Supply Chain Resilience and Food Supply Chains

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Abstract

During the first few months of the COVID-19 pandemic, food producers threw out millions of pounds of food while grocery store shelves stood empty. Despite the overall efficiency of the modern food system, COVID-19 uncovered a general lack of resilience in food supply chains. While we know quite a bit about what it means for a supply chain to be resilient, there are few formal theoretical or empirical models that provide quantitative measures of resilience. We interpret observations of wasted food during this period as a lack of resilience in the food supply chain. We develop both a theoretical explanation for the lack of resilience and an empirical example that demonstrates how a lack of resilience affects food supply chains. We base our definition of resilience on the theory of real options and economic hysteresis. Economic hysteresis is the perpetuation of a particular course of action after the original rationale has disappeared, or, in our case, failing to invest in new distribution channels. Our analytical model of supply chain resilience demonstrates how the real option embedded in investments to adapt to a disruption leads to hysteresis and a lack of resilience. Although hysteresis results from rational responses to uncertain economic environments, managers should be aware that delays in responding to disruptions have real social consequences – wasted food in our empirical example. Indeed, we find that a firm's rational responses to disruptions result in excessive hysteresis compared to what is best for society as a whole because a firm's "value of waiting" differs from a social planner's. We demonstrate the comparative static properties of hysteresis and examine a range of policy solutions for mitigating the supply-chain loss that results from hysteresis. We show how building redundancy, increasing flexibility, and increasing supply-chain collaboration are all ways in which the hysteretic effect of uncertainty on supply chain resilience can be reduced. More generally, we provide a framework that can help policymakers assess the merits of alternative interventions to improve supply chain resilience.

Keywords: COVID-19, flexibility, food supply chains, hysteresis, real options, switching costs.
JEL Codes: D22, G32, Q12

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1 Introduction

The shelter-in-place orders designed to reduce the spread of COVID-19 (FINRA 2020) caused a near collapse in food consumed away from home, with total sales from eating and drinking places declining by nearly 50% from February 2020 to April 2020 (Grindy 2020). While consumers shifted purchases of food to traditional (supermarkets) and non-traditional (online) shopping modes in response, food that was destined for foodservice channels could not be easily redirected to retail channels due to specialized foodservice packaging, and a general lack of coordinated distribution relationships between foodservice and retail channels (Felix et al. 2020). This was especially true for highly perishable items like fresh fruits and vegetables, eggs, milk, and fresh meats which were often destroyed, or at best donated to food banks (Peters 2020; Yaffe-Bellany and Corkery 2020). Despite the overall efficiency of the modern food system, COVID-19 uncovered a general lack of resilience in food supply chains. Namely, COVID-19 revealed the inability to easily shift product from one distribution channel (foodservice) to another (retail) during a time of catastrophic disruption to one of these channels. In this paper, we use a real-options framework to explain the delay in firms' response to COVID-19 related shutdown orders, and interpret the lack of resilience in food supply chains as an example of economic hysteresis. We provide an empirical approach to estimating the extent of hysteresis, and show how both firm-level policies and regulatory strategies can mitigate its severity.

Investing in recovery to restore an entire distribution channel is costly. Felix et al. (2020) argue that "...the dilemma is around the two- to five-year payback period of new packaging lines..." to support the ability to pivot to retail packaging especially as "...many food-service producers have already invested in equipment and facilities to produce and package food in large multi-serving formats..." (p.4). Furthermore, investments are needed to build alternative supplier and buyer relationships. Interviews with professionals in the fresh produce industry suggest that the cost of building this level of flexibility, including the installation of alternate packing lines and developing parallel business relationships with buyers in other distribution channels, can range from approximately 12% to more than 40% of the costs of building infrastructure to market to just one channel depending on the level of sophistication of equipment. Consequently, many firms in the food industry tend to specialize in one distribution channel, and ignore the potential resilience benefits in maintaining alternative distribution systems. Once a disruption occurs, the amount of time a firm, or indeed an entire system, takes to recover is largely driven by the dynamics of investing in flexibility (Hendricks and Signhal 2005).[1]

Flexibility is a critical attribute of resilient supply chains (Scholten and Shilder 2015; Kamalahmadi and Mellat-Parast 2016; Ali et al. 2017). In general, flexibility refers to the ability of firms in a supply network to change quickly, and a high degree of flexibility "...facilitates coordination processes and enables organisations to cope with high levels of environmental and operating uncertainty..." (Scholten et al. 2014, p. 215) should a situation demand it. Surveying the broad literature on supply chain resilience, Ali et al. (2017) find

[1]This is particularly true if COVID-19 is thought to be a longer-term "as-a-process" rather than a one time "crisis-as-an-event" (Pournader et al. 2020; Williams et al. 2017).

that flexibility is the second-most common attribute of resilient supply chains, next to network design, or structural features, and above redundancy. Flexible supply chains are inherently agile, which in our context means that firms are able to switch quickly between distribution channels (Christopher and Peck 2004; Juttner and Maklan 2011; Scholten and Shilder 2015; Jain et al. 2017; Ali et al. 2022), but in others can refer to flexibility in purchasing instead of distribution. For example, Tomlin (2006) compares Chiquita and Dole's sourcing bananas through Hurricane Mitch in 1998 as an example of how a flexible sourcing strategy can add firm value. In particular, he demonstrates that Chiquita's multiple-sourcing strategy allowed them to earn the revenue that Dole lost through its own single-sourcing strategy, and describes multi-sourcing as a flexible supply-chain strategy. Despite the clear importance of flexibility, we still do not know why firms fail to invest in flexible supply-chain relationships, nor how this failure to invest manifests in supply chain performance.

We differentiate between *a priori* and *ex post* flexibility. Firms that have invested in flexible distribution systems in the past are less likely to suffer financially after a disruption, so in that sense are more resilient in the readiness stage of a disruption, while firms in the recovery stage are more interested in investing to build a level of flexibility they never had (Blackhurst et al. 2011). We explain delays in the latter type of flexibility, and focus on a firm's attempts to recover quickly from a disruption that has already occurred, when the length and severity of the disruption are unknown. In this way, our notion of resilience is similar to the "time-to-recovery" of Simchi-Levi et al. (2014) and Gao et al. (2019) in the sense that we develop an explanation, and empirical measure, of the ability of firms to recover from a disruption, rather than to anticipate another. Our setting is arguably more relevant to disruptions like COVID-19 which was not only unforeseen, but some would argue unforeseeable (Schwartz 2020).

Due to underlying uncertainty in the length of time a disruption will persist, and in the profit lost during the disruption, investments in supply chain flexibility create a real option – the right but not the obligation to exercise a business initiative (Dixit 1989, 1992; Trigeorgis 1993; Hult, Craighead and Ketchen 2010; Trigeorgis and Reuer 2017; Trigeorgis and Tsekrekos 2018). In the context of a pandemic in which governments order public shelter-in-place mandates, firms that ship food to restaurants do not know how long the pandemic will continue, nor precisely how much profit they lose each week by not being able to ship to another distribution channel due to the inherent variability of output prices. While the existence of real options in *ex ante* investments flexibility are also likely relevant to firm-resilience, we are more interested in the implications for recovery-delay that results from the real option embedded in *ex post* investments.

Our real-options approach explains the apparent lack of food-system resilience, defined as a delay in recovery time, observed in the spring of 2020. McDonald and Siegel (1986) show that there is a "value of waiting to invest" in the presence of a real option. That is, if returns to an investment are uncertain, and uncertainty is resolved over time, then a rational investor (firm) has an incentive to wait and invest tomorrow rather than today. Dixit (1992) describes the value of waiting as hysteresis, as firms are likely to stay with an investment that has proven to be currently unprofitable, or wait to make an investment that has

positive returns in the current period. Importantly, hysteresis is not irrational as firms still optimize under uncertainty, and yet invest in ways that may prove to be suboptimal from a social, *ex post*, supply-chain level perspective.

From a system perspective, hysteresis manifests as a lack of resilience. In this sense, our example demonstrates the importance of "scale" in supply-chain analysis (Novak et al. 2021): A decision may be rational from the perspective of an individual firm, but does not lead to ideal outcomes from the perspective of broader food-supply system. Hult, Craighead, and Ketchen (2010) explain delays in investing in uncertain supply-chain settings as behavioral in nature as managers may misperceive the real option value of low net present value (NPV) projects. More recently, however, Grossman, Helpman and Sabal (2023) argue that Nash (1951)-type bargaining in any vertical channel will generate the sort of externality that drives a wedge between private- and social-optimal outcomes. We do not include Nash bargaining in our model, but we frame our real-option model in terms of a vertical channel in which imperfectly competitive firms choose distribution outlets in which they earn positive rents. The outcome in our model is similar to Grossman, Helpman and Sabal (2023) in that the existence of a real option in flexibility investments generates an externality in which the private level of investment is less than socially optimal. From the scale of the entire supply chain, the externality appears as a lack of resilience.

In this regard, our insights echo Cohen and Kouvelis (2021) in that recognizing the causes and consequences of real options in flexibility investments can allow firms to move beyond "agile, adaptable, and aligned" supply chains to achieve "robust, resilient, and re-aligned" relationships with supply chain partners. If firms are indeed concerned with sustainable supply chains (Carter and Rogers 2008) then understanding the causes of supply-chain fragility can help firms internalize the real-option externality.

Our findings suggest that the level of observed hysteresis is a function of the cost of investment in flexibility, the mean return and volatility of the channel revenue stream, the cost of capital, and the likelihood that a channel recovers in the presence of a major disruption as was seen with COVID-19. In particular, we find a positive relationship between the cost of investing in flexibility and the level of hysteresis, as well as a positive relationship between the volatility of channel revenue and hysteresis, and that relatively small changes in these variables considerably reduce the duration of hysteresis. This suggests that policies or business strategies that reduce the level of investment needed for promoting flexible supply chains, as well as strategies that can reduce channel revenue volatility, likely have the greatest impact in promoting channel switching in the face of a major disruption rather than waiting for channel recovery.

Our paper contributes to several streams in the literature. First, we contribute to the supply chain resilience literature by explaining why delaying an investment in disruption-recovery can be rational, in the context of a food supplier's decision to switch between foodservice and retail channels. While others consider the importance of flexibility in either conceptual or empirical frameworks (Christopher and Peck 2004; Manuj and Mentzer 2008; Juttner and Maklan 2011; Scholten and Shilder 2015; Jain et al. 2017; Ali et al. 2022) none seek to quantify flexibility within a conceptual, real options model. We measure a firm's

lack of *ex post* flexibility by considering the cost of investing in flexibility, relative to the probability of the disruption disappearing on its own, obviating the need to replace a lost losing a revenue stream from one of two distribution channels.

Second, we contribute to the supply chain literature on COVID-19, and pandemic responses in general (Ivanov and Dalgui 2020; Dohmen et al. 2023; Sodhi, Tang, and Willenson 2023; Shen and Sun 2023). In our empirical analysis, we quantify the extent of loss due to COVID-19 shutdowns in the fresh produce sector by estimating the hysteresis effect associated with the option value in investing in post-disruption flexibility, and estimating the amount of lost revenue due to the delay in shifting production from foodservice to retail channels. We interpret hysteresis in recovery as a market failure in the sense that privately-optimal investment decisions in the presence of real options lead to socially-suboptimal levels of flexibility and resilience.

Third, we contribute to the supply chain risk management literature, particularly elements concerned with food supply chains, by documenting and explaining the extent of supply-chain hysteresis associated with returns-volatility, catastrophic events, and the likelihood of their resolution (Trigeorgis and Reuer 2017; Pournader et al. 2020). In this regard, we provide the first empirical estimates of the extent of post-disruption flexibility, and how hysteresis delays the recovery stage of resilience. We derive analytical expressions for the optimal delay in recovery investments that are driven by the real-option value embedded in investments in supply-chain flexibility. We then use this model, and data from a specific case study from the fresh-produce industry, to examine an empirical real options model of supply-chain flexibility, and generate evidence of the extent of hysteresis that likely took place in 2020. Our value function clarifies how characteristics such as revenue growth and volatility, the size of the investment in flexibility, and the probability of returning to normal interact to affect the time to recovery for an optimizing firm in our example supply chain.

Fourth, we provide a theoretical basis for the temporal notion of resilience developed elsewhere (Simchi-Levi et al. 2014; Behzadi et al. 2017; Gao et al. 2019; Behzadi, O'Sullivan and Olsen 2020; Jain et al. 2022; Qi et al. 2022; Shen and Sun 2023). While the "time to recover" (TTR) measure in Simchi-Levi et al. (2014) provides a practical way of thinking about resilience, we provide a clear theoretical and empirical basis for what drives variation in TTR between different systems. Our real options model isolates the importance of switching costs, the inherent volatility of returns in alternative channels, and the probability that a disrupted distribution channel is restored as key empirical constructs driving a hysteretic measure of resilience. We use counterfactual simulations of our hysteresis model to examine the likely impact of potential policy responses to the delay in recovery.

The rest of the paper is organized as follows. In the next section, we review the literature on supply chain resilience, and frame our analysis as an example of supply-chain risk management. We present an analytical model of resilience, or the lack thereof, in Section 3, and derive our core hypothesis regarding why the food supply chain appeared to lack resilience during the early days of the COVID-19 pandemic. In Section 4, we offer some summary evidence of the lack of resilience observed in early 2020. In Section 5 we

describe the simulation model and provide some insights from its calibration, while in Section 6 we describe the specific empirical setting and present and interpret our empirical findings. In doing this, we consider some implications for both firm-management, and potential policy responses to the food supply chain issues that arose. A final section concludes.

2 Supply Chain Resilience

The supply chain management literature offers a number of different definitions of resilience (Rice and Caniato 2003; Christopher and Peck 2004; Ponomarov and Holcomb 2009; Pettit et al. 2010; Scholten et al. 2014; Sheffi 2015; Kamalahmadi and Parast 2016; Ali et al. 2017; Pettit et al. 2019) so, by now, we have a good sense of what it means for a supply chain to be resilient.[2] However, we argue that these general definitions are not entirely useful for managers in some supply chains that are constrained by the nature of their production process. In the food industry, for example, objectives of flexibility and redundancy are conditioned by the biological nature of production: Output in some sectors is not available for sale until months or years after the production decision is made, its quality is dependent upon growing conditions, and, once harvested, is highly perishable so must be sold almost immediately (Ahumada and Villalobos 2009; Grimm et al. 2014). Craighead et al. (2007) characterize the supply chains most susceptible to severe disruption as those that are complex, dense, and dependent upon particular nodes or firms that are central to the entire network. Food supply chains are perhaps unique in that they meet all of these criteria. Our concept of resilience, therefore, is grounded in the economic and agronomic fundamentals of food supply chains.

Our analysis also reflects a fundamental empirical trade off between efficiency and resilience (Sheffi 2005; Sheffi and Rice 2005; Tomlin 2006; Ponomarov and Holcomb 2009; Pettit et al. 2010, 2013; Blackhurst et al. 2011; Juttner and Maklan 2011). In the US, as in other developed countries, the food industry has evolved from a near-primitive state into a remarkably efficient system, able to provide food far in excess of our domestic needs.[3] In fact, some 75% of the US labor force was engaged in food production in 1800, only to decline to 2.5% by 2000 (Alvarez-Cuadrado and Poschke 2011). However, we have achieved this level of efficiency, arguably, at the expense of resilience, or at least without a similar consideration of resilience. For example, Christopher and Peck (2004) highlight the trade-off between supply-chain efficiency and resilience, and emphasize the importance of agility, visibility, and increasing velocity to achieve resilience. While they use the fast-moving consumer good supply chain as an excellent example of a resilient supply-chain, fresh food is neither agile, visible, nor rapid. Our real-options model is based on the underlying assumption that managers optimize firm value in a setting with stochastic uncertainty, so our approach incorporates considerations of efficiency and resilience, optimizing the tradeoff between the two as a portfolio

[2] Generally defined, resilience is "the capacity for an enterprise to survive, adapt, and grow in the face of turbulent change" (Fiksel 2006).

[3] We acknowledge the well-known co-existence of excess and hunger in the US (Gundersen and Ziliak 2018), but distributional problems associated with domestic food insecurity are beyond our current research objectives.

of organizational objectives (Bode et al. 2011).

Resilient supply chains are inherently flexible, where flexibility is defined as not only the ability to recover from a shock, but to absorb it in the first place (Pettit et al. 2010). Christopher and Peck (2004) and Scholten et al. (2014), for example, both argue that a resilient system is one that returns to its former state following a severe disruption. Ponomarov and Holcomb (2009) describe resilience as "...the capacity of a system to experience disturbance and maintain its functions and controls..." (p. 125) so if the COVID-19 crisis is defined as a disturbance, then resilience is defined in terms of a firm's ability to absorb a shock and retain its prior function, or to evolve into something better (Novak et al. 2021). Our empirical notion of resilience is intuitive as it envisions supply chains as absorbing a disturbance, retaining their ability to function, serving their intended objectives, such as moving food from the farm to the ultimate consumer, and returning to their former function quickly following a disruption. Ali et al. (2017) cite many other definitions of resilience that capture a similar notion of flexibility.

Our concept of resilience in the context of food supply chains includes a more prominent role for flexibility and redundancy (Tang and Tomlin 2008; Wallace and Choi 2011; Kamalahmadi and Parast 2016; Ali et al. 2017) in the sense that flexibility implies that the system is able to respond to disruption in a way that leaves the functioning of the entire system unaffected. In other words, people are fed, and food does not go to waste during the process of recovery. In this sense, the food supply chain failed spectacularly during the COVID-19 pandemic (Yaffee-Bellany and Corkery 2020).

Many definitions of resilience capture a positive notion of what it takes for organizations to achieve resilience, but pay little attention to explaining why some supply chains appear to lack resilience. Craighead et al. (2007) is an exception, outlining why some disruptions are more severe than others, but not why whole organizations appear to lack flexibility. Our real-options framework maintains that slow recovery from a disruption is a firm-level manifestation of hysteresis that appears at the level of the supply chain, or system, as waste and a socially sub-optimal level of supply-chain services. Hysteresis, or the notion that an economic phenomenon is likely to continue after its initial cause has disappeared in an environment of uncertainty and fixed costs (Dixit 1992), is a natural and intuitive implication of our real-options theoretical framework.

Hysteresis forms a key part of Ponomarov and Holcomb's (2009) extended definition of resilience, as it reflects the notion that the return to normal function is not a mirror image of its initial degradation. While hysteresis is a phenomenon that occurs as a result of firm-level, rational investment decisions, at the level of the supply chain it appears as a market failure as the supply chain fails to provide a flow of services where it is demanded, on time, and without wasted resources. In this sense, our model formalizes what researchers in the supply chain risk management literature have argued informally for many years.

Others frame the value of flexibility in terms of a real-option theoretical framework (Kulatilaka 1988; Tiwana et al. 2007). More recently, Hult et al. (2010) provide several concrete examples in which real options can potentially change managerial strategy, although neither considers the type of option we have in mind here. Further, Trigeorgis and Tsekrekos (2018) classify over 160 real-option studies into sub-branches of the

more general supply-chain management literature. They find more than a dozen studies that concern supply-chain flexibility, but each considers a different notion of flexibility than ours (Martzoukos and Trigeorgis 2002; Fontes 2008). While they consider the real-option value embedded in postponement, scale, and other investments, we examine the delay in switching distribution channels as a rational firm-level outcome when the time that a disrupted channel returns to normal operations is uncertain.

Rather than consider the value of maintaining multiple sources of supply in a real-options framework (Costantino and Pelligrino 2010; Meena et al. 2011; Kamalahmadi and Mellat-Parast 2016; Carbonara Pelligrino 2018), our problem is different as we consider a lack of flexibility in selling downstream, not buying upstream. We regard this gap in the literature as important, as downstream-failure is likely to be equally as important as upstream-failure in many industries, particularly in the face of disruptions similar to COVID-19.[4]

Importantly, we show how a lack of post-disruption flexibility is a natural outcome of rational managers pursuing their own objectives. In fact, we show how food supply chains embody a fundamental lack of flexibility that emerges as a result of independent firms optimizing in an environment with high, fixed costs of switching between distribution channels. Dixit and Pindyck (1994) argue that "...a social planner also gets information by waiting..." which suggests that hysteresis is not inherently a market failure, but the problem arises when "...firms face a different value of waiting than does society as a whole..." (p. 19). We agree with Grossman, Helpman and Sabal (2023) in that real options generated through vertical relationships that involve an allocation of channel surplus produce market failures. In their model, the result is underinvestment in agility and redundancy, whereas in ours the consequence is less flexiblity, and resilience, than would be socially optimal. In that regard, our hysteretic outcome is a market failure akin to monopoly power, public goods, or asymmetric information.

Our analysis highlights the fundamental economic concepts that underlie what should become a new set of best practices for food suppliers of all types: Shippers, manufacturers, processors, and packers need to have in place a measure of flexibility and interoperability between retail and foodservice distribution. Without guidance from empirical estimates, however, managers are left making critical investment decisions in the absence of hard information on the value of supply chain flexibility (Blackhurst et al. 2011; Pettit et al. 2013).[5] It is our intent to add concrete empirical estimates of the value of supply chain interoperability to the considerable behavioral and structural literature on supply chain resilience.

We are not the first to consider the temporal dimension of supply-chain resilience (Simchi-Levi et al. 2014; Gao et al. 2019; Behzadi, O'Sullivan and Olsen 2020; Qi et al. 2022; Shen and Sun 2023). The TTR concept of Simchi-Levi et al. (2014) captures "...the time it would take for a particular node (such as a supplier facility, a distribution center, or a transportation hub) to be restored to full functionality after a disruption..." (p. 98) so it is similar, but not identical to our measure of hysteresis. Rather than measure

[4]Snyder et al. (2016) believe that disruptions of this sort should not even be considered rare, as they are always occurring somewhere in the world when supply chains are truly global.

[5]Ambulkar et al. (2015) and Chowdhury and Quaddus (2017) develop empirical scales to measure resilience, but from entirely different theoretical perspectives from the one we adopt here.

the time it would take a firm to restore full functionality, our measure refers instead to the time it takes a fully-rational firm to begin the investment process, or to have the resources in place to begin to return to full functionality. Whereas their measure refers to an outcome, ours describes the temporal delay inherent in making the decision to initiate recovery in the first place.

We contribute to the emerging literature on sustainable supply chains, and specifically the branch of the literature that targets agricultural supply chains as unique and important (Ivanov et al. 2016; Behzadi et al. 2017; Stone and Rahimifard 2018; Behzadi et al. 2020). Sustainability is a primary concern in the operation of food supply chains, not only because consumers now demand accountability from food suppliers on environmental impact, but firms realize that reductions in waste and carbon-minimization also can reduce operating costs. That said, Hofmann et al. (2014) document how a focus on sustainability can itself be a source of potential disruption. Given the amount of food wasted in the early weeks of the COVID-19 pandemic, our research can inform strategies to minimize the likelihood of future disruption-related losses, and shocks to food-system sustainability. While Pournader et al. (2020, p. 28) argue that "...risk management principles and portfolio theory have been applied across traditional SCRM [supply chain risk management] platforms, less discourse has been articulated on this particular debate regarding risk management strategies when considering sustainability...," our real-option approach explicitly considers the portfolio implications of maintaining alternative distribution-channel strategies as a means of diversifying, and adding firm value through flexibility.

We also contribute to a growing literature on government policy and supply chains. By April 2020, there were a number of government programs intended to compensate farmers for output lost due to supply-chain disruptions associated with COVID-19, generally the loss of the foodservice channel.[6] Given the rise in retail prices for most food products during the pandemic, and the lack of evidence that shipments were impacted for a significant period of time (Chenarides et al. 2020), the stated economic rationale for these programs is debatable. In terms of our analysis, however, such short-term aid can be seen as a means of providing growers and packers the means to invest in flexibility. Packing lines and transportation are highly capital-intensive infrastructure that may be beyond the means of many small-to-medium enterprises (SME). In essence, the federal government attempts to address the system-externality of hysteretic investment decisions by buying the real option to invest in flexibility from growers, packers, and shippers.

3 Analytical Model of Supply-Chain Resilience

In this section, we develop a theoretical model of *ex post* supply-chain resilience. We briefly outline the setting. There are two distribution channels, e.g., foodservice and food retail. The firm operates in one distribution channel that we refer to as the *primary* channel (e.g., the most profitable channel for the firm).

[6]For example, the Farmers to Families Foodbox Program (FFFP) sought to provide some $3.0 billion in US Department of Agriculture funding to help farmers and packers redistribute output destined for foodservice buyers to charitable organizations like food banks, community food pantries, and churches (USDA 2020a). The FFFP is part of the larger Coronavirus Food Assistance Program (CFAP), which seeks to distribute a total of $19.0 billion in direct and indirect aid to farmers who are able to document losses tied directly to supply-chain disruptions associated with the pandemic (USDA 2020b).

The firm's primary channel ceases to operate at time $t = 0$ whereas the other (*secondary*) channel continues to operate. The firm may elect to make changes in its operations to earn profits from the secondary channel. The firm will switch back to its primary (more profitable) channel when it comes back online. The decision of whether or when to switch to the secondary channel is complicated by three fundamental factors: (1) switching cost, (2) uncertain time to primary-channel recovery, (3) uncertain secondary-channel net revenues over time.[7] For example, if there is no cost to switch, then it is optimal for the firm to switch immediately. Alternatively, if switching cost is positive, but time-to-recovery and secondary-channel net revenues are deterministic, then it is optimal for the firm to either switch immediately or never switch. However, in the presence of these three factors (that reflect real-world operations), it can be optimal for the firm to delay a switch to a future point in time before the primary channel is back online. This delay, which itself is random under an optimal switching policy, is hysteresis.

We characterize the optimal switching policy and the probability distribution of random delay under an optimal policy. The results in this section provide the foundation for numerical investigation in sections 5 and 6. Our goal is to characterize the optimal switching policy and use this characterization to study how characteristics of the environment affect hysteresis, thereby lending insight into possible interventions for improving supply-chain resilience. While our model and analyses are motivated by food supply chains, our results extend to other supply chains for which there are multiple distribution channels and (at least some) firms specialize in a single channel.

3.1 Optimal switching policy

We model the random net revenue rate from the secondary channel as geometric Brownian motion (GBM), $dR = \mu R dt + \sigma R dz$ where $R_0 > 0$ is the net revenue at time $t = 0$ and R_t denotes random net revenue at time t. The cost to switch is $K > 0$, the discount rate is r, and the random time-to-recovery for the primary channel $\tilde{T}$ is an exponential random variable with rate λ (and mean time to recovery is $1/\lambda$). We assume that time to recovery and secondary channel net revenue are independent. As we describe below, this model has been analyzed under the assumption $\lambda = 0$, i.e., the primary channel never recovers. Our goal is to develop new results that help us understand the optimal switching policy and associated hysteresis for the general, and much more realistic case for our setting, of $\lambda \geq 0$.

At time t with net revenue R_t, the expected discounted payoff from switching can be expressed as

$$Z_S(R_t) = E\left[\int_0^{\tilde{T}} e^{-rs} R_{t+s} ds\right].$$

Note that the expectation operator applies to both random time to recovery and the random net revenue from the secondary channel until recovery. It can be shown that the above expression simplifies to

$$Z_S(R_t) = E\left[R_t \frac{1 - e^{-(r-\mu)\tilde{T}}}{r - \mu}\right]. \tag{1}$$

[7] Formally, *net revenue* in this context is the change in the profit rate after a switch to the secondary channel.

(see E-Companion). Observe that if $\lambda = 0$ (i.e., no recovery possible), then the function is finite if and only if $r > \mu$. In other words, $\mu \geq r$ (and $\lambda = 0$) implies that the value of switching is unbounded, and consequently, it is optimal to switch immediately for any finite K; otherwise, it is optimal to delay. If $\lambda > 0$, then the necessary and sufficient condition for finite $Z_S(R_t)$ becomes

$$\lambda + r > \mu \tag{2}$$

(see E-Companion). Given eq. (2), $Z_S(R_t)$ simplifies to

$$Z_S(R_t) = \frac{R_t}{\lambda + r - \mu}$$

and the expected net discounted revenue from switching at time instant t with current revenue R (subscript t is suppressed to simplify notation) is

$$Z(R) = Z_S(R) - K = \frac{R}{\lambda + r - \mu} - K \tag{3}$$

(see E-Companion). Setting $\lambda = 0$ in eq. (3) yields the value of switching in Dixit (1992) who analyzes the special case of $\lambda = 0$. If eq. (2) does not hold, then it is optimal to switch immediately. Throughout the remainder of this section, we assume that eq. (2) holds.

With the value of switching characterized, we next turn our attention to the option value of delaying a switch, denoted $V(R)$. The optimal switching policy is specified by a threshold net revenue R^*; it is optimal to switch when observed net revenue from the secondary channel crosses this threshold from below. In effect, at secondary net revenue $R_t = R^*$, the option value of delaying a switch is equal to the expected net discounted payoff from switching. The next result characterizes R^*.

Proposition 1 *If* $\lambda + r > \mu$ *and*

$$b = \frac{\sqrt{\left(\mu - 0.5\sigma^2\right)^2 + 2r\sigma^2} - \left(\mu - 0.5\sigma^2\right)}{\sigma^2} > 1, \tag{4}$$

then

$$R^* = \frac{b(\lambda + r - \mu)K}{b - 1}. \tag{5}$$

As noted above, if $\lambda + r \leq \mu$, then it is optimal to switch immediately (i.e., $R^* = -\infty$). Inequality (4) is a technical condition known as *smooth pasting*; the inequality assures a unique R such that $V(R)$ is tangent to the linear function $Z(R)$.[8] Without this condition, the problem of identifying an optimal switching policy becomes intractable. Expression (5) in Proposition 1 generalizes the optimal switching policy given in Dixit (1992) that applies to the special case of $\lambda = 0$.

[8] We refer the interested reader to the proof of Proposition 1 in E-Companion for the derivation and presentation of function $V(R)$.

3.2 Hysteresis

Let $\tilde{\tau} = \min\{t : R(t) \geq R^*\}$, which is the random first-passage time for threshold R^* (given that $R^* > R_0$; otherwise it is optimal to switch immediately). The next result characterizes $\tilde{\tau}$.

Proposition 2 *Suppose $R_0 < R^*$. The threshold-hitting probability is*

$$\Pr(\tilde{\tau} < \infty) = \begin{cases} \left(\frac{R^*}{R_0}\right)^{\frac{2(\mu - 0.5\sigma^2)}{\sigma^2}} & \text{if } \mu - 0.5\sigma^2 \leq 0 \\ 1 & \text{if } \mu - 0.5\sigma^2 \geq 0 \end{cases} \tag{6}$$

and expected first-passage time is

$$\tau = E[\tilde{\tau}] = \begin{cases} \infty & \text{if } \mu - 0.5\sigma^2 \leq 0 \\ \frac{1}{\mu - 0.5\sigma^2} \ln\left(\frac{R^*}{R_0}\right) & \text{if } \mu - 0.5\sigma^2 \geq 0 \end{cases} \tag{7}$$

Recall that $\tilde{T}$, the random time to recovery for the primary channel, is an exponential random variable with rate λ. The expected delay under an optimal switching policy is

$$h = E\left[\tilde{h} = \min\{\tilde{\tau}, \tilde{T}\}\right],$$

which is a measure of hysteresis. The following proposition shows that h is decreasing in R_0 and increasing in K.

Proposition 3 *Suppose $R_0 < R^*$. Then h is decreasing in R_0 and increasing in K.*

The directional effects of increases in other parameters on τ are ambiguous, let alone the directional effects on h. Furthermore, while $E[\tilde{T}] = 1/\lambda$ is clearly decreasing in λ, R^* is increasing in λ, and thus the effect of a shorter mean time to recovery on h is ambiguous. We numerically investigate comparative statics in Section 5.

We remark that Proposition 3 carries an important implication for a policy maker interested in improving social welfare. Net revenue R_0 (and more generally, R_t), which is the increase in the firm's profit rate from switching to the secondary channel, is less than the contribution to social welfare from switching that is the sum of firm and consumer surplus. Proposition 3 implies that supply chains are insufficiently resilient from a social welfare perspective, i.e., the value of h that maximizes firm welfare is larger than the value of h that maximizes social welfare. Indeed, a policy maker may apply our model and propositions to assess the degree of misalignment between firm-level and society-level hysteresis, and to evaluate the merits of alternative interventions to improve supply chain resiliency.

4 Data and Model-Free Evidence

In this section, we describe the data used to parameterize our model of supply-chain resilience, and provide some summary, or model-free, evidence that examines the extent of resilience in the US fresh-produce

supply chain through the initial COVID-19 shock, and subsequent recovery. Although we use data on onion shipments to parameterize our model of supply chain resilience, we present data from a sample of different commodities in order to examine the potential generality of our insights.

We use data from the Market News Reports (MNR) collected by the Agricultural Marketing Service (AMS) of the US Department of Agriculture (USDA) from January 2, 2019 to January 5, 2021. We rely on three primary MNR data products for our analysis. First, we use MNR movement data, which consists of weekly shipments reported from packers, or distributors responsible for aggregating, storing, cooling, and arranging distribution to either retail or foodservice sales locations. The movement data include shipments from countries importing commodities into the US. We restrict our sample to those grown in the US, i.e., exclude shipments from producers whose origin is outside of the US. Second, we use MNR pricing data from the shipping point and retail reports, which record open spot-market prices across shipping points throughout the country at the wholesale level, and an average of regional market prices for retail-level pricing, respectively.

Our data are appropriate because they account for some 90% of all fresh produce that is grown and sold in the United States, and comprise the data set of record for both industry practitioners and USDA regulators.[9] We focus on five example commodities – strawberries, carrots, onions, lettuce, and potatoes – for our summary analysis, and focus on onions as a representative case study for a more complete analysis of our model of supply chain resilience.

We begin by analyzing shipping volume and prices (farm- and retail-levels) for five commodity markets listed above. For the sake of completeness and comparability across commodities, we present only conventionally produced varieties, as the data on organic produce is generally incomplete. The purpose in presenting these trends is to examine whether there is any summary evidence of a lack of resilience in the US fruit and vegetable supply chain. As previously mentioned, the significance of using US fruit and vegetable supply chains is due to their perishability and high levels of consumption in the US (Minor et al. 2020). Furthermore, within the fruit and vegetable supply chain, we select these five crops as they each vary according to other relevant dimensions associated with supply chain flexibility within each sector. These elements are the ease of storability (or shelf life for food retailers), labor costs associated with production and harvest, and the proportion of volume allocated between food-at-home and foodservice.

Table 1 presents summary statistics for the net weight shipments (total volume), shipping point (farm-level) prices, retail-level prices, and farm-to-retail price spreads for 2019 and 2020. For each data point, we present the yearly average values, and report the p-values from two-sided t-tests that test the difference in means between 2019 and 2020. The difference between 2020 and 2019 total US shipment volume is only statistically significant for carrots and lettuce, which is not surprising given that many crops were planted before the pandemic spread. However, a more detailed view that compares differences in total volume by

[9]Our estimate of 90% coverage is based on conversations with managers of the MNS data set at the USDA (USDA 2020c). While this still leaves 10% not accounted for, there is no reason to believe that the COVID-19 pandemic changed this coverage level, so a consistent gap over time will not bias our estimates. See USDA (2020d) for specific details on the data gathering method.

Table 1. Summary Statistics, by Commodity (2019 vs. 2020)

	Carrots			Lettuce			Onions			Potatoes			Strawberries		
	Mean	S.d.	p	Mean	S.d.	p	Mean	S.d.	p	Mean	S.d.	p	Mean	S.d.	p
Total Volume															
2019	1,383.64	170.58		4,803.31	514.32		9,045.96	1,081.14		16,773.42	2,027.84		3,206.58	1,598.63	
2020	1,505.96	244.04	0.004	4,573.56	642.28	0.047	9,023.81	1,196.04	0.921	16,647.96	2,303.17	0.769	3,354.79	1,625.32	0.640
Shipping Point Price															
2019	0.354	0.021		0.354	0.154		0.319	0.088		0.250	0.025		1.640	0.617	
2020	0.357	0.024	0.535	0.346	0.168	0.793	0.251	0.032	0.000	0.270	0.044	0.006	1.636	0.405	0.972
Retail Price															
2019	1.108	0.084		1.143	0.115		0.911	0.074		0.619	0.057		2.615	0.457	
2020	1.082	0.093	0.148	1.203	0.145	0.023	0.879	0.064	0.020	0.643	0.051	0.031	2.647	0.518	0.744
Farm-to-Retail Price Spread															
2019	0.753	0.086		0.789	0.182		0.592	0.089		0.369	0.064		0.976	0.490	
2020	0.725	0.090	0.108	0.857	0.169	0.053	0.628	0.057	0.017	0.373	0.074	0.801	1.011	0.458	0.708

Source: USDA-Agricultural Marketing Service Market News Reports; Author's calculations. Total Volume is measured in 10,000 lb. units. Farm-to-Retail Price Spread is calculated as the average difference between retail and shipping-point prices, at the unit level over the 52 weeks of the calendar year. The value of p is the probability that the difference between yearly means for each respective variable are statistically different from zero.

month reveals evidence that some sectors exhibited a clear lack of resilience during the shutdown period (months 3 - 4) (Table 2). That is, shipments following the shutdown of the foodservice sector declined and, with the exception of lettuce, only appeared to have recovered by October.[10]

Table 2. Differences in Volume by Month and Commodity (2019 - 2020)

Month	Carrots	Lettuce	Onions	Potatoes	Strawberries
1	276	-2,649*	-2,842*	-4,746*	1,280**
2	944***	3,842*	7,130	11,614*	6,955***
3	-1,564	-8,029*	-4,092	-9,304	193***
4	437	-2,100	-7,206***	-3,182	-2,983
5	1,257	4,091**	10,908	14,684	10,378
6	-613	-3,849**	-10,425	-21,118**	-4,078
7	1,246**	528	145	-1,821	-1,994**
8	423	715	-1,130	-4,177	-180
9	-105	-133	2,119	3,977	-981
10	1,394**	5,426**	15,908**	23,795*	1,372
11	1,300***	-7,323*	-9,094	-15,137	-2,594
12	1,366*	-2,466***	-2,573**	-1,109	339

Note: USDA, Agricultural Marketing Service, Market News Reports. A single asterisk (*) indicates significant difference in means at 10% level of significance, ** at 5%, *** at 1%.

Due to the seasonality of produce markets and other factors that affect production volume (e.g., weather, US labor laws), produce prices can be highly volatile (Fleege et al. 2004; Minor et al. 2020). Thus, we summarize average shipping point (farm-level) and retail prices for each commodity (Table 1). For these five commodities, although we do not detect statistically significant differences in farm-level prices for carrots, lettuce, and strawberries, we do observe strongly significant differences for onions (lower) and potatoes (higher) between 2019 and 2020 observed prices. Retail prices represent similar patterns, yet statistically significant differences are only detected for onions (lower) and lettuce (higher).

The case of onions generally demonstrates the value lost due to the inability to easily switch between distribution channels. Figure 1 graphically depicts the total volume of domestically produced onions in 2019 and 2020, where week ten marks the beginning of the shelter-in-place (SIP) orders for most of the US. The sharp drop in 2020 corresponds to the month of the lockdown (April) when many foodservice establishments, a dominant purchaser of onions, were closed. Between 2019 and 2020, the estimated revenue deficit, compared to 2019, for onion growers amounted to over $58.0 million in the four weeks following the SIP orders, as shown in Figure 2. By week 38, estimated onion revenues began to consistently surpass 2019 levels. The gap between farm and retail prices for onions, depicted in Figure 3, shows a significant decline in the weeks following the SIP orders, but by week 36 of 2020, price fluctuations at the farm and retail level appear to remain more stable. Using the shipping point and advertised retail prices, we calculate farm-to-retail price spreads to compare 2019 and 2020 averages (Figure 4). The most notable difference in farm-to-retail price spreads appears in the weeks following the SIP orders, and only by the end of the year do we observe 2020

[10]Differences in 2019 and 2020 potato and strawberry volume are not statistically different from zero. Onions present an interesting case, as they faced declines in shipment volume in nearly every month of the year.

price spreads more closely mirroring 2019.

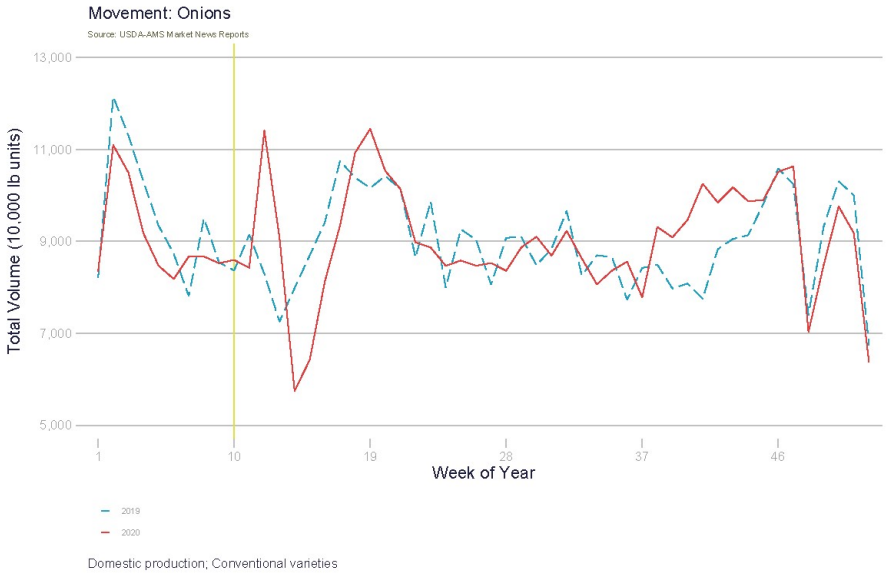


Figure 1: Volume of Onion Movement

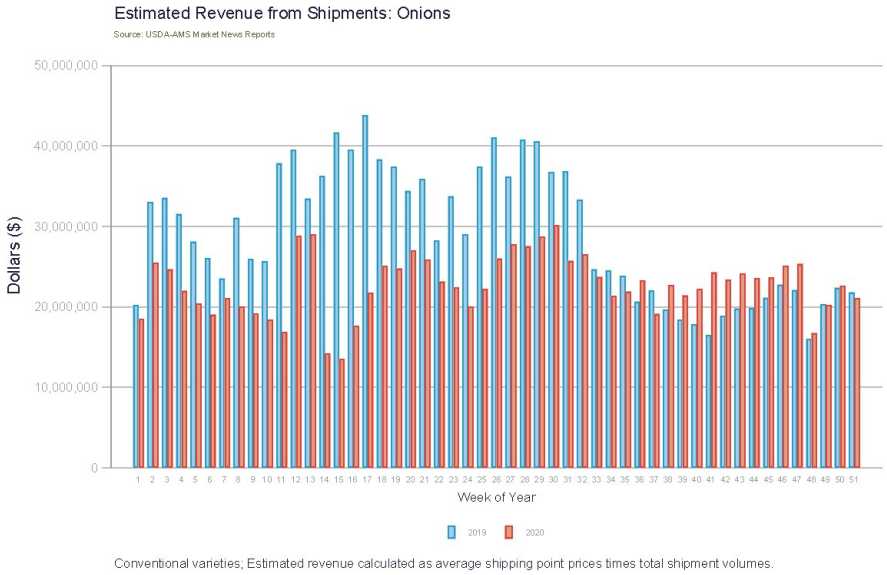


Figure 2: Onion Revenue

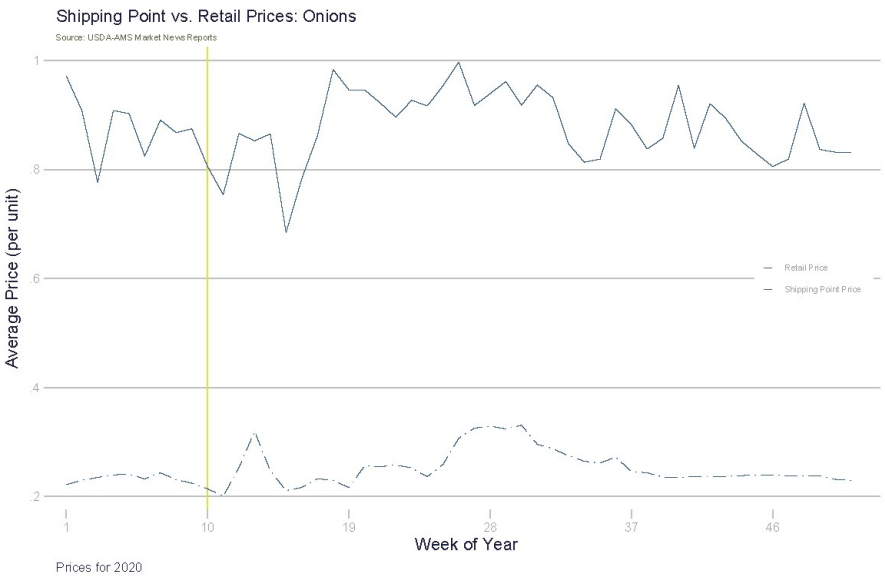


Figure 3: Onion Price Spreads: Retail - Wholesale



Figure 4: Onions: Average Price Spreads

In terms of our focal commodity, onions, the data in Tables 1 and 2 provide evidence that suggests a fundamental lack of resilience, defined in terms of the length of time required by shippers to return to previous delivery patterns. While shipment volumes, and prices, ultimately returned to their 2019 levels by the summer of 2020, the loss of foodservice clearly overwhelmed higher shipments to retailers in a 6 - 8 week period. Onion shippers were able to absorb the shock, and return to something approximating their former function, but the delay in doing so is evidence of a lack of resilience in terms of the definition outlined above.

In summary, therefore, there is relatively clear observational evidence of a lack of resilience in the fruit and vegetable supply chain through at least the early days of the COVID-19 pandemic. However, whether the data are consistent with the real-options-based model of supply-chain hysteresis remains an empirical question. In the following sections we attempt to resolve this issue by applying a Monte Carlo simulation modeling strategy in order to demonstrate the empirical importance of hysteresis.

5 Simulation Model and Model Calibration

We develop a simulation model to demonstrate the empirical importance of hysteresis, and numerically investigate the sensitivity of our definition of resilience to the parameters that govern our real options model. The simulation model follows the development of the analytical model presented in Section 3. We numerically investigate the comparative statics of h with respect to changes in the monetary investment in flexibility (K), the appropriate cost of capital for making the investment (r), the historical mean (μ) and volatility (σ) of the underlying revenue stream (R_t) assuming the revenue process approximates GBM, and assumptions on the random time to channel recovery (λ).

In creating the simulation model, we first use the parameter values of K, σ, μ, r, and λ to estimate b from equation (4) and the threshold revenue R^* in equation (5). We assume R_t evolves weekly as a GBM process where $R_t = R_{t-1}e^{\mu-0.5\sigma^2+\sigma Z}$ and $Z \sim N(0,1)$ as the revenue data we eventually use in the next section (onions) is weekly. Therefore, estimates of μ, σ, and r used in the simulation are consistent with the weekly evolution of the GBM process. Given the estimate of R^* and and the evolution of R_t, we develop an algorithm that records a switch from the primary channel to the secondary channel, which occurs when $R_t \geq R^*$. This point in time is t^* or the optimal switching time. The algorithm generates a large sample of t^* values, with the sample mean of t^* being an estimate of hysteresis (h).

The algorithm generating t^* is a four-step process. To initialize the process (step 1), we set t^* to zero ($t^* = 0$). If the starting revenue at time $t = 0$, R_0, is greater than or equal to R^*, then the algorithm is stopped and the switch to the alternative channel, and corresponding investment in the switch, is made immediately and recorded. However, if $R_0 < R^*$ then the algorithm is advanced to the next period where $t^* = t^* + 1$ (step 2). Next, at step 3, the algorithm first checks for recovery at the end of t^*. The probability of recovery at the end of period t^* (and start of period $t^* + 1$), denoted as ρ, is set equal to the random time to channel recovery λ ($\rho = \lambda$).[11] To simulate recovery time, we define a zero-one uniform random variable $U \sim$ uniform[0,1]. If $U \leq \rho$, then channel 1 recovers at the end of period t^* and no switch takes place. Therefore, t^* is the recovery period and the algorithm stops. If this condition does not hold (e.g., $U > \rho$) the algorithm advances to the end of the next period (step 4) to determine if the switch condition, $R_t \geq R^*$, is satisfied. If this condition holds, then a switch is recorded. Otherwise, the algorithm returns to stage

[11] The discrete-time analog of an exponential random variable is a negative binomial random variable with the number of "successes" set to 1, i.e., the number of Bernoulli trials before a "success" occurs with success-probability ρ. Accordingly, the expected time to recovery, including the current downtime period t^* is $1 + (1-\rho)/\rho = 1/\rho$. Recall that the expected time to recovery under our continuous-time model of Section 3 is $1/\lambda$, which leads to setting $\rho = \lambda$ in our discrete-time model.

2 and repeats the cycle until either a switch or recovery occurs thus stopping the algorithm. Monte Carlo simulation is used in running this algorithm, implementing 100,000 iterations.

Before using this model to estimate levels of hysteresis found in the market for onions during the COVID-19 shutdown, we calibrate the simulation model using a general set of predetermined values for model parameters. This calibration helps us to consider the change in h with respect to changes in model parameters (comparative statics) and to see if the directional changes in h are consistent with the theoretical framework presented in Section 3. In addition to gauging theoretical consistency, the results from the calibration provide some guidance as to potential policy prescriptions and business strategies designed to enhance flexibility and reduce observed hysteresis. In calibrating the model, we set the values of λ, μ, r, and σ such that the following four conditions hold: (1) $\lambda > \mu - r$ to ensure convergence of the exponential moment generating function, (2) $r > 0$ and $\sigma^2 > 0$ to exclude trivial models, (3) $b > 1$ to satisfy the smooth pasting condition, and (4) $\mu - 0.5\sigma^2 > 0$ so that the expected first-passage time, $E[\tilde{\tau}]$, is finite. We also set the level of investment (K) so that R^* is slightly above the starting revenue R_0. This ensures that switching is not immediate in Step 1 of the simulation (e.g., $R_0 \geq R^*$ at $t = 0$), yet there is nearly a 100% chance that either switching or recovery will take place at some week t^* over the course of the simulation. To keep the simulation analysis tractable and efficient, we also set the maximum number of weeks that R_t can evolve to 1,400.

Table 3 reports the first set of model calibration results assuming $\lambda = 0$ such that there is zero probability that channel 1 will come back on line over the course of the simulation (no recovery) and only switching can occur. To keep the calibration general, R_0 is set equal to one dollar ($R_0 = \$1$). The other parameter values are $K = \$630$, $\sigma = 0.03$, $\mu = 0.0006$, and $r = 0.001$. These parameter values ensure conditions 1) to 4) outlined above hold. For these values, the estimate of hysteresis (h) is 48.88 weeks, with the standard error of this estimate $SE(h) = 0.641$ and the 95% lower and upper confidence levels at 47.63 and 50.14 respectively. This estimate of h is generally in line with the expected first-passage time $E[\tilde{\tau}] = 53.12$ (see eq. (7)).[12] Holding all other parameters constant, and considering small changes in the investment K, a decrease to \$620 from \$630 reduces R^* such that switching occurs immediately ($h = 0$). However, an increase in K from \$630 to \$640 increases the threshold revenue R^* forcing h to increase to 72.37 weeks. Therefore, h is increasing in the level of K. A similar directional impact is seen with small changes in weekly volatility holding all other parameter values constant. Relative to the baseline scenario, slight changes in σ impact the levels of b and R^* and subsequently h more than small changes in K. For example, changing σ to 0.025 from 0.03 causes switching to immediately occur ($h = 0$), while an increase in σ to 0.032 causes h to rise to 121.45 weeks.

[12]The estimate of h approaches the expected first-passage time $E[\tilde{\tau}]$ as the GBM moves from a discrete weekly model to discrete periods approaching continuous time such as mili-weeks

Table 3. Comparative Statics for Key Parameters

Value	b	R^*	$1/\lambda$	$E(\tilde{\tau})$	h	SE(h)	CI-L	CI-H
Baseline	1.333	1.008	-	53.121	48.881	0.641	47.626	50.137
$K = 620$	1.333	0.992	-	-	0.000	-	-	-
$K = 640$	1.333	1.024	-	158.110	72.368	0.770	70.859	73.877
$\sigma = 0.025$	1.387	0.903	-	-	0.000	-	-	-
$\sigma = 0.032$	1.314	1.054	-	596.809	121.445	0.998	119.488	123.402
$\mu = 0.0005$	1.436	1.037	-	729.729	101.455	0.926	99.639	103.270
$\mu = 0.0007$	1.239	0.981	-	-	0.000	-	-	-
$r = 0.00081$	1.183	0.844	-	-	0.000	-	-	-
$r = 0.00119$	1.470	1.168	-	1034.052	282.553	1.393	279.823	285.283
$\lambda = 0.05$	1.333	127.008	20.000	32,295.001	20.056	0.062	19.935	20.177
$\lambda = 0.10$	1.333	253.008	10.000	36,889.474	10.050	0.030	9.991	10.109

Note: Baseline Values: K=\$630, σ=0.03, $\mu = 0.0006$, $r = 0.001$, $\lambda = 0$

A reduction in weekly mean returns (μ) to 0.0005 from the baseline of 0.0006, however, increases h to 101.46 weeks, while an increase in μ to 0.0007 increases b and R^* yielding immediate switching ($h = 0$). A decrease in the weekly cost of capital r from 0.001 to 0.00081, all other parameter values constant at baseline values, reduces the estimate of h to 0 (immediate switch) while an increase in r to 0.00119 increases h to 282.55 weeks. Therefore h is decreasing in the value of r, but the standard error of h for this increase in r, $S(h) = 1.393$, is the largest standard error resulting from changes in any of the parameter values. Finally, while the baseline assumptions here assume that recovery cannot occur ($\lambda = 0$), changing λ to 0.05 (e.g., a mean recovery time $1/\lambda$ equal to 20 weeks) subsequently changes h to 20 as well. That is, keeping all other parameter values constant, at $\lambda = 0.05$ recovery will dominate switching and h will be consistent with mean recovery time. This also holds true for when $\lambda = 0.10$ ($1/\lambda = 10$ weeks) demonstrating h is increasing in mean recovery time $1/\lambda$.

Table 4 presents additional results for model calibration where the baseline values of R_0, σ, μ, and r are the same as in Table 3. The only difference is that λ is set to 0.10 (mean recovery time $1/\lambda = 10$ weeks) and the level of investment K is set to 2.5 such that R^* is slightly above the starting value R_0 allowing for the possibility of switching to occur during the simulation with R_t crossing R^* from below. Given that there is a positive probability of recovery of channel 1 with a mean recovery time of 10 weeks, the level of investment K is substantially lower than when $\lambda = 0$. At these new baseline values, the estimate of h is 3.42 weeks with $S(h) = 0.015$. Consistent with the results in Table 3, the estimate of h is increasing in K. For example, reduction of K to 2.0 from 2.5 yields an immediate switch (h=0), while an increase of K to 3.0 raises R^* and subsequently h to 9.60 weeks which is nearly equal to the mean recovery time of 10 weeks.[13] Lowering

[13]At 100,000 iterations of the Monte Carlo simulation, for $K = 3.0$, 95.53% of the iterations recover prior to the switching

σ to 0.025 from the baseline value once again yields $h = 0$ (immediate switch), while an increase in σ to 0.032 takes the estimate of h to 6.27 weeks. The direction of the relationship between μ and h, however, reverse under these new baseline assumptions relative to that in Table 3 when there was no possibility of recovery in channel 1. While the estimate of b remains the same as that in Table 3, a decrease in μ to 0.0005 decreases R^* to 0.827 invoking immediate switching ($h = 0$) and an increase in μ yields an h estimate of 9.91 weeks which is nearly equal to the mean recovery time of 10 weeks. The relationship between r and h is also reversed relative to the results presented in Table 3, with a reduction in r increasing R^* to 1.617 (vs. 0.844 in Table 3) and subsequently the estimate of h to 10.05 consistent with the mean recovery time of 10 weeks. Raising r to 0.00119 relative to the baseline results in an estimate of $h = 0$ (immediate switching). The relationship between mean recovery time $1/\lambda$ and h remains the same as in Table 3, with h equaling mean recovery time of 6.67 when $\lambda = 0.15$, and $h = 0$ when $\lambda = 0.05$. The results of the calibration help establish consistency with the theoretical framework as well as intuition into the relationship between h and model parameters useful for applying the model in the context of industry scenarios.

Table 4. Comparative Statics for Key Parameters

Value	b	R^*	$1/\lambda$	$E(\tilde{\tau})$	h	SE (h)	CI-L	CI-H
Baseline	1.333	1.004	10.000	26.613	3.416	0.015	3.386	3.446
$K = 2.0$	1.333	0.803	10.000	-	0.000	-	-	-
$K = 3.0$	1.333	1.205	10.000	1,242.091	9.596	0.028	9.541	9.650
$\sigma = 0.025$	1.387	0.899	10.000	-	0.000	-	-	-
$\sigma = 0.032$	1.314	1.050	10.000	551.625	6.269	0.021	6.227	6.310
$\mu = 0.0005$	1.436	0.827	10.000	-	0.000	-	-	-
$\mu = 0.0007$	1.239	1.302	10.000	1,054.683	9.909	0.029	9.852	9.966
$r = 0.00081$	1.183	1.617	10.000	3,202.065	10.045	0.030	9.986	10.104
$r = 0.00119$	1.470	0.787	10.000	-	0.000	-	-	-
$\lambda = 0.05$	1.333	0.504	20.000	-	0.000	-	-	-
$\lambda = 0.15$	1.333	1.504	6.667	2,720.855	6.667	0.019	6.629	6.705

Note: Baseline Values: K=\$2.5, σ=0.03, $\mu = 0.0006$, $r = 0.001$, $\lambda = 0.10$

6 Results - Representative Onion Operation

The above calibration of the model provides important insights not only in terms of the relationships between model parameters and h, but also in terms of potential policy prescriptions and supply chain resilience strategies that perhaps could have reduced the duration of the observed hysteresis in fresh produce supply

condition $R_t \geq R^*$ being met, stopping the simulation algorithm at the end of step 3. Therefore h is consistent with the percentage of iterations that recover prior to the switching condition

chains during the COVID-19 pandemic. Consistent with our focus on firm-level decision making, we apply the model using values of revenue derived from enterprise budgets for a representative onion grower compiled by farm management extension services (Oregon State University 2019). We use these crop budget values to estimate the starting value of weekly net revenue as R_0 = \$32,484 for a representative 150 acre farm in Western Idaho/Eastern Oregon. The discount rate (r) used is 0.001042 weekly (5.42% annualized) which was the opportunity cost of capital used in the crop budget. We parameterize the GBM process by assuming onion revenue is proportional to observed market values. In our case, this is the product of the weekly shipping point price multiplied by the reported total volume shipped as reported by the Agricultural Marketing Service of the USDA (USDA 2021) from January 4th, 2019 to March 6th, 2020 just prior to the issuance of shelter-in-place orders.[14] As is standard in this literature, we express the GBM process in terms of the log-difference of weekly revenue (i.e., revenue returns) and estimate the parameters of the stochastic revenue process as the sample mean and variance (standard deviation). In terms of the onion revenue data described here, we find the estimated estimates of μ = -0.00155 and σ = 0.161063. Although these values reflect market-level aggregates, due to the fact that the onion market consists largely of undifferentiated, commodity sales, these parameters are likely to hold for individual firms within the industry.

Table 5 reports the comparative statics of our estimates of h in the context of the onion enterprise described with σ = 0.161063, μ = -0.00155, r = 0.001042, and λ = 0.10 such that recovery is possible with the mean time to recovery being $1/\lambda = 10$ weeks. Similar to the calibration results in Tables 3 and 4, the level of K (\$50,000) is set such that R^* (\$32,535.60) is slightly above that of the starting revenue R_0 (\$32,484) allowing the simulated value of R_t to cross R^* from below in the simulation. The baseline value of h resulting from the simulation is 3.67 weeks, with a standard error $SE(h)$ of 0.017. At an investment level K = \$45,000 switching occurs immediately, while the hysteresis estimate grows to approximately 5 weeks (h = 5.09) when K is increased by \$5,000 to \$55,000. This suggests that for an onion operation with a similar scale of weekly revenues that a relatively small dollar difference in the costs to switch to the alternative channel can either decrease or increase the number of weeks of delay in investment in the face of a major disruption event such as that witnessed during the shelter in place orders during COVID-19. Interestingly, small changes in the volatility of revenues have a nearly identical impact on the level of hysteresis h (approximately 5 weeks) as small changes in the dollar value of investment K. For example, a 1% reduction in the standard deviation of revenues relative to the baseline (σ = 0.151063), leads to immediate switching (h=0) while a 1% increase in the weekly standard deviation of onion revenues (σ = 0.171063) leads to an increase in h of nearly 2 weeks, from 3.67 to 5.07.

[14] The timing of the shelter-in-place orders varied from state to state, but the aggregate impact on the foodservice channel and the corresponding shock to nationwide suppliers was largely felt by April 1. Our findings are not sensitive to the exact timing of the shutdown of the foodservice channel.

Table 5. Comparative Statics for Key Parameters

Value	b	R^*	$1/\lambda$	h	SE(h)	CI-L	CI-H
Baseline	1.187	32,535.680	10.000	3.674	0.017	3.640	3.708
K = \$45,000	1.187	29,282.112	10.000	0.000	-	-	-
K = \$55,000	1.187	35,789.248	10.000	5.094	0.021	5.054	5.135
σ = 0.151063	1.211	29,412.653	10.000	0.000	-	-	-
σ = 0.171063	1.167	35,852.162	10.000	5.065	0.021	5.025	5.105
μ = -0.00165	1.194	31,538.119	10.000	0.000	-	-	-
μ = -0.00145	1.180	33,613.812	10.000	4.143	0.018	4.106	4.179
r = 0.00085	1.175	34,337.516	10.000	4.472	0.019	4.434	4.510
r = 0.001234	1.199	30,981.062	10.000	0.000	-	-	-
λ = 0.05	1.187	16,678.849	20.000	0.000	-	-	-
λ = 0.15	1.187	48,392.511	6.667	5.837	0.017	5.803	5.870

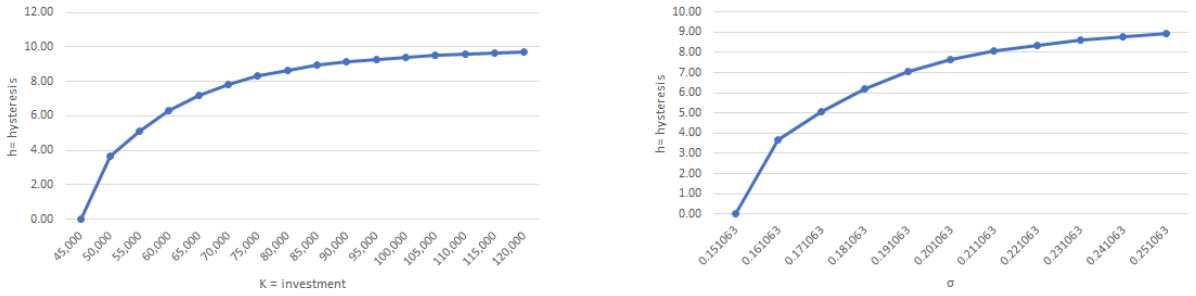
Note: Baseline Values: K=\$50,000, σ=0.161063, μ = -0.00155, r = 0.001042, λ = 0.10

Similar to the model calibration results in Table 3, there is a positive relationship between μ and h. While μ is negative in the baseline case consistent with the onion revenue data, a more negative return μ = -0.00165 relative to the baseline yields immediate switching ($h = 0$) in the simulation. Furthermore, a less negative μ of -0.00145 leads to approximately a 1 week increase in the hysteresis estimate ($h = 4.14$) relative to the baseline. With respect to the discount rate r, as with the calibration results presented in Table 3, h is negatively related to r such that increases in r reduce the value of h in the simulation. A reduction in r from the baseline increases h by approximately 1 week (4.47 vs. 3.67) while an increase in r from 0.001042 to 0.001234 (approximately 1% on an annualized basis) reduces h to 0. Changes in λ are also consistent with the results in Tables 3 and 4 in that h is increasing in λ and subsequently the mean recovery time $1/\lambda$. When lowering λ to 0.05 ($1/\lambda = 20$ weeks) switching is immediate (h=0), while h = 5.837 weeks which is relatively close to the mean recovery time of 6.667 weeks when $\lambda = 0.15$. An important caveat here relative to the calibration results presented in Tables 3 and 4 is that the condition $\mu - 0.5\sigma^2 > 0$ does not hold when considering the onion data. Therefore, it is possible that the expected first-passage time with respect to switching, $E(\tilde{\tau})$, is infinite (∞) in the simulation. Practically speaking though, this is not an issue in the simulation given that for a positive probability of recovery, and hence a positive value for the mean recovery time, recovery at some point in each iteration of the simulation is assured regardless if the switching condition is ever reached.

The results using the onion revenue data provide insight into the potential causes of hysteresis seen during the COVID-19 shutdown. These results, coupled with the calibration results, also suggest that the level of hysteresis is heavily and consistently influenced by the level of investment in flexibility and the volatility in

underlying channel revenue. Strategies that impact the mean level of periodic returns, as well as the cost of capital, are more difficult to generalize from the model given the changes in direction between these variables and the level of hysteresis. Indeed, the relationship between r and h and μ and h are dependent on parameter assumptions which are likely heterogeneous depending on the specific revenue dynamics of the channel and assumptions regarding market recovery time. Therefore, policy prescriptions and business strategies that can reduce the costs of flexibility while also reducing the volatility of channel revenues have the best potential to reduce hysteresis in fresh produce supply chains should another major disruption similar to COVID-19 occur again in the future.

For example, Figure 5a shows the resulting simulation estimates of h for given levels of K using the baseline parameter estimates for onion revenue of σ, μ, r, and λ and the R_0 = \$32,484 as presented in Table 5. The level of h increases at a decreasing rate, asymptotically approaching h = 10 weeks as K increases on the horizontal axis in \$5,000 increments. As noted earlier, it took approximately 6 to 8 weeks for the foodservice supply channel to recover during the COVID-19 shutdown. So, at a level of h = 8 weeks, the approximate K associated with this level of hysteresis is \$70,000. A reduction of this level of investment in switching costs to \$45,000, say via a government subsidy of \$25,000 to compensate for the needed investments in switching, would have promoted switching to the alternative channel immediately (h = 0). Similarly, Figure 5b shows the simulation results for h relative to σ, with h asymptotically approaching h = 9 as volatility of onion revenues increase. At an observed 8 week level of hysteresis, the associated σ is approximately 0.21 (21% weekly), a reduction of volatility in onion revenues by approximately 6% to 0.15 would invoke immediate switching (h=0).



(a) Hysteresis (h) vs. Investment (K)

(b) Hysteresis (h) vs. Std. Dev. of Revenue (σ)

Figure 5: Comparison of Hysteresis (h) with Investment (K) and Standard Deviation of Revenue (σ)

It is important to note that costs incurred to immediately switch from the foodservice channel to retail channels are not just a function of fixed investments (e.g., investments in plant and equipment), but also reflect time and labor needed to fully switch. Indeed, these frictions may have contributed to the observed delay in the foodservice channel coming back on line. Similarly, monetary as well as non-monetary outlays, such as resources and time needed to cultivate simultaneous relationships between shippers and alternative channel players, are not trivial, potentially adding to observed hysteresis. In other words, a severe event like

COVID-19 where the probability of coming back on line in any given week may be positive but low (e.g., $\lambda = 0.10$), with a likely mean level recovery time of $1/\lambda = 10$ weeks, suppliers may just chose to wait for recovery or engage in actions that only partially helped to engage the alternative retail marketing channel.

The results presented in Table 4 and Figure 5 also suggest that strategies to promote channel interoperability may not necessarily need to be expensive. Rather, there is value in nimble and low tech strategies which can reduce K. For example, interviews with onion grower / shippers suggest that investments in complete channel interoperability between retail and foodservice channels require unique sorting lines and heavy infrastructure costs in the neighborhood of $500,000 for a medium to large-sized operation. For a representative farm such as the one used to produce the results in Table 5, this investment would be too great for a firm of this scale, resulting in no switching in the simulation model as R_t would effectively never cross the threshold revenue R^* when $K = \$500{,}000$. However, a more nimble and less expensive strategy could be to keep some pipeline retail packaging on hand and use additional labor to hand pack onions into bags during a time of disruption, albeit disruptions in the labor market during COVID-19 would have made this strategy difficult if not impossible. Also, while a state-of-the-art, high-tech packing line with automated and digitized size sorting would cost in excess of $500,000, a less technologically advanced sorting line (e.g., mechanical sorting) may cost considerably less. Therefore, keeping a relatively low-tech solution in standby mode may help in a disaster situation like COVID-19. Indeed, the decision to fully engage in retail and foodservice supply chain interoperability, and the commitment of the substantial investment to do so, is more likely a strategic marketing decision. That is, the decision by the produce grower/packer/shipper to fully market to both foodservice and retail is a strategy to garner revenue from both channels and to diversify the revenue stream during normal times, rather than a pure mitigation strategy in the face of a shutdown event.

7 Conclusions and Implications

In this paper, we use a real-options framework to explain the delay in recovery of the fresh-produce supply chain during the COVID-19 pandemic of 2020, and consider this lack of resilience as hysteresis. We provide a new theoretical definition of supply-chain resilience, grounded in the economic fundamentals of real-options theory, and generate empirical estimates using the US fresh-produce supply chain as our case study.

In general, there is no strict definition in the literature for what it means for a supply chain to be resilient. Most definitions, however, contain elements that refer to a supply chain's ability to absorb a shock, return to its former function, achieve its previous objectives, and to do all of these things quickly following a disruption. Based on the empirical evidence of the food system's performance during the COVID-19 pandemic of 2020, it failed at least in the temporal dimension of this definition. That is, it returned to approximate its former function, but it took several weeks to do so. During this period of instability, we witnessed meaningful consequences in terms of food insecurity, waste, shortages, and inefficient allocations of scarce food across distribution channels. In this paper, we contribute a new definition of resilience, based

on the economic principles of investing under uncertainty, and the real-option value of maintaining flexibility across distribution channels.

Our analytical model of resilience therefore envisions a firm that considers an investment to switch to an alternative distribution channel when the primary channel is disrupted. If a firm can avoid the worst consequences of supply-chain disruption by investing in flexibility across different distribution channels, then we argue that this investment opportunity embodies a real option. Moreover, we can explain the temporal lack of resilience, or the time taken by firms to restore their former function after a disruption, as the hysteretic effect associated with real options. If there really is a "value of waiting to invest" (McDonald and Siegel 1986; Dixit 1992) then the length of the wait manifests in a lack of resilience. Our analytical model and subsequent numerical comparative statics show that the level of hysteresis is impacted by channel revenue dynamics, the cost of capital, and the level of investment or switching costs associated with maintaining channel flexibility.

We further demonstrate the ability of our model to describe what happened to fresh-food supply chains during the COVID-19 pandemic through an empirical example of a representative commodity: onions. Onion growers sell through either retail (e.g., supermarkets) or foodservice (e.g., restaurants) distribution channels in roughly equal importance, so if there is value to maintaining flexibility across supply chains, it will be apparent to onion growers. We summarize shipment data in early 2020 relative to a similar time period in 2019, and argue that it took onion shipments roughly 6 to 8 weeks to return to normal following the virtual shutdown of foodservice distribution in 2020. Our empirical calibration shows that we can explain a period of investment hysteresis of approximately 3.7 weeks on average given our baseline values of onion revenue dynamics, cost of capital, time to natural channel recovery, and investment costs to switch channels. This hysteresis value rapidly approaches the period of time that it took growers to adjust to the foodservice shutdown and resume their former shipment levels with modest increases in the investment costs and volatility of onion revenues relative to baseline values. More importantly, the comparative statics of our model provide insight into policy prescriptions and business strategies that can promote investment in supply chain flexibility thus reducing observed hysteresis.

Our findings have important implications for both firm management, and policy responses to disruptions such as the COVID-19 pandemic, and related shutdowns. If current supply chain risk-management practice considers only "normal volatility" associated with operating in commodity markets, and not the type of tail-event associated with pandemics, or other disasters, then managers need to carefully consider the value of investing in flexibility. Importantly, our findings suggest that a lack of resilience may result from perfectly rational investment decisions that produce sub-optimal outcomes from the perspective of the system as a whole.

Future research could consider a broader sample of risks, perhaps coming from different parts of the supply chain, and an expanded sample of industries for which the same types of risk we consider here may be relevant. We chose to demonstrate the relevance of our concept of resilience through the onion industry as

a matter of expedience. However, we believe our findings are more general as nearly every food-supply chain experienced a similar sort of disruption as the one we document here. Others may also want to consider different stochastic processes for the underlying returns facing the firm or different statistical concepts of risk. While our modeling effort is typical of others that appear in the financial economics and supply-chain literatures, there are other interpretations of supply-chain risk that are relevant to our objectives.

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