements, and international travel controls, and other work has used the full index as a continuous measure of pandemic effects (Greve, 2024). We instead used their ordinal sub-indicator, "Restrictions on International Travel," which is measured daily on a five-point scale that varies from "no restrictions" (value 0) to "ban on arrivals from all regions or total border closure" (value 4). Screening of arrivals, quarantining of arrivals from some or all regions, and travel bans from some regions are the intermediate categories. We coded a COVID-19 treatment variable that equals unity for the first month when this sub-indicator index takes the value of 3 or 4 for a majority of days for that month. It remains unity in subsequent periods, as we are interested in airline responses to the first treatment, so the treatment is absorbing. As an illustration, Figure 1A plots monthly passenger volumes (from the TSA website) for the USA. The US declared a national emergency on March 13 but imposed travel restrictions slightly earlier. The travel restrictions sub-indicator reached 3 for the first time on March 2, the exact month when passenger volumes declined by 53%. The sub-indicator remains at 3 until November 2021. Our treatment variable takes the value unity from March 2020 for US airlines.

Our measure is most pertinent in the context of the treatment impacting airlines for various reasons. First, not all Stringency sub-indicators are relevant for airlines (e.g., school closures may encourage travel). Second, in terms of case counts, airlines respond to people's mobility rather than to the proportion of people who are sick. Travel restrictions remained in place in many countries, such as Singapore, even when case counts came down, affecting airline decisions. Finally, COVID-19 infections come in waves that are not wholly aligned with the restrictions that impacted airlines. For example, India locked down severely in March 2020, banning all international flights, but had its most significant COVID-19 surge in April 2021, more than a year later. Preliminary analysis confirmed our conjecture that the case count did not explain airline responses well. Despite this, we include case counts as a control in all our specifications, which helps us identify the impact of the regulatory shock.

Firm financial constraints. To test the heterogeneity of treatment effects, we use two variables for sub-sample splits, each measuring the extent to which firms are financially constrained. Our first measure is the one-year probability of default from Bloomberg. This measure, termed the Default Risk Model, integrates market-based (credit-default swaps, credit ratings) and fundamental data, including capital adequacy, to capture the default probability. Financially constrained firms have higher default probabilities and have a harder time obtaining external financing (Farre-Mensa and Ljungqvist, 2016), and the measure directly quantifies this risk using structural underpinnings[6]. We used the default probability from December 2019 and

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[6] Other popular financial constraint indices (the Kaplan and Zingales, 1997, Whited and Wu, 2006, and Hadlock and Pierce, 2010 indices) have been shown not to identify plausibly constrained firms. Farre-Mensa and Ljungqvist (2016) show that constrained firms identified based on these proxies are found to have no difficulty obtaining external capital. Unlike other proxies (e.g., dividend payment status or credit ratings), the default probability measure provides a continuous, market-sensitive, indicator of financial distress.

classified airlines above the median as financially constrained. Using the pre-COVID level ensures that no airline is classified as constrained and unconstrained in different periods, which would make interpretation of the results difficult.

Our second measure of financial constraints is whether airlines received a government *bailout*. Bailouts are coded as an indicator variable, taking the value one if the airline has been given a government bailout during the pandemic. Bailouts tend to be justified as a way to avoid long-term damage to a firm's resource base, which is a politically acceptable use of government funds if the firm provides a societally important product or service. Historically, airlines have been the target of bailouts multiple times, but bailouts are not universal. This variable is set to unity regardless of when the bailout was announced, as bailout decisions take time and can even be predicted by the airline based on past government actions (e.g., the 9/11 bailouts of some US airlines) (Humire & Reichel, 2020). The correlation of these two measures is -0.17, so they are distinct.

Controls. Our event study design includes firm and month-year fixed effects. These eliminate all time-invariant firm-specific and cross-sectional invariant time-varying confounders. Firm fixed effects account for time-invariant characteristics such as alliance structure, whether the airline is a low-cost and/or a flag carrier, revenues from international travel relative to total travel before the pandemic, and time-invariant characteristics of the markets they operate in.[7]

We add additional control variables. In the face of rising COVID-19 cases or anticipating a rise in cases, travelers possibly cut back on flying even without stringent restrictions. Therefore,

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[7] For the difference-in-difference methodology, controls are not used to account for differences in treated and control groups. Instead, they are used to justify the parallel trends assumption. A flag carrier for instance, may face fewer constraints in asset adjustment decisions compared to a non-flag carrier. Similarly, alliance structure may obviate the need to invest in aircraft. Both could violate the parallel trends assumption. Additionally, controlling for measures after the treatment can lead to post-treatment bias.

we add a control for the number of cases per 100,000. We use data from reports from the World Tourist Organization's website that list countries experiencing complete closure of international borders. We code a time-varying dummy for the complete closure of borders and include it as a control. Finally, while the COVID-19 treatment indicator and the controls above are based on the country where the airline is headquartered, those with significant international flights may be indirectly exposed to the COVID-19 shock. Therefore, for each country, we construct a control variable based on the complete closure of borders in partner countries as follows:

$$Exposure_{it}^{complete} = \sum_{j} Closure_{jt}^{complete} \left(\frac{P_{ij}}{\sum_j P_{ij}} \right)$$

where P_{ij} is the total number of international passengers flying between country *i* and partner *j* in the year 2016[8], $Closure_{jt}^{complete}$ is a dummy variable taking the value 1 if partner country *j* implemented complete closure at date *t*. Each variable is thus a weighted average of closures in other countries with weights as the fraction of international passengers to and from country *j*.

Finally, we include all three disinvestment variables as a control for the treatment estimates, with investments as the dependent variable to account for the fact that investments would be conditional on the disinvestments undertaken earlier.

First Look at the Data

We first provide evidence that the COVID-19 shock led to a sharp decline in air travel followed by a slow but steady recovery. Importantly, we show an immediate spike in uncertainty followed by a gradual decline in uncertainty interspersed with spikes coinciding with the

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[8] The variable measuring passengers is time-invariant, so it changes only as a response to closure. The data are from Recchi, Deutschmann, and Vespe (2019) covering 195 countries. We used the last year for which this data are available. Except for US airlines, we lack data on their routes and revenues from these routes.

emergence of new variants of the virus. We also highlight the staggered treatment of airlines in our sample and show the evolution of asset disinvestment and investment.

COVID-19 Shock. As COVID-19 hit and countries opted for lockdowns and travel restrictions, airline travel plummeted. Figure 1A uses monthly data from the US Bureau of Transportation Statistics on the number of airline passengers. The number of monthly passengers plunged from 80 million in February 2020 to a low of 2 million in April 2020, a 96.25% decline over two months. By August 2022, passenger traffic had not recovered to its pre-COVID level. Similarly, Figure 1B shows the monthly number of flights in Europe. It declined from 786,311 flights in January 2020 to a low of 13,882 flights in April 2020, a 98% decline over a three-month period.

Second, we proxy uncertainty from the airlines' perspective by calculating a 3-month rolling standard deviation of passenger traffic in the US and passenger flights in Europe. Figures 2A and 2B show a large spike in uncertainty around March 2020 during the first COVID-19 wave. Uncertainty declines subsequently, with minor spikes (relative to the first) around Jan 2021 during the Delta wave and a third one during the Omicron wave. Interestingly, uncertainty is relatively muted in the US compared to Europe in the later stages. Partly, this could be due to COVID-19 hitting European countries at different times, while in the US, the impact was more clustered over time, and some areas in the US relaxed restrictions very quickly.

Figure 3 shows the variation in the treatment for the 47 countries in our sample. On the horizontal axis, we measure the number of months since June 2019, and the vertical axis lists the countries that experienced the COVID shock. The grey bars indicate that the airlines in this country have not experienced a COVID shock, while the blue bars show that they have been treated. Note that the UK and Ireland are treated last, given that travel restrictions were imposed much later in these two countries. Moreover, all airlines in our sample are eventually treated, so there are no "never-treated" airlines.

Finally, Figure 4 shows the number of airlines receiving bailouts each month starting January 2020. 46 out of 83 airlines received a bailout, with most of the bailouts clustered around the beginning of the COVID shock.

Asset Adjustments. To see the time variation in airline asset decisions, we summed all firm-level asset decisions across airlines and plotted these over time. Figure 5A shows the asset disposal spikes in terms of storage in the months of Feb-April 2020, retirement of aircraft peaks in April 2020, and no discernible pattern for sales. Figure 5B shows that airlines started returning aircraft to service over May-June 2020, while aircraft purchases declined at the onset of COVID and peaked in April 2021. Importantly, in the pre-COVID period we do not see the presence of any trend in any of these variables.

Methodology

A standard event study specification estimates a fully parametric regression-based estimator with a binary treatment, as shown below:

$$y_{it} = \alpha_i + \lambda_t + \beta X_{it} + \sum_{l=-2}^{-K} \mu_l D_{i.t}^l + \sum_{l=0}^{L} \mu_l D_{i.t}^l + \varepsilon_{it} \tag{1}$$

y_{it} is the outcome of interest for airline *i* at time *t*, α_i and λ_t are airline and month-year fixed effects and X_{it} is a vector of time-varying covariates. In our context, airline *i* is treated at time E_i, and $D_{i.t}^l$ is a relative time indicator that takes the value 1 when airline *i* is l periods away from its initial treatment at calendar time *t*. Often, the coefficients μ_l for $l \in [-k, -2]$, the pre-treatment leads are used to test the parallel trends assumption. Due to multicollinearity (the relative time indicators $D_{i.t}^l$ sum to 1,) we drop the time period -1, one period prior to the treatment, and the time period -10, a distant time period as recommended in Sun-Abraham. We set $K = 5$ and $L = 10$ to evaluate the impact of the COVID-19 shock over a 16-month window. We bin all relative time leads before -5 and all lags after 10.[9]

Sun and Abraham (2021) show that when equation (1) is estimated via two-way (firm and time) fixed effects (TWFE), the dynamic treatment estimates are biased. First, extending Goodman-Bacon (2021), they show that the TWFE dynamic effect estimate for every relative-time period (relative to the treatment) is contaminated by causal effects of other periods, both leads and lags. [10] A second and more important source of bias arises when there is variation in treatment timing and heterogeneous treatment dynamics across cohorts exposed to the treatment at different times. TWFE uses early-treated groups as a control for late-treated groups, a case of "bad controls" that leads to biased estimates in the presence of treatment dynamics. To the extent airlines adjust slowly to the COVID shock, TWFE would underestimate the impact by comparing late-treated groups to early-treated groups. [11] In our context, we observe both variation in treatment timing and heterogenous treatment dynamics. COVID-19 spread sequentially across countries, and government decisions on lockdowns in different nations meant airlines were exposed to the COVID-19 shock at different times. Treatment effects may be heterogeneous both across airlines (e.g., airlines based in small countries like Singapore may not have domestic flights) and over time (e.g., airlines exposed to the COVID-19 shock early in 2020 when there was a higher degree of uncertainty would exhibit different reactions as compared to

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[9] The coefficient on the COVID shock at lag 10 may be interpreted as the long-run impact. However, given that all airlines are eventually treated, we can estimate lags from 0 to 12 periods after the COVID shock.

[10] Like Goodman-Bacon (2021), it is possible for the average treatment effect to be positive for all units, but the TWFE estimate to be negative because of negative weights. A standard two-way fixed effects regression also includes comparisons between newly treated units and already treated units, which is a flawed comparison because the path of outcomes for already treated units is not the same as the path of untreated potential outcomes. They also show that the treatment lead coefficients are not guaranteed to be zero even if parallel trends is satisfied in all periods.

[11] See Section A1 in the Appendix for a comparison of the two-way fixed effect estimator and the Sun-Abraham estimator used in the paper. The TWFE consistently underestimates the impact as expected.

those exposed later to the disease). Given differences in underlying regulations, the evolution of our understanding of the disease, and variations in the intensity of lockdowns, treatment effect dynamics are likely heterogeneous.

We use the event study methodology of Sun and Abraham (2021) to obtain sensible estimates of dynamic treatment effects from the COVID-19 shock. The estimator uses the last-treated as the control group. The building block is the cohort average treatment effect on the treated ($CATT_{e,l}$) defined as the expected difference between the observed outcome variable for the *cohort* of firms at all treated at the same time and the outcome had the firms not received treatment, l periods from the initial treatment date *e*.

$$CATT_{e,l} = \mathbb{E}[Y_{i.e+l}(1) - Y_{i.e+l}(0) |\, E_i = e]$$

where E_i is the time when unit i receives the treatment, $E_i = e$ for all firms in cohort *e* that receive treatment at the same time, and l is a relative time indicator when the unit is l periods away from its initial treatment. $Y_{i.e+l}(1)$ is the outcome of unit i when treated. $Y_{i.e+l}(0)$ is the potential outcome of unit *i* when it is untreated. As an example, $CATT_{2020m2,l}$ would be the average treatment on the treated for the cohort of airlines treated in February 2020, *l* periods after the treatment.

The Sun and Abraham estimator addresses the problems highlighted above. First, we avoid the forbidden comparison of “treated” vs. “already treated” units by using the “last-treated” units as the control group, thus avoiding bias. Second, given that we have many airlines treated early during COVID-19, the standard TWFE will put negative weights for these early treated units in late periods in the sample. Under treatment heterogeneity, the standard TWFE estimator will not recover the causal effect. Finally, the fact that the CATT can be different from one another captures variation in treatment timing and heterogeneous treatment dynamics across cohorts.

Sun and Abraham (2021) propose an interacted weighted estimator as a consistent estimator for $\mu_l's$ in equation (1). They derive the estimator in three steps. First, the $CATT_{e,l}$ is estimated by regressing the outcome Y_{it} in a linear two-way fixed effects specification that interacts relative period indicators with cohort indicators. Second, weights are calculated as the sample share of each cohort in each period l. Finally, a weighted average of the estimated $CATT_{e,l}$ is calculated with weights from the second step and averaged across cohorts using shares of the cohort as weights. The resulting estimates of μ_l do not represent the treatment effect of any one cohort, as these are heterogeneous, but it is a weighted average uncontaminated by differential timing and strength of treatments. Under parallel trends and no anticipation this is a consistent estimator, asymptotically normal, and robust to treatment heterogeneity.[12] We use multi-way clustering of standard errors at the airline and treatment date level.

RESULTS

Effect of the COVID-19 Shock on Airline Investment and Disinvestment Decisions

We present our results using a series of event-study graphs, showing both the point estimate and 95% confidence intervals of the impact of the COVID-19 treatment at various lags and leads relative to the timing of the COVID-19 shock. We show graphs instead of regression tables because they present the same information more concisely. The exact coefficients and standard errors are reported in Tables 1-3B in the Appendix (available in link https://osf.io/fb974/?view_only=e64d5f26a25f48f3bcb74793b122f6c7). Some of our figures display the same information as six tables and, unlike tables, allow easy comparison of effect

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[12] Parallel trends are sensitive to functional assumptions, and they are more likely to hold in levels (disinvestment and investment in the number of planes) rather than in fleet proportions or any other monotonic transformation (see Roth and Sant'Anna, 2023).

magnitude and significance level. We also show the pre-COVID-19 shock mean of the dependent variable in 2019 to illustrate the magnitude of the impact.

Figure 6A shows the impact of the COVID-19 shock on the three measures of disinvestment: storage, retirement from service, and sales. There is a clear impact on storage the month of the COVID-19 shock with a spike in planes sent into storage. The impact peaks two months after the shock and then declines but remains elevated 10 months after the shock. In terms of economic magnitude, the initial impact is 35 times the pre-COVID mean, declining to 11.7 times the mean, 10 months after the shock. The impact on retirements is initially negative, even if the magnitude is small, but then turns positive and significant two months after the COVID-19 shock. The magnitude of impact is 4.1 times the pre-COVID. Retirements in the longer term (lag 10 and higher) is positive and significant and 1.23 times the pre-COVID mean. Finally, we observe a slight spike in aircraft sales four months after the COVID-19 shock. While these estimates are imprecise, the magnitude of impact is twice that of the overall sample mean and the mean during the four months before the COVID shock. Our results partially support Hypothesis H1a, showing that airlines initially prioritize the most easily reversible option, storage, followed by a more irreversible option, retirements. We do not observe any significant increase in sales. Possibly, this is because retirements can be done unilaterally, while sales require finding a willing buyer and agreeing on the price. Alternately, the impact manifests itself for only a subset of firms.

Next, we examine the impact on asset investment decisions. Figure 6B suggests that return to service declines 3-5 months after the shock relative to the control group, though the coefficients are insignificant. Airlines start returning aircraft to service six months after the initial shock, and we observe a statistically significant impact from month 8 onwards. The magnitude of impact in month 9 is 89 times the sample mean measured the year prior to COVID-19. Airplane purchases/leases show a significant rise only 5, 6 and 7 months after the shock. Our results are different from what we hypothesized in H1b. There are consistent increases in return to service only 8 months after the shock, while purchases show a small but significant increase earlier, 5, 6 and 7 months into COVID.

Financial Constraints and Heterogeneity of Treatment Effects

Default Probability. Figures 7A and 7B show the heterogeneity of the COVID-19 shock impact on airline disinvestment and investment decisions for two mutually exclusive sub-samples – airlines with a high (top panels in 7A and 7B) vs. a low default probability (bottom panels)[13]. Figure 7A for storage shows that financially constrained airlines slowly and steadily send aircraft into storage. The impact on constrained airlines persists throughout the entire 10 months, while unconstrained airlines send aircraft into storage only in the first three months of the COVID-19 shock. Moreover, for the latter, the relative magnitudes of the coefficient estimates, while comparable at lag 0, are more than twice as high at lags 1, 2 and 3. Finally, the long-run effect (lag 10) is positive and significant for constrained airlines but insignificant for financially unconstrained airlines.

For retirements, we see a positive impact for both types of airlines two months after the shock, but the magnitude of impact for financially constrained airlines is 9 times that of unconstrained airlines (see Section A2 in the Appendix for exact magnitudes). We also observe an increase in retirements 6 and 7 months after the COVID shock for financially constrained airlines. In the long run (lag 10 and higher), there is also a significant positive impact on

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[13] The control group are the same airlines we use in Figure 6. We lack sufficient number of airlines to construct a control group based on last-treatment and a high default probability.

retirements for constrained airlines and an insignificant impact for unconstrained airlines. For airplane sales, the results are ambiguous. Constrained airlines are initially less likely to sell aircraft but eventually are more likely to sell aircraft at lags 3-5 compared to the control group. However, the significant coefficient for sales *prior* to the COVID-19 shock for airlines with bailouts means that the parallel trend assumption for aircraft sales is unlikely to hold for this sub-sample. Unconstrained airlines, for whom the parallel trends assumption does not seem to be violated, are less likely to sell aircraft.

Figure 7B shows that financially constrained airlines returned planes to service more quickly (positive and significant coefficients for nearly all months after the shock), while unconstrained airlines bailouts are less likely to return aircraft initially (negative and significant coefficients at lags 3-4). They start returning aircraft only 8 and 10 months after the shock. We do not see any evidence that constrained airlines purchase/lease new aircraft. Financially unconstrained airlines, conversely, are more likely to purchase/ lease airlines 4-10 months after the shock, while we do not detect any significant purchases for constrained airlines. As for sales, the assumption of parallel trends here seems questionable for unconstrained airlines.

These results are in line with but more nuanced than hypothesized in H2 and H3. Aligned with H2, we find that for disinvestments, financially constrained airlines stagger the relatively reversible decision like storage over time. Moreover, the magnitude of impact is many times higher for unconstrained airlines in the case of storage. Constrained airlines also choose to retire many more aircraft, which is more irreversible than storage, compared to financially unconstrained airlines. We lack the confidence to make such a claim for sales of aircraft. Financially constrained airlines return more planes to service and do so relatively quickly compared to ones without bailouts, in line with Hypothesis H3. We also do not observe any change in their purchases/leases over the time period.

Bailouts. Figures 8A and 8B show the heterogeneity of the COVID-19 shock impact on airline disinvestment and investment decisions for two mutually exclusive sub-samples – airlines that did not receive a bailout (top panels in 8A and 8B) and those that did (bottom panels). Figure 8A for storage shows a delayed impact on airlines that did not receive a bailout by a month (lag 0 is significant for airlines with bailouts), so that airlines that received a bailout are quicker to send aircraft into storage. The impact on airlines without bailouts persists throughout almost the entire 10 months, while those with bailouts send aircraft into storage only in the first three months of the COVID-19 shock. Interestingly, the magnitude of the effect for airlines with a bailout is 6 times that of those without one during the month of the COVID shock. In subsequent months, the impact is greater for airlines without a bailout. Finally, the long-run effect (lag 10) is positive for those without a bailout and negative but insignificant for airlines with a bailout.

For retirements, we see a positive impact for both types of airlines two months after the shock. We also observe an increase in retirements 7 months after the COVID shock for airlines with bailouts. In the long run (lag 10 and higher), however, there is no significant impact on retirements for airlines with bailouts compared to a positive and significant one for those without one. For airplane sales, the results are ambiguous. Airlines with bailouts are less likely to sell aircraft compared to the control group 8 and 9 months into COVID. For sales, the significant coefficient *prior* to the COVID-19 shock for airlines with bailouts means that the parallel trend assumption for aircraft sales is unlikely to hold for this sub-sample.

Figure 7B shows that airlines that received bailouts returned planes to service more quickly than those without bailouts (positive and significant coefficients for 4-6 months after the shock), while those without bailouts started returning aircraft only 8 or more months after the shock. Moreover, the magnitude of impact is higher for airlines with bailouts, peaking at 4 months after the shock, compared to those that did not receive a bailout. Finally, there seems to be no systematic pattern in terms of impact on purchases/new leases for airlines with bailouts, while those without one are more likely to purchase airplanes in months 6 and 7 after the COVID shock.

These results are in line with but more nuanced than hypothesized in H2. First, airlines with bailouts quickly sent their aircraft into storage, while those without bailouts stagger the storage over time. Moreover, the instantaneous magnitude of impact is many times higher for those with bailouts, while airlines without bailouts continually send aircraft into storage. Second, for retirements, a more irreversible decision, we see a positive impact for airlines with bailouts only in the short term, while the impact on airlines that did not receive bailouts manifests itself both in the short and the longer term. That is, we see more of an impact on retirements for airlines without bailouts, especially in the long term. Third, airlines with bailouts are less likely to sell aircraft. Therefore, airlines with bailouts chose more reversible options for asset disinvestment decisions. Further, they are less likely to choose more irreversible ones, in line with Hypothesis H2.

We do not find support for H3; in fact, we observe the opposite pattern. Airlines with bailouts return more planes to service and do so relatively quickly compared to ones without bailouts. Moreover, compared to what we hypothesized, airlines without bailouts are more likely to buy aircraft, while those with bailouts are less likely to do so. Even though we controlled for disinvestments, our findings show that airlines with bailouts were more able to protect their fleet and saw a lower need to purchase aircraft subsequently. One reason for this finding could be that while default probabilities are an ex-ante measure of financial constraints, bailouts provided after the onset of COVID are ex-post measures of COVID. If bailouts are more likely to go to ex-ante financially constrained airlines, this could confound our results. Therefore, as a robustness check, we defined a set of airlines as financially constrained if they had high default probabilities *and* did not receive a bailout. Figure 8C shows these are the airlines that very quickly returned aircraft to service as predicted in H3. However, we do observe a spike in purchases at lag 6 in contrast to the predictions of H3.

ROBUSTNESS CHECKS

First, as a robustness check, we used the diff-in-diff estimator from Calloway and Sant'Anna (2021), which, unlike the Sun-Abraham estimator, also uses the "not-yet-treated" group as a control. Our results remain qualitatively the same, though the magnitude is somewhat larger. Second, we attempted to create a composite measure of financial constraints, combining our two variables: default probability and bailouts. The two are not highly correlated, making the interpretation of results difficult. Third, we restricted our set of airlines to only those that fly transcontinental routes. We get very similar results. Finally, we checked the no-anticipation assumption by switching on our treatment variable during the month when travel restrictions crossed the threshold for at least ten days. This recoding usually sets the treatment date back by a month. Our results are very similar in response to this perturbation.

DISCUSSION AND CONCLUSION

This study offers a new perspective on how firms respond to uncertainty during a crisis by integrating real options theory with the reality of financial constraints. Real options logic tells us that delaying irreversible actions and preserving flexibility is valuable under uncertainty. Yet our findings show that this flexibility is conditional: it is available primarily to firms that can afford to wait. In a crisis or economic downturn, constrained firms may be numerous enough that the “average” firm response will deviate from real options predictions. At the same time, financial constraints do not merely accelerate disinvestments and suppress investments. Instead, they reorder their timing relative to one derived from ROT logic – delaying reversible disinvestments and accelerating reversible investments.

Our empirical analyses yield three central findings. Consistent with our baseline hypotheses H1a and H1b, airlines responded to the COVID-19 demand collapse by undertaking reversible actions (storing aircraft) before resorting to irreversible divestments (retirements or sales). Similarly, when demand rebounded, they reactivated stored aircraft before committing to new purchases/leases. This sequencing supports the ROT prediction that firms prioritize relatively reversible commitments relative to irreversible ones. While prominent earlier work has examined planned reductions in investments during a crisis (Campello et al., 2010), we present dynamic treatment effects for both investments and disinvestments in the context of a single shock.

More critically, we document the heterogeneity of treatment effects by comparing constrained vs. unconstrained airlines. While the sequencing within each sub-sample remains broadly similar, there were differences across these sub-samples. For both measures of financial constraints, less constrained firms (low default probability or state bailout) were decisive in quickly using reversible disinvestments, with more constrained firms drawing this action out over a more extended period. For irreversible disinvestments, we observe airplane retirements and some evidence for sales for more constrained firms. Unconstrained firms, in contrast, did not sell planes. This is in contrast to the real option prediction where financial constraints simply reduce the option value of waiting. Instead, consistent with Hypothesis H2, the empirical findings show that in a crisis, firms prioritize liquidity needs, and the option value of waiting is exercised by firms that are not financially constrained and can afford to wait.

Finally, constrained firms, in terms of high default probability, were more decisive in quickly opting for reversible investments, while less constrained firms waited longer before returning planes to service. These constrained firms are also less likely to purchase/new leases compared to unconstrained ones. However, these effects were not visible for firms that received a state bailout. This is contrary to our hypothesis H3 and has two potential explanations. One, as we explored, bailouts are more likely to be given to airlines that lack access to external finance. Second, firms without state bailouts faced no political constraints in their investment decisions, unlike those with state bailouts. From the comparison of the responses to the two kinds of financial constraint, it seems likely that both explanations are at work in these data. Overall, our findings for investments are consistent with the financial flexibility logic as opposed to the real options logic.

Methodologically, we apply the novel Sun-Abraham estimator, using last-treated as the control group, thus avoiding the biases in the usual two-way fixed-effects implementation of event study specifications that use previously-treated groups as a control group. Since the treatment and control groups are defined in terms of travel restrictions, and given that the control group also faced a reduction in demand before restrictions were imposed, our estimates provide a lower bound on the effects. Using a binary absorbing treatment indicator does not fully capture the evolution of uncertainty as well as the waves of COVID. Our analysis ends in January 2021 when all airlines become treated, so we focus only on the first wave of COVID. We made this choice to prioritize reliable causal estimates. A continuous "dose" measure that captures the varying intensity of the COVID shock requires stronger parallel trends assumption and restrictions on treatment effect heterogeneity to identify a causal response (see the working paper

Callaway, Goodman-Bacon, & Sant'Anna, 2024).

Additional implications can be drawn beyond the scope of real options theory. Strategy research currently examines asset redeployment (Chang & Matsumoto, 2022) and resource allocation capabilities (Helfat & Maritan, 2024), both of which are important decisions that are a natural fit with real options theory, possibly combined with financial constraints. This theoretical connection does not appear to be realized in work on these topics, but it could be a useful addition. Real options theory has also been criticized for making overly stringent assumptions of rationality and information availability, suggesting that a more behavioral approach would be better (Posen, Leiblein, & Chen, 2018). This critique may be correct, but we should also consider that some of the heterogeneity observed in earlier studies is not behavioral but plausibly produced by heterogeneous financial constraints, as demonstrated in this study.

Our results have practical implications for firm responses to significant crises. Our findings suggest that immediate liquidity needs can significantly override traditional strategic flexibility considerations for managers navigating crises. This implies building up financial buffers in tranquil times. Intuitively, one might think that financially constrained firms would rapidly seek to reduce the running cost of their production assets by idling them or even reducing the total asset base if the post-crisis demand is estimated to be low or has great uncertainty. This intuition contradicts the logic of real options theory when combined with financial constraints. Airlines with low default likelihood quickly idled but slowly reactivated their fleets, thus managing real investment options better than financially constrained firms. For bailouts, this could be seen as a state intervention functioning as intended, as one of the purposes of airline bailouts is to prevent harm to a logistical infrastructure with positive economic externalities. However, it contradicts the widespread impression that airline bailouts coddle a privileged industry without producing socially beneficial effects. For default probability, the findings indicate that airlines with solid financing are not holding back funds that could be returned to shareholders; they can translate their financial structure into quicker idling and subsequent investments.

As another practical consequence, we also speculate that airlines that managed to retain their fleets during the COVID shock may face greater hurdles in adjusting their fleets to future demand changes. The high profitability of the premium economy class (higher than economy and business) was known before the pandemic and the installation of more premium economy seats had started (Powley, 2019). The pandemic accelerated this demand because greater distance between seats became more valued (most airline passengers do not know that the aircraft circulation and filtration systems make adjacent economy class seats similar to office desks 6 feet apart). Airlines who retired or sold aircraft may find it easier to adapt to such changes than those who retained their fleet. Similarly, passenger reluctance to board multiple flights for a single trip increased demand for aircraft models that can economically fly point-to-point routes. Airlines that retired and sold their aircraft now have more flexibility in deploying such aircraft.

While our findings are highly promising, further research is still needed. Lacking data, we could not examine other margins of adjustment, such as converting passenger aircraft to cargo, exiting the industry, or shifts in alliance structure, . We did not study the performance implications of airlines' choices during COVID. It would be interesting to analyze whether and how such choices affected their survival and return to profitability. For strategy scholars concerned with the generalizability of our findings, it would be interesting to see if our findings are replicated for other industries with significant real assets when facing demand losses in combination with liquidity crises. Other asset-heavy sectors, such as car rental agencies, hotels, cruise lines, shipping, etc., faced similar demand reductions, were impacted by lockdowns, and encountered significant liquidity crunches. Beyond physical assets, firms during COVID had to make similar choices concerning human capital – they could fire people, furlough them, or reduce working hours, each of which has various degrees of reversibility. Finally, given the increasing frequency and severity of global disruptions and the fact that global pandemics are a once-in-a-century event, future research can examine the generalizability of our findings in other crisis settings.

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Table 1: Reversible vs. Irreversible × Investment vs. Disinvestment

	Reversible	Irreversible
Disinvestment	Baseline H1a: Undertaken *earlier* H2: Slower disinvestment for constrained firms	Baseline H1a: Undertaken *later* H2: Faster disinvestment for constrained firms
Investment	Baseline H1b: Undertaken *earlier* H3: Faster investment for constrained firms	Baseline H1b: Undertaken *later* H3: Slower investment for constrained firms

Figure 1a: Airline Passengers in the US. Monthly Data Seasonally Adjusted

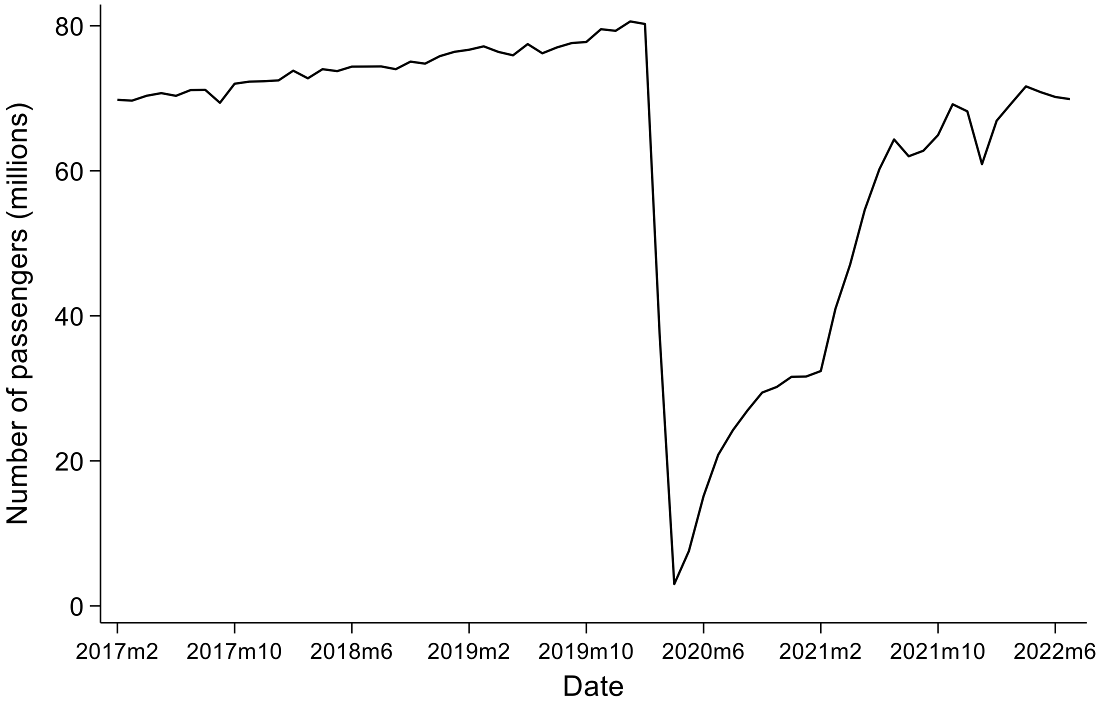


Figure 1b: Airline Traffic in Europe. Monthly Data

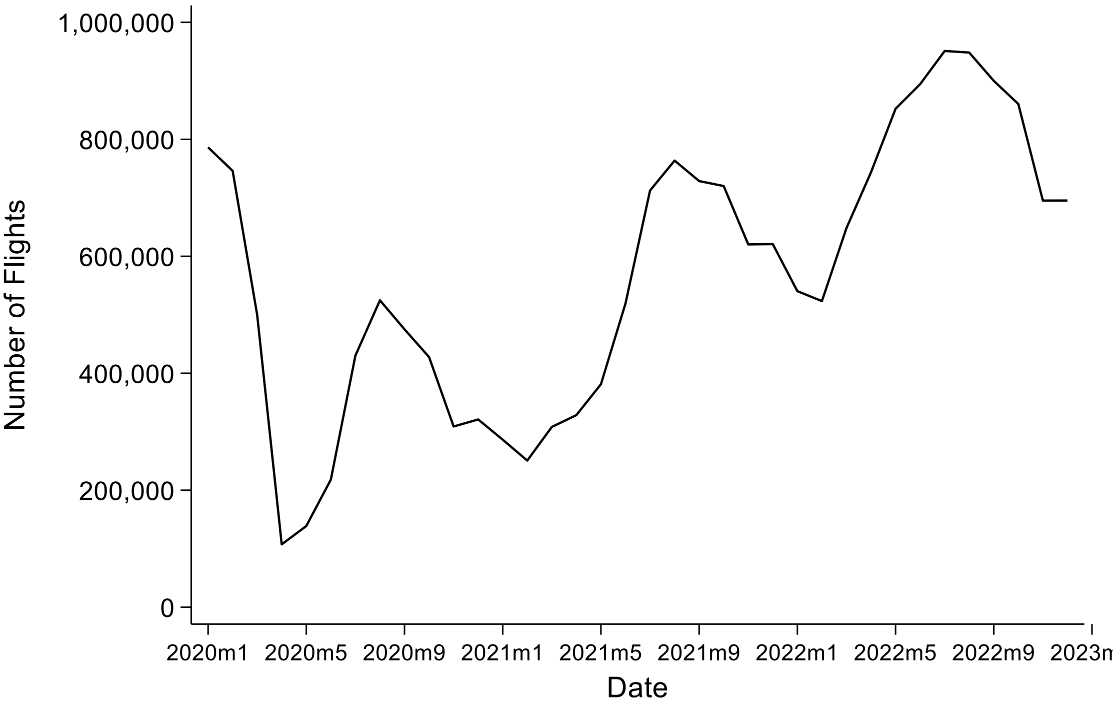


Figure 2: Variation in Passenger Traffic (left) and Flights (right). Rolling Std. Dev.

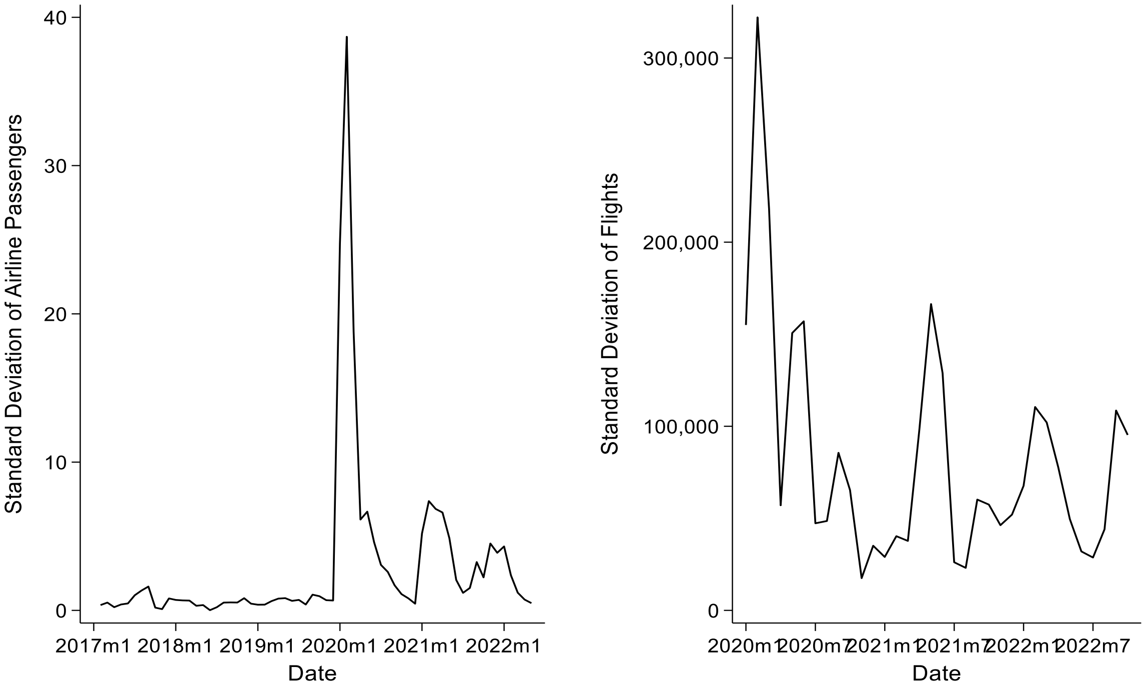


Figure 3: Treatment Status by Timing Group

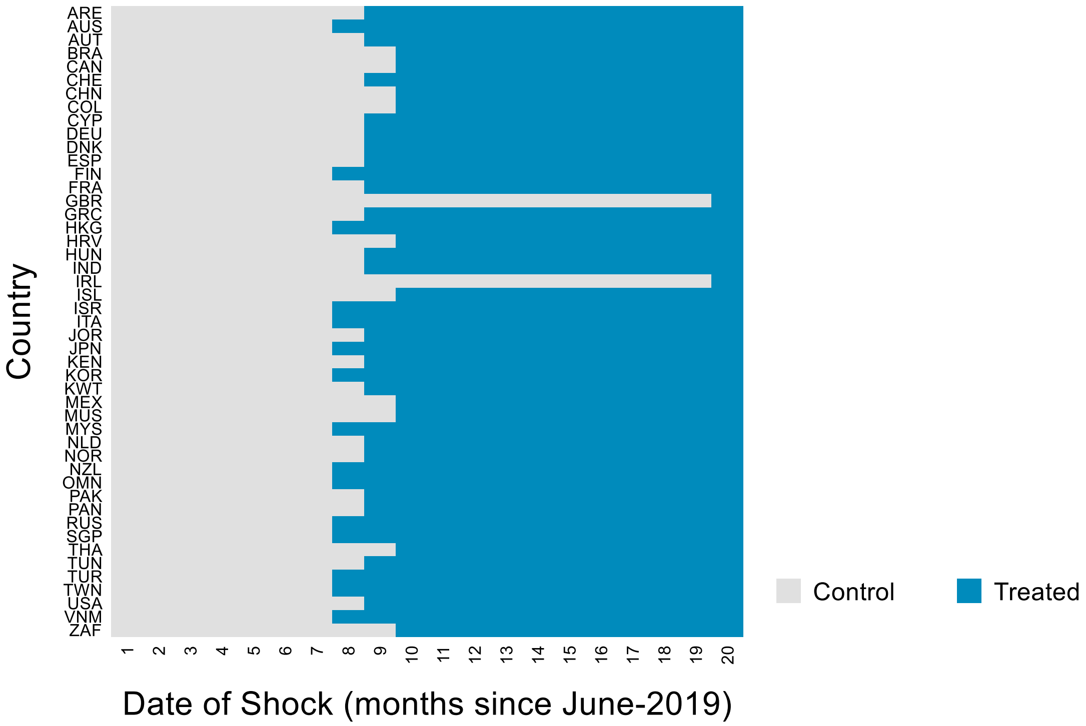


Figure 4: Bailouts During COVID

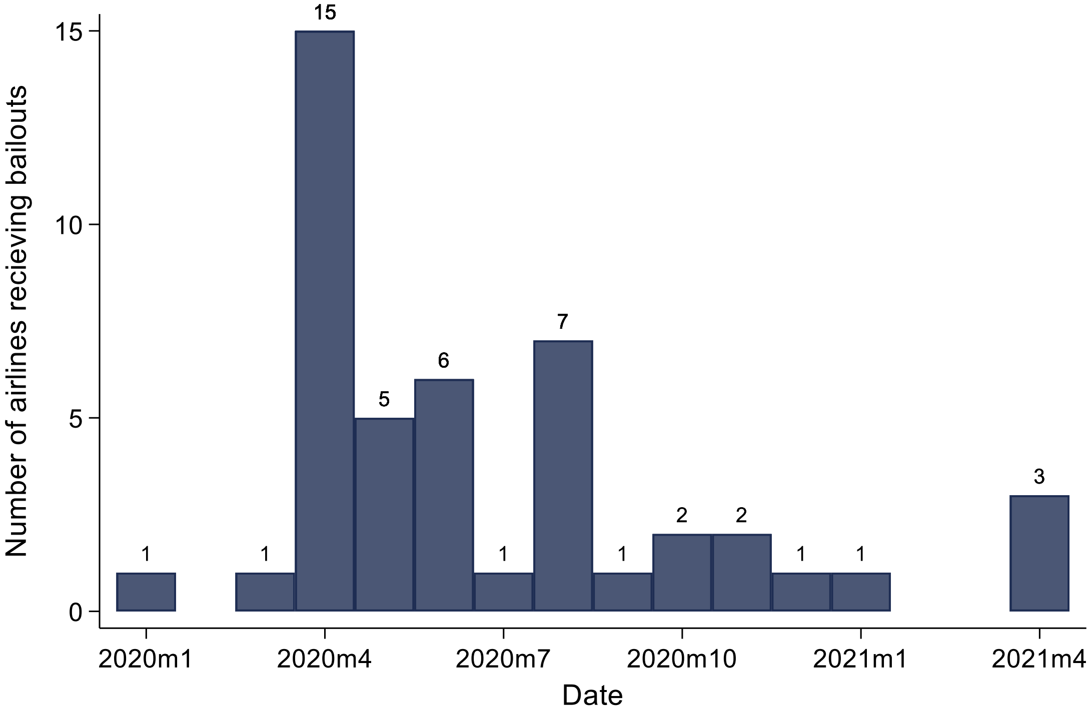


Figure 5A: Airline Disinvestments
Left-Axis for Retirements & Sales
Right-Axis for Storage

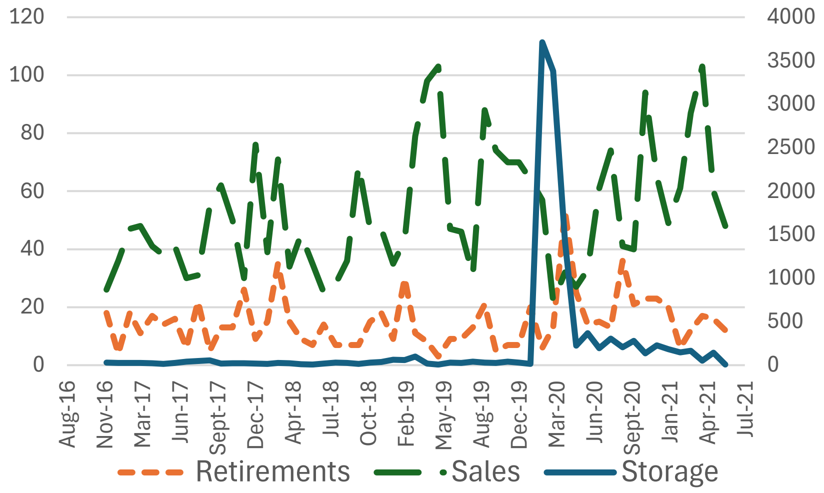


Figure 5B: Airline Investments
Left-Axis for Return to Service
Right-Axis for Purchases/New Leases

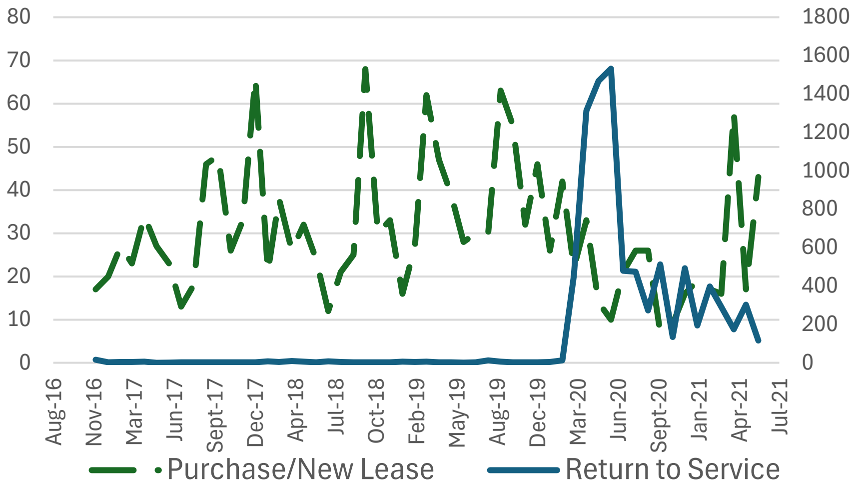


Figure 6A: Impact of COVID-19 Shock on Asset Disinvestments

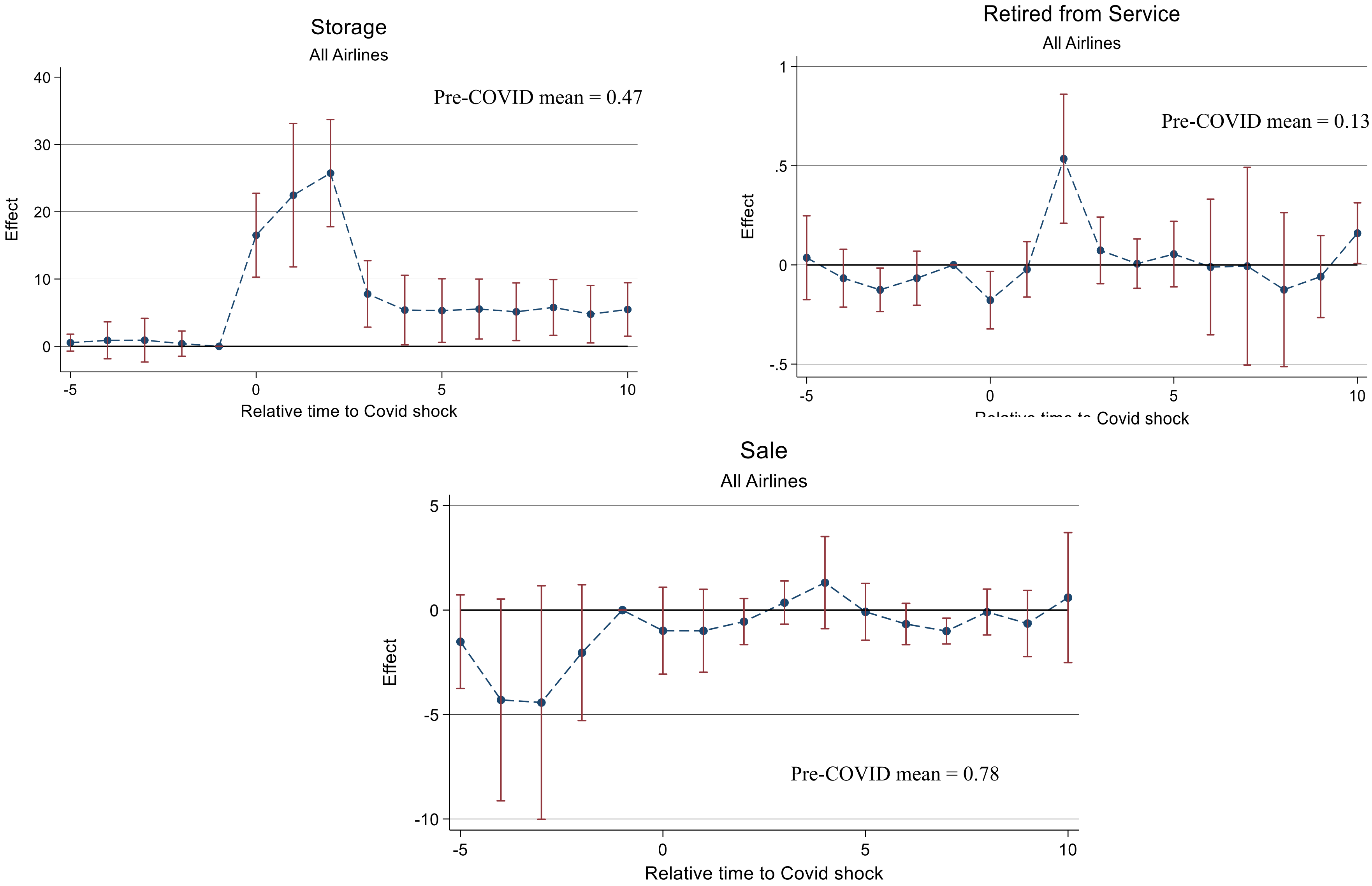
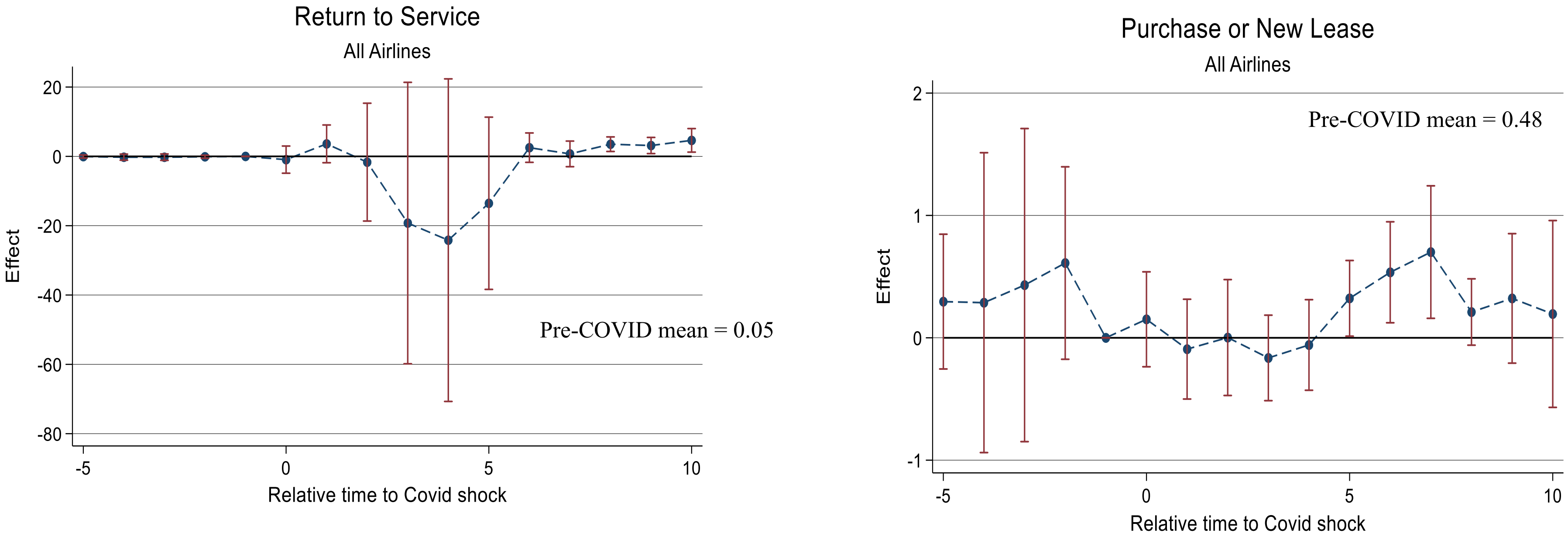


Figure 6B: Impact of COVID-19 Shock on Asset Investments



Return to Service

All Airlines

Purchase or New Lease

All Airlines

Figure 7A: Impact of COVID-19 Shock on Asset Disinvestments High vs. Low Default Probability

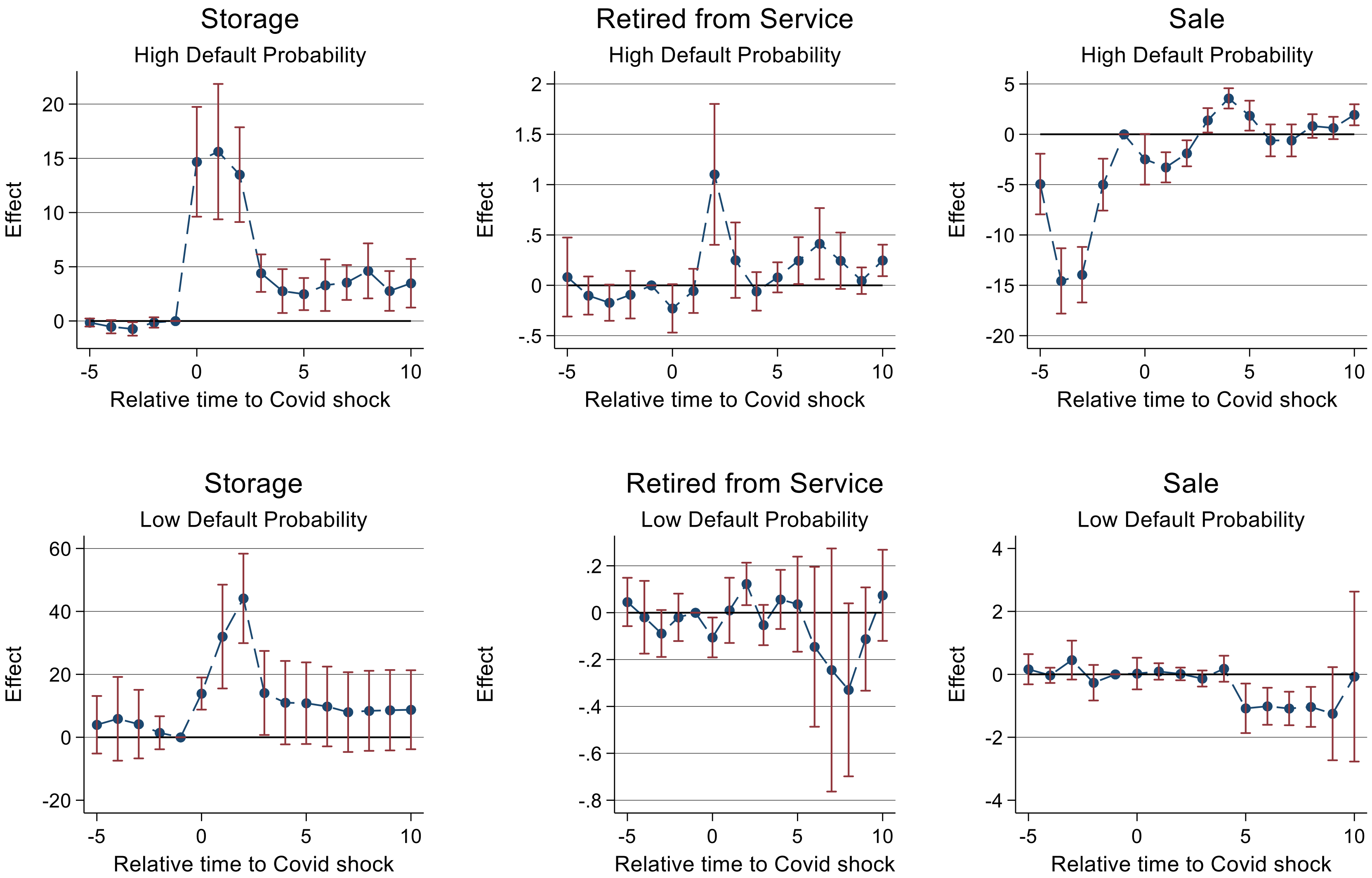


Figure 7B: Impact of COVID-19 Shock on Asset Investments High vs. Low Default Probability

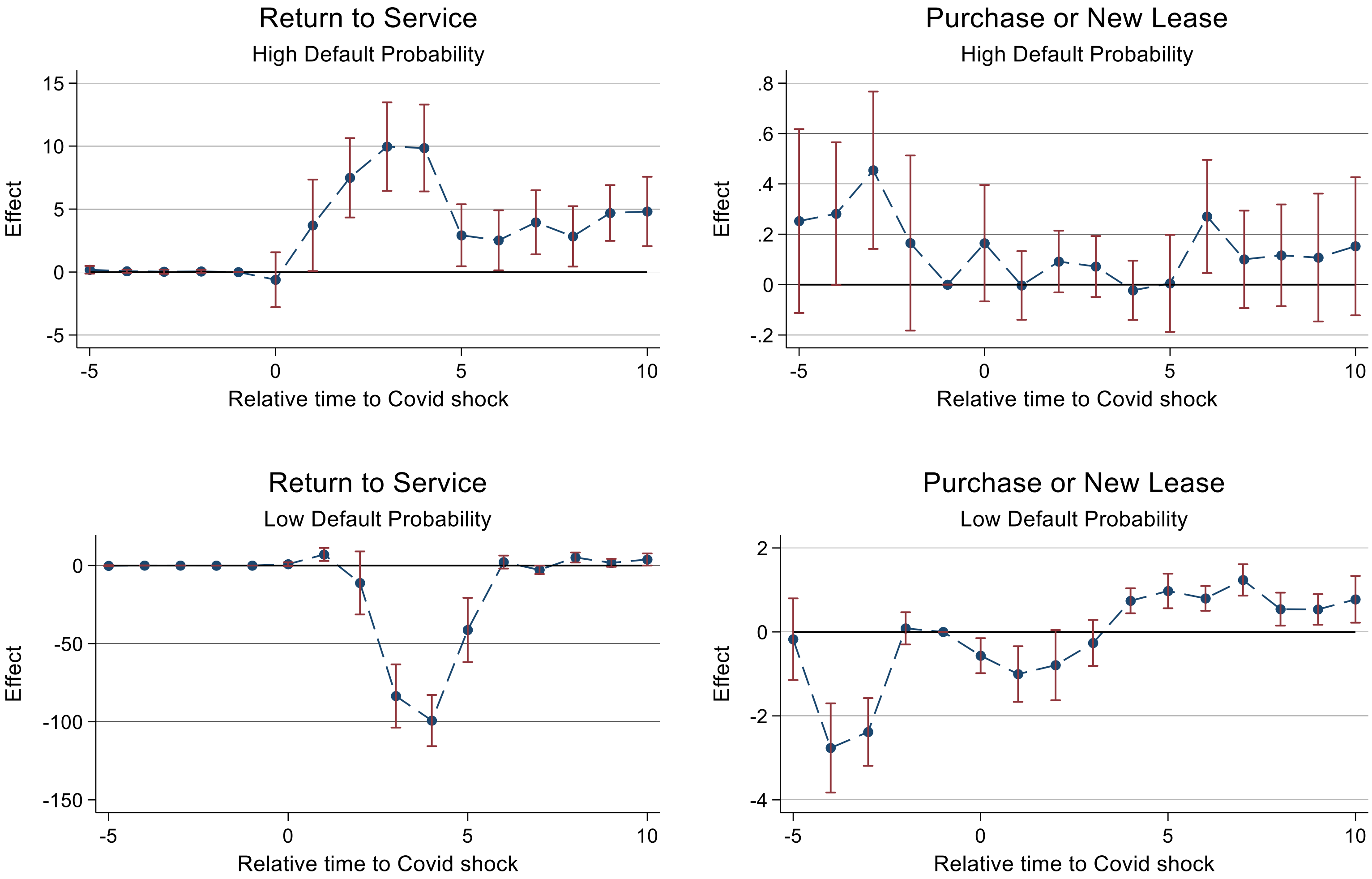


Figure 8A: Impact of COVID-19 Shock on Asset Disinvestments With and Without Bailouts

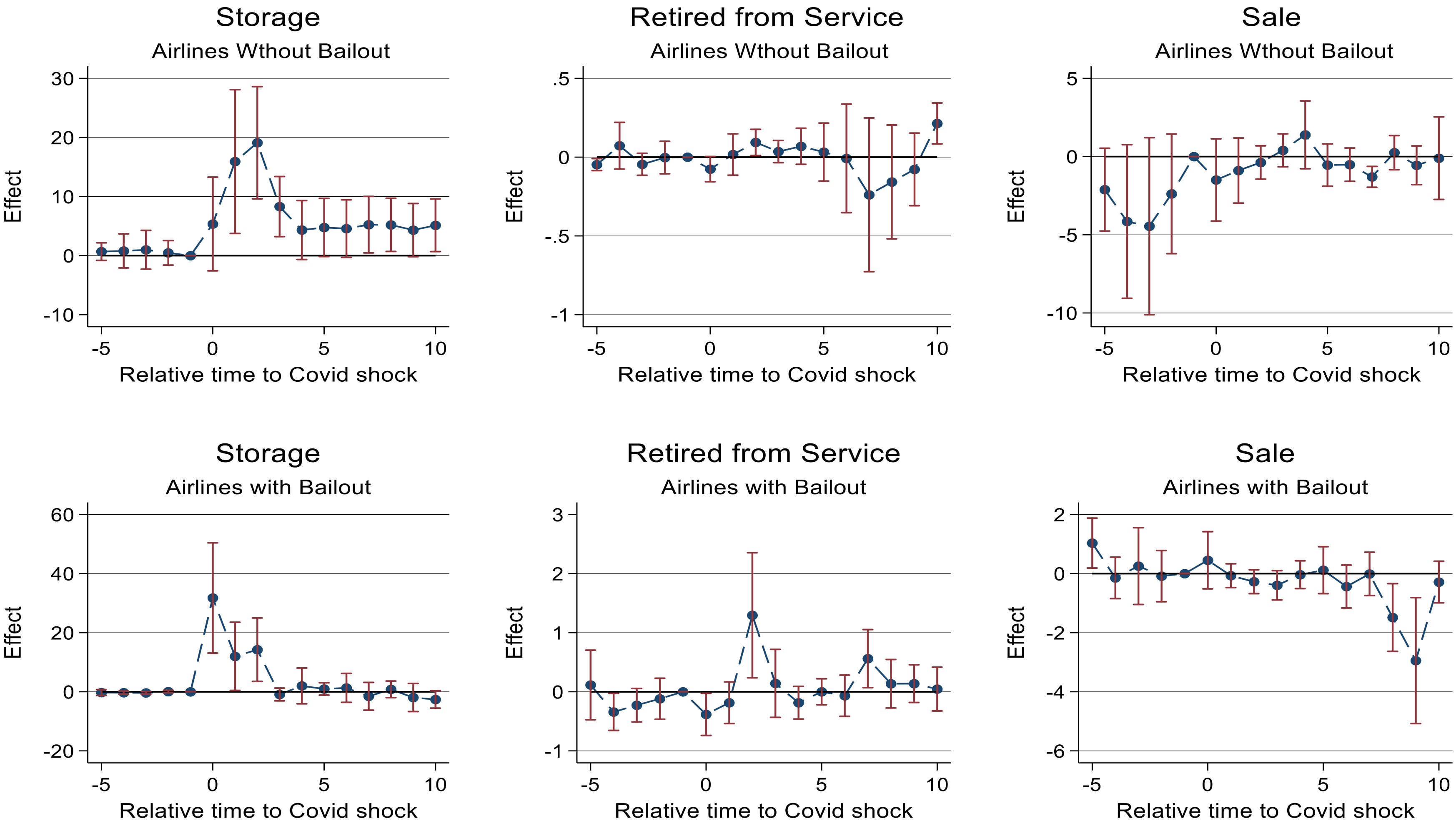


Figure 8B: Impact of COVID-19 Shock on Asset Investments With and Without Bailouts

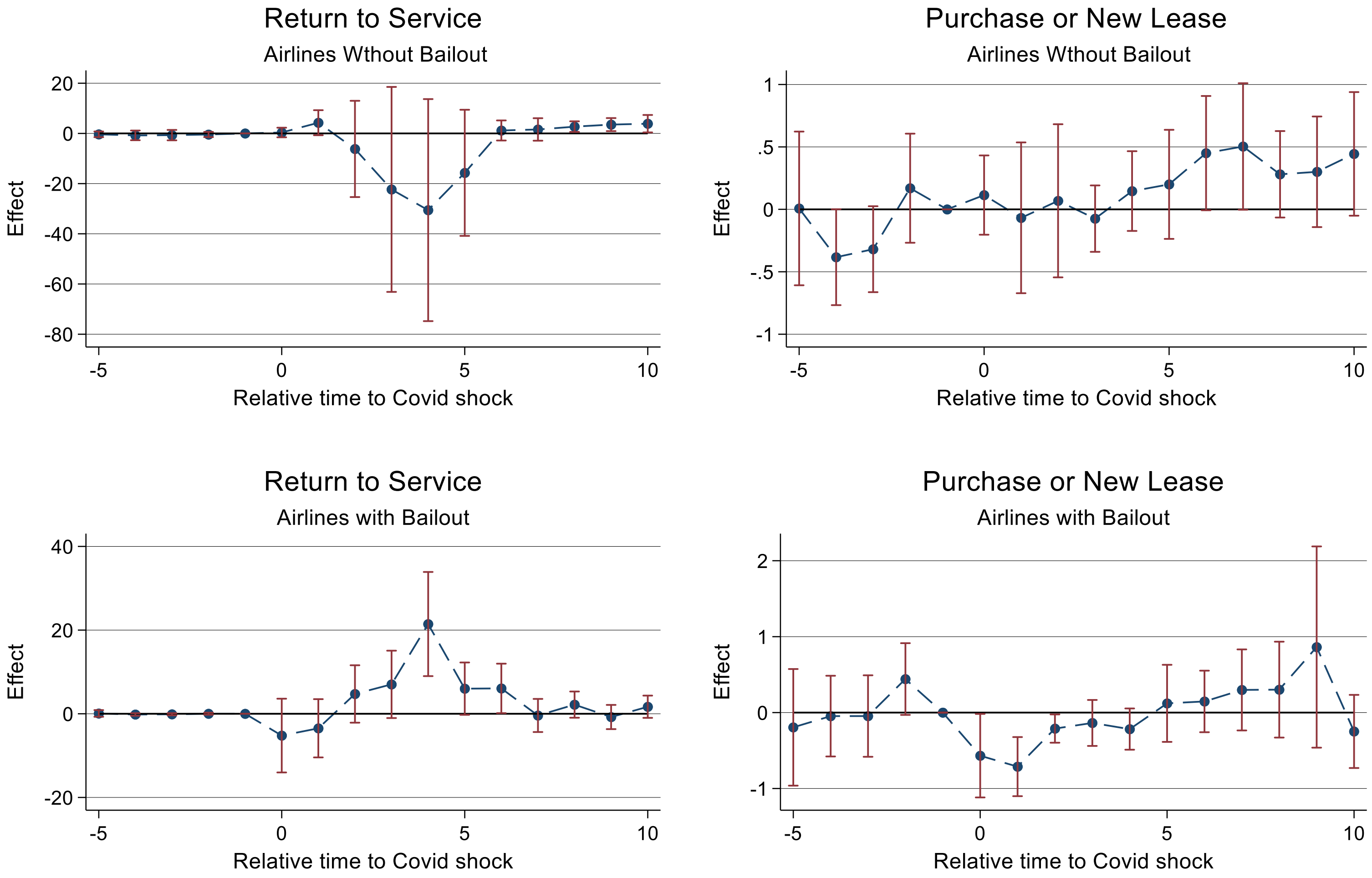


Figure 8C: Impact of COVID-19 Shock on Asset Investments For Highly Financially Constrained Firms