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Decision Support for Dynamic Risks to Improve Supply Chain Resilience

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16. Abstract

This report describes work examining the element of timing within risk mitigation decisions with the goal of building decision support tools to better manage transportation and supply chain risks. This research then develops analytical frameworks to derive insight to two overarching research questions involving how the timing of information affects mitigation decisions and how these scenarios can be modeled. The frameworks examine a two-action decision scenario and a multiple action decision. Within the two-action decisions, we find that scenarios in which the cost of the risk is relatively low relative to the mitigation costs are most sensitive to these issues of timing. We find differences between the two-action and multiple-action decision that underscore the importance of understanding the parameters of the decision situation. Finally, the results underscore the important role played by specifications to represent the decision maker's belief about factors affecting the decision-making context.

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Abstract

This report describes work examining the element of timing within risk mitigation decisions with the goal of building decision support tools to better manage transportation and supply chain risks. This research then develops analytical frameworks to derive insight to two overarching research questions involving how the timing of information affects mitigation decisions and how these scenarios can be modeled. The frameworks examine a two-action decision scenario and a multiple action decision. Within the two-action decisions, we find that the scenarios most sensitive to issues of timing are those in which the cost of the risk is low relative to the mitigation costs. We find differences between the two-action and multiple-action decision that underscore the importance of understanding the parameters of the decision situation. Finally, the results underscore the important role played by specifications to represent the decision maker's belief about factors affecting the decision-making context.

Chapter 1 Introduction

The COVID-19 pandemic resulted in significant supply chain disruptions across many industries. Increased demand caused shortages of medications (Bookwalter 2021) and personal protective equipment (PPE) (Mahmood et al. 2020) in the healthcare industry. Reduced supply due to labor shortages at meat-packing plants caused shortages of agricultural products such as chicken (Luckstead and Devadoss 2020). These supply disruptions negatively impacted the economic strength of the U.S. and also disproportionately affected vulnerable populations. Further complicating matters, the severity of these disruptions varied over time, creating a dynamic element to risk prediction and mitigation. These challenges lead to difficulty in managing transportation and supply networks, motivating the current research to investigate the issue of time-varying risks posing challenges to the management of transportation and supply chain networks.

The examination of these time-varying risks focuses on two overarching research questions:

(1) How can the timing of information, which may be of varying quality/accuracy at different points in time, affect the value to a decision maker and be represented analytically within the context of risk management decisions?

(2) What are the tradeoffs between the quality/accuracy of a prediction and the lead time of that prediction within the context of risk management decisions for transportation and supply chain networks?

By better understanding how data-driven models perform within a dynamic risk landscape and how this performance relates to risk mitigation and operational decisions, the results of this research will alleviate the negative consequences posed by both large systemic shocks such as a worldwide pandemic as well as those posed by smaller shocks. Improved management of transportation and supply chain networks in the face of disruptions can improve the safety of the users and beneficiaries of those systems.

The remainder of this report presents a literature review and categorization of supply chain risks in Chapter 2, as well as a mapping of risk mitigation strategies to risk events and the approximate time horizon of each in Chapter 3. Chapters 4 and 5 develop technical models for the analysis of the two research questions in the case of a single-period risk event in which the available risk mitigation actions comprise either a two-action or a multiple action decision. These chapters also present the results of a sensitivity analysis to parameters specified to represent a range of scenarios. Chapter 6 synthesizes the results and how they support the development of dynamic decision support for risk mitigation, in addition to discussing important additional research questions that must be addressed to realize a commercially viable decision support system.

Chapter 2 Review of Supply Chain Risks

Supply chain networks are complex and include networks of diverse participants, encompassing lower-tier suppliers to end customers, established with fundamental objectives to minimize costs, maximize value, and explore new markets through effectively managed relationships among members (Hallikas et al., 2002; Trkman and McCormack, 2009; Tuncel and Alpan, 2010). While networking serves to leverage collaboration and partnership among various supply chain players, it simultaneously acts as both a source and a medium through which risks are generated and propagated throughout the entire network.

The issues related to supply risks are associated with the design of the supply system, including the number of suppliers (single/multiple sourcing), the location of suppliers (local/global sourcing), and the agility, flexibility, delivery reliability, and infrastructural strength of suppliers, as well as coordination and information sharing. These aspects are covered in our classification and illustrated visually in Figure 2.1.

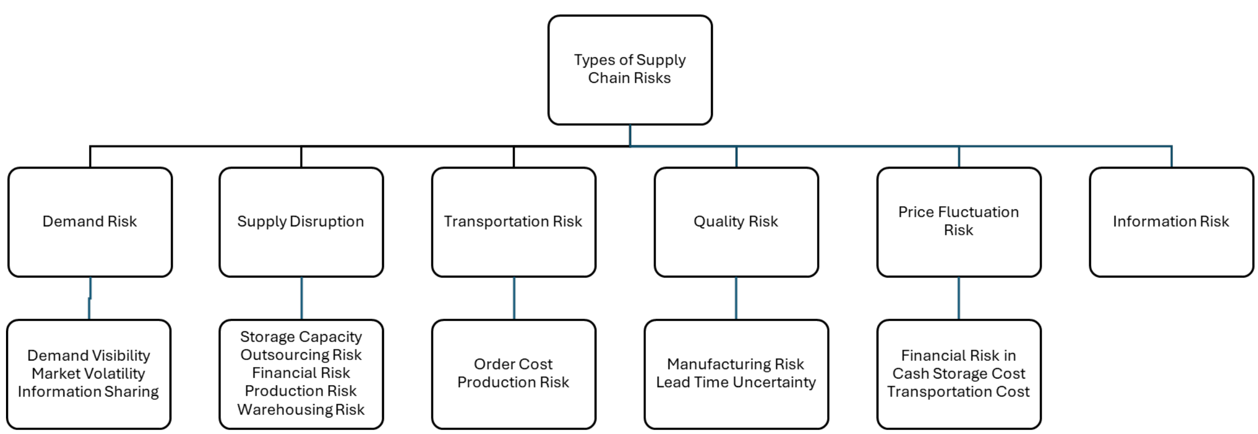


Figure 2.1 A categorization of supply chain risks

Literature contains suggestions for managing demand-side risks including coordination and information sharing among wholesalers, dealers, and retailers, along with shorter planning horizons (Gupta and Maranas, 2003; Chen and Lee, 2004; Boute et al., 2007). Additionally, there are proposals to examine information-sharing levels from a security perspective and adopt trust-based mechanisms under volatile market conditions (Xiao et al., 2007).

2.1 Demand Risk

Various researchers investigated the impact of demand volatility on inventory management, providing insights on safety stock reduction (Cachon 2004; Talluri, Cetin, and Gardner 2004; Betts and Johnston 2005; Sodhi 2005; Xiao and Yang 2008; Radke and Tseng 2012). Ballou and Burnetas (2003) compared traditional inventory planning with cross-filling, a method involving customer demand fulfillment from multiple stocking locations, revealing that cross-filling can reduce safety stocks. Talluri, Cetin, and Gardner (2004) introduced a safety stock model, demonstrating its cost-saving effectiveness in managing make-to-stock inventories based on a case study at a pharmaceutical company. Betts and Johnston (2005) presented a multi-item constrained inventory model, determining that just-in-time (JIT) replenishment is more effective than component substitution due to lower safety stock investment.

Additionally, scholars explore the impact of demand visibility and the bullwhip effect on supply chain performance. Smaros et al. (2003) employed a discrete-event simulation model, indicating that partial improvement in demand visibility enhances production and inventory control efficiency. Reiner and Fichtinger (2009) developed a dynamic model evaluating supply chain process improvements, noting that reducing order variability decreases the bullwhip effect and average on-hand inventory but comes with a decrease in service level. Sucky (2009) suggested order variability increases up the supply chain, emphasizing the overestimation of the bullwhip effect in simple supply chain assumptions with risk pooling effects.

A common limitation across these studies is the lack of implementation in real industrial cases (Ballou and Burnetas 2003; Smaros et al. 2003; Cachon 2004; Betts and Johnston 2005; Sodhi 2005; Xiao and Yang 2008; Reiner and Fichtinger 2009; Sucky 2009; Radke and Tseng 2012). The absence of actual implementation and verification raises doubts among potential users regarding the effectiveness and efficiency of the proposed methods. Moreover, several studies simplify problems by using stylized supply chains (Ballou and Burnetas 2003; Smaros et al. 2003; Cachon 2004).

2.2 Supply Disruption

Supply risk assessment is currently a central focus in research, particularly concerning supplier evaluation and selection. Numerous articles explore various supply risks, including factors such as poor quality (Talluri, Narasimhan, and Nair 2006), late delivery (Talluri, Narasimhan, and Nair 2006), uncertain capacity (Kumar, Vrat, and Shankar 2006; Viswanadham and Samvedi 2013), supplier failure (Kull and Talluri 2008; Ravindran et al. 2010; Ruiz-Torres, Mahmoodi, and Zeng 2013), supplier's financial stress (Lockamy and McCormack 2010), supply disruption (Olson and Wu 2010; Meena, Sarmah, and Sarkar 2011), poor supplier service (Wu et al. 2010; Chen and Wu 2013), suppliers' risk management ability and experience (Ho, Dey, and Lockström 2011), and lack of supplier involvement (Chaudhuri, Mohanty, and Singh 2013).

Quantitative methods proposed to address these challenges include mathematical programming, data envelopment analysis (DEA) approaches (Kumar, Vrat, and Shankar 2006; Talluri, Narasimhan, and Nair 2006; Ravindran et al. 2010; Olson and Wu 2010; Wu et al. 2010; Meena, Sarmah, and Sarkar 2011), multicriteria decision-making, and AHP approaches

(Blackhurst, Scheibe, and Johnson 2008; Kull and Talluri 2008; Ho, Dey, and Lockström 2011; Chen and Wu 2013; Viswanadham and Samvedi 2013), Bayesian networks (Lockamy and McCormack 2010), decision tree approach (Ruiz-Torres, Mahmoodi, and Zeng 2013), and fuzzy-based failure mode and effect analysis (FMEA) with an ordered weighted averaging approach (Chaudhuri, Mohanty, and Singh 2013).

Other supply risks have been examined including second-tier supply failure (Kull and Closs 2008), offshore sourcing risk (Schoenherr, Tummala, and Harrison 2008), unreliable dual sourcing network (Iakovou, Vlachos, and Xanthopoulos 2010), supplier non-conformance risk (Wiengarten, Pagell, and Fynes 2013), supplier incapability (Johnson, Elliott, and Drake 2013), and supplier unreliability (Cheong and Song 2013).

In contrast to approaches focused on assessing supply risks, some articles developed supply risk assessment methods and models. Zsidisin et al. (2004) examined tools and techniques within an agency theory, emphasizing addressing supplier quality issues, improving supplier processes, and reducing the likelihood of supply disruptions. Ellegaard (2008) analyzed supply risk management practices using a case-based methodology, revealing predominantly defensive practices among small company owners. Wu and Olson (2008) compared three risk evaluation models, while Azadeh and Alem (2010) benchmarked supplier selection models under various conditions.

Although supplier evaluation and selection dominate research attention, many studies in this category rely on conceptual model development and demonstration with simulated data, lacking real-world testing. Additionally, some articles exhibit technical limitations, such as the use of a single input measure in DEA analyses (Talluri, Narasimhan, and Nair 2006), assumptions about unchanged supplier capabilities (Kull and Talluri 2008), and reliance on assumptions of deterministic input parameters and supplier characteristics (Ruiz-Torres, Mahmoodi, and Zeng 2013). Addressing these limitations and incorporating real data testing could enhance the practical applicability of these methods.

2.3 Transportation Risk

We identified only a few studies that relate to transportation risk mitigation. Hishamuddin, Sarker, and Essam (2013) formulated an integer nonlinear programming model to determine the optimal production and ordering quantities for the supplier and retailer, as well as the duration for recovery subject to transportation disruption, which yields the minimum relevant costs of the system. Their results showed that the optimal recovery schedule highly depends on the relationship between the backorder cost and the lost sales cost parameters. They studied a simple two-tier supply chain with one supplier and one retailer and assumed the demand to be deterministic.

2.4 Quality Risk

The subsequent publications addressed the mitigation of diverse manufacturing risk factors, encompassing quality risk (Kaya and Özer 2009; Sun, Matsui, and Yin 2012), lead time uncertainty (Li 2007), random yield risk (He and Zhang 2008), non-conforming product design (Khan, Christopher, and Burnes 2008), and machine failures (Kenné, Dejax, and Gharbi 2012). The methodologies employed included a longitudinal case study (Khan, Christopher, and Burnes 2008), a newsvendor model (Li 2007), a linear programming model (Kaya and Özer 2009), a stochastic dynamic model (Kenné, Dejax, and Gharbi 2012), P-chart solution model (Sun, Matsui, and Yin 2012), and unconstrained and constrained mathematical programming models (He and Zhang 2008). Certain limitations were associated with some of these articles. Specifically, Li (2007) and Kenné, Dejax, and Gharbi (2012) focused solely on one type of product in their models, while He and Zhang (2008) and Sun, Matsui, and Yin (2012) considered only one supplier and one retailer in their analyses. Additionally, Kaya and Özer (2009) assumed the demand function to be linear.

2.5 Price Fluctuation Risk

Hofmann (2011) explored the notion of natural hedging within supply chains and reveals that mitigating currency and commodity price fluctuations can decrease vulnerability in the supply chain. Raghavan and Mishra (2011) created a nonlinear programming model demonstrating that a joint decision on the loan amount when one firm in the supply chain has significantly low cash benefits both the lender and borrowing firms more than an independent decision. Lundin (2012) employed network flow modeling to address financial risks in cash supply chains, discovering that centralizing from two to one central bank storage facilities unintentionally results in increased transportation costs and financial risk. However, there were limitations in these studies. Hofmann (2011) relied on a brief literature review and a conceptual research design. Raghavan and Mishra (2011) focused on a simple two-tier supply chain with a single manufacturer and retailer. Lundin (2012) considered only transportation and cash opportunity costs while overlooking production and warehousing costs.

2.6 Information Risk

Du, Lee, and Chen (2003) proposed that companies should create attribute correspondence matrices for databases to facilitate data sharing with both upstream and downstream supply chain partners, while preventing the leakage of information to competitors. Their focus is solely on the vertical relationships among companies, with no consideration for the horizontal relationships with new partners. In contrast, Le et al. (2013) investigated the risk introduced to enterprises in retail supply chain collaboration through data sharing. They put forward an association rule-hiding algorithm designed to eliminate sensitive knowledge from the released database and minimize data distortion.

2.7 Supply Chain Risk Management

SCRM can be divided into two broad categories of approaches. The first is the strategy for comprehensive risk management approach (Jabbarzadeh et al. 2012; Christopher and Peck 2004; Craighead et al. 2007; de Matta 2016), and the second is a focused approach to a specific disruption. These specific disruptions could be security (Véronneau and Roy 2014), lead times (Kouvelis and Li 2008), or terrorism (Sheffi 2001). Although these methods provided enormous value and insights, the events causing disruption were presumed to be unintentional. The lack of risk managing strategies to understand the cause of disruption leaves a gap from a theoretical perspective, exposing firms to unavoidable risks in the environment.

2.8 Synthesis

This literature review synthesizes insights from various researchers on supply chain risk types, providing a comprehensive overview of the multifaceted challenges faced by modern supply chains. Researchers such as Harland, Brenchley, and Walker (2003) identified risks at strategic, operational, customer, financial, and legal levels, establishing a foundational understanding. Jüttner, Peck, and Christopher (2003) focus on environmental, network-related, and organizational risks, while Cavinato (2004) expands the perspective to include physical, financial, informational, relational, and innovational risks.

Chopra and Sodhi (2004) delve into specific operational risks, emphasizing disruptions, delays, systems, and intellectual property concerns. Tang (2006a) broadens the scope to include operational and disruption risks associated with uncertain customer demand and unforeseen events like natural disasters. Wu, Blackhurst, and Chidambaram (2006) distinguish between internal and external risks, providing a nuanced perspective on controllable and uncontrollable factors.

The comprehensive categorizations continued with Bogataj and Bogataj (2007), Blackhurst, Scheibe, and Johnson (2008), and Manuj and Mentzer (2008), covering supply, process, demand, organizational, and environmental risks. Tang and Tomlin (2008) extend the analysis to include intellectual property, behavioral, and political/social risks. Wagner and Bode (2008) introduced a framework incorporating demand side, supply side, regulatory, legal, infrastructure, and catastrophic risks.

The subsequent classifications by Trkman and McCormack (2009), Kumar, Tiwari, and Babiceanu (2010), Olson and Wu (2010), and Ravindran et al. (2010) provided insights into endogenous, exogenous, internal, and external operational risks. Lin and Zhou (2011) categorized risks in the external environment, within the supply chain, and internal to the organization, while Tang and Musa (2011) emphasized material, financial, and information flow risks. Tummala and Schoenherr (2011) compiled an exhaustive list covering demand, delay, disruption, inventory, manufacturing breakdown, capacity, supply, system, sovereign, and transportation risks. Finally, Samvedi, Jain, and Chan (2013) identified risks in supply, demand, process, and environmental dimensions.

Chapter 3 Supply Chain Risk Mitigation Decisions

This chapter is concerned with the decisions within different risk mitigation strategies and the time required to implement each. If a supply disruption is likely to occur in the next month, six months, or year, the decision maker needs to understand what actions are available to mitigate the potential risk. Structural changes to the network comprise most long-term strategies, whereas operational decision such as inventory levels and transportation routing decisions comprise short-term strategies.

3.1 Risk Mitigation Decisions with Short Time Horizons

Even the shortest term risk mitigation strategies require several months advance notice, although less may be required depending on lead and production times. These strategies provide immediate actions that can help stabilize the operations of the supply chain. Three main strategies have been identified: transportation network adjustments, inventory level adjustments, and risk mapping/scenario planning.

Managing transportation networks requires many operational decisions that must be made over a short time horizon. For example, adjusting staffing levels and the specific shift hours for delivery drivers. However, due to constraints of vehicle fleet size and the number of available drivers, it may be easier to make adjustments in one direction (e.g. reductions) than the other, limiting the available decision alternatives. Increasing capacity may require hiring more personnel, purchasing more equipment, or contracting with a third-party service.

In addition to these decisions, other adjustments can be made to the transportation network. Specific loads and routes may also be adjusted. For example, the objective function specified when determining routes can be updated to reflect anticipated short term needs or immediate risks.

A second decision with a relatively short time horizon is determining what inventory level to hold for products. By increasing inventory levels, decision makers can avoid supply disruptions by having additional units, whether it be materials needed for production or finished product, available when it is needed. Changing inventory levels is dependent on the item's lead time (if it is being purchased) or production time (if it is being manufactured).

Finally, risk mapping and scenario planning can often be conducted on a shorter time horizon. These strategies represent a proactive approach to identifying risks or things that could go wrong and determining whether they can be ameliorating. The time horizon for implementing mitigation strategies to risks identified in a risk mapping can vary. Thus, while this strategy is included within the short-term strategies because the proactive mapping can be conducted relatively quickly, it is unclear the time frame for mitigation as it depends on the specifics of a scenario identified.

3.2 Risk Mitigation Decisions with Medium Term Time Horizons

Medium-term risk mitigation strategies require more planning and coordination than short-term measures but can still be implemented within a timeframe of several months to a few years. These strategies focus on strengthening supply chain resilience by addressing vulnerabilities that cannot be immediately resolved but do not require long-term structural changes. Three primary strategies have been identified: supplier diversification, infrastructure investments, and contractual adjustments.

Supplier diversification is a key medium-term strategy that reduces dependence on a single source by identifying and onboarding alternative suppliers. If one supplier experiences disruption related to a critical part, then another supplier is required in order to source that part during the disruption. This process includes vetting potential suppliers, negotiating terms, and establishing redundancy in sourcing critical materials. While diversification enhances supply chain flexibility, it can also increase complexity and requires greater monitoring as the number of suppliers increases.

Infrastructure investments, such as expanding warehousing capacity or upgrading production facilities, also fall within this time horizon. These investments allow for increased storage of critical inventory, improved manufacturing efficiency, and greater adaptability to disruptions. Unlike short-term inventory adjustments, medium-term infrastructure changes require capital allocation, regulatory approvals, and integration with existing supply chain operations.

Contractual adjustments provide another avenue for mitigating risk. Supply agreements can be renegotiated to include more flexible terms, such as volume commitments, delivery guarantees, or force majeure clauses that account for unexpected disruptions. Additionally, establishing contingency contracts with alternative logistics providers ensures continued operations in the event of transportation network failures.

Medium-term strategies provide a bridge between immediate responses and long-term structural changes. By implementing these measures, organizations can proactively manage risk and improve supply chain resilience before disruptions escalate into critical failures.

3.3 Risk Mitigation Decisions with Long Time Horizons

Long-term risk mitigation strategies focus on structural changes that enhance supply chain resilience over multiple years. These strategies require significant investment, strategic planning, and coordination across stakeholders. Unlike short- and medium-term measures, long-term strategies address systemic vulnerabilities. Three primary strategies have been identified: supply chain network redesign, technological innovation, and policy and regulatory engagement.

Supply chain network redesign involves reconfiguring sourcing, production, and distribution networks to improve resilience. This may include relocating manufacturing facilities, establishing regional distribution centers, or adopting nearshoring strategies to reduce dependency on distant suppliers. Because these changes require extensive feasibility assessments, capital investment, and logistical adjustments, they can take years to fully implement.

Technological innovation plays a critical role in long-term risk mitigation. Companies invest in advanced analytics, automation, and digital supply chain platforms to improve forecasting, optimize operations, and enhance visibility across the supply chain. Emerging technologies such as blockchain for traceability, artificial intelligence for demand planning, and robotics for warehouse automation offer long-term benefits but require substantial upfront investment and integration efforts.

Policy and regulatory engagement help ensure that supply chains remain adaptable to evolving legal and trade environments. Organizations may participate in industry coalitions, work with policymakers to influence trade regulations, or develop compliance frameworks for sustainability and ethical sourcing requirements. These efforts help mitigate risks associated with regulatory changes, geopolitical instability, and environmental concerns.

Long-term strategies create a foundation for supply chain stability, reducing the likelihood of severe disruptions while improving overall efficiency and adaptability. By investing in these structural changes, organizations can position themselves for sustained growth and resilience in an increasingly uncertain global landscape.

3.4 Risk Mitigation Decisions with Uncertain Time Horizons

Some risk mitigation strategies do not fit neatly into short-, medium-, or long-term categories because their implementation timelines can vary significantly based on organizational readiness, industry constraints, and external factors. These strategies may be completed in a matter of months or could take years to fully realize, depending on complexity and scale. Four primary examples of such strategies include software adoption and technology integration, workforce development, regulatory compliance adaptation, and process standardization.

Software adoption and technology integration can range from relatively quick implementations to multi-year transformations, depending on the complexity of the system and the extent of required infrastructure changes. For instance, adopting a cloud-based inventory management system may be completed within months, while integrating an enterprise-wide supply chain visibility platform with real-time tracking, predictive analytics, and automated decision-making can take years. Factors such as data migration, system compatibility, employee training, and regulatory compliance also influence the timeline for full adoption.

Workforce development encompasses hiring, training, and upskilling employees to improve supply chain resilience. The time required to develop a skilled workforce varies widely based on factors such as the availability of qualified candidates, the depth of required training, and changes in industry demand. For example, hiring additional warehouse staff to address seasonal fluctuations can be achieved in a short period, while developing specialized technical expertise in areas such as predictive analytics or advanced manufacturing may require multi-year training programs and partnerships with educational institutions.

Regulatory compliance adaptation is another area where timelines can fluctuate significantly. Changes in trade policies, environmental regulations, or labor laws may require businesses to adjust supply chain operations quickly, while others allow for phased implementation over several years. For instance, adapting to new customs regulations in response to geopolitical shifts may demand immediate action, whereas achieving full compliance with sustainability reporting standards could be a long-term process requiring gradual operational adjustments.

Process standardization involves streamlining workflows, documentation, and best practices across a supply chain network. While some standardization efforts, such as updating internal guidelines or implementing new supplier approval processes, can be executed in months, broader efforts—such as harmonizing operations across multiple regions or integrating new international compliance frameworks—can take years. The complexity of internal coordination, external partnerships, and industry-wide collaboration affects the speed of implementation.

Because of their variable timelines, these strategies require flexible planning and continuous reassessment. Organizations must balance short-term operational needs with long-term strategic goals, ensuring that mitigation efforts align with evolving workforce requirements, regulatory landscapes, and technological advancements.

3.5 Summary and Implications for Research

This chapter categorized risk mitigation decisions by the time horizon over which the decision alternatives can be implemented and the time horizon over which the outcomes and impacts can be observed. This research is particularly interested in information timing issues and potential changes in information as updates occur. When modeling changes to information that will affect a decision, it is important to consider the rate of change of that information relative to the time horizon of the specific decision of interest and ensure that the relationship between the two makes sense.

In the subsequent chapters of this report, we consider decisions with relatively short time horizons. The short time horizon decisions reflect a scenario where a major change in the operating environment has occurred suddenly, and a decision maker is determining whether to take immediate action to address that change. The immediate available decisions are those with shorter time horizons. These scenarios reflect the situation in early 2020 with the emergence of COVID-19 when people and organizations were determining how to react and what actions to take. These scenarios also represent opportunity for the introduction of decision support tools because the short time horizon increases the challenge of determining the best course forward. It is for these reasons that preparing for a potentially imminent weather disaster is used as an illustrative example in Chapter 4 and why inventory management is selected as the illustrative example in Chapter 5.

Chapter 4 Two-Action Decisions to Mitigate Risk

This chapter is concerned with single time period risk mitigation decisions in which a risk event occurs within a single time period. In this case, the decision maker has several time periods over which to prepare for the risk event and some indication that a risk event will occur in a specified future time period. The impact of the risk event occurs in a single time period, hence the nomenclature of this type of problem as a single time period risk event. Anticipated extreme weather events such as hurricanes are an example of this type of single period risk event and will be used as an illustrative example throughout the chapter.

Within this chapter, we consider a two-action risk mitigation decision. Two-action decision problems describe scenarios in which the decision maker has two alternatives available to them. This class of problem applies to a variety of applications and has been widely studied (e.g. Raiffa and Shlaiffer 1961; Abbas et al. 2013). For example, consider the scenario of an anticipated adverse weather event such as a hurricane in which the decision maker must determine whether to evacuate or to stay. In this example, the decision maker has two alternatives, making the scenario a two-action decision problem. Alternatively, this two-action decision scenario also applies to scenarios where some mitigation action—such as fortifying a plan or moving inventory to a safer location—is discrete, and the alternatives are to either act or not act.

4.1 Problem Formulation: Trusted Information Source

The analysis is interested in the tradeoff between the accuracy of the prediction concerning the risk event over the time leading up to the potential risk event. We model the situation using a traditional decision tree approach (Raiffa 1968; Clemen 1991). Circular nodes represent uncertainties while square nodes represent decisions. In our analysis, we consider an uncertainty node representing an information source on the likelihood of a risk event occurring, a decision node representing the opportunity to make a risk mitigation decisions, and finally another uncertainty node to represent whether the risk event occurs or not. Figure 4.1 illustrates this general decision tree structure for a two-action decision in a given time period.

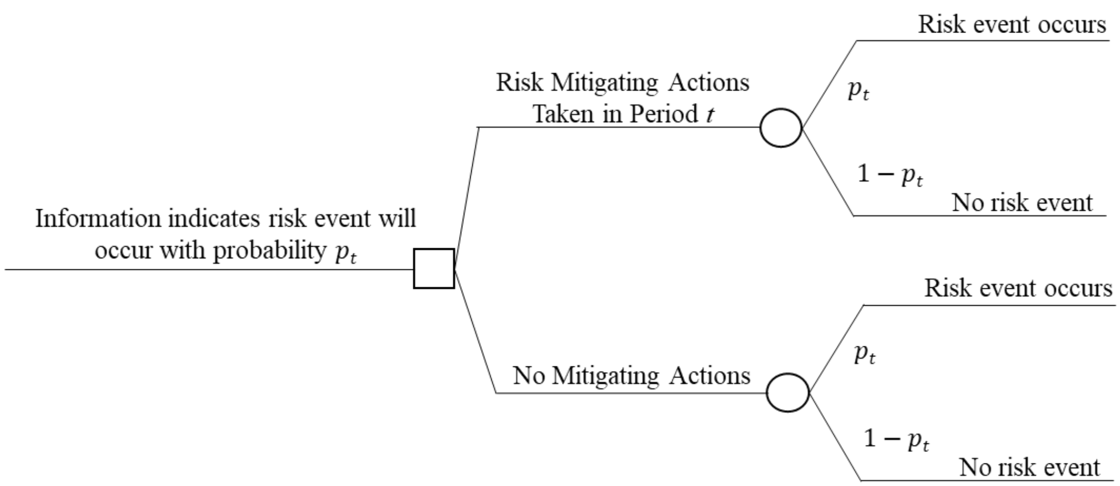


Figure 4.1 A general structure of the single period, two action decisions considered

Although the risk event occurs in a single time period, the decision maker has multiple time periods leading up to the potential risk event over which to act. The information available to the decision maker evolves over time. We consider k total time periods t, with $t = 0,1, \dots, k$. We use subscripts to indicate a probability at a specific time, such that p_t is the estimated probability at time t that a particular risk event will occur by time $t = k$.

When considering the tradeoffs between forecast accuracy and the timing of risk mitigating actions, we observe that if the cost/value associated with risk mitigation does not change over time, then the optimal course of action is to wait until the last time period available to act when the prediction is most accurate. In some cases, "no lost value" may accurately describe the setting. However, in other cases, the cost or value may change over time. Consider the case of evacuating for an impending storm. The later the decision maker chooses to evacuate, fewer routes may be available, increasing the time to evacuate and limiting lodging options, all resulting in higher costs. Such increases in cost over time must be represented in the value function.

An important component of the problem formulation is the development of value functions to represent how the different combinations of selected decision alternatives and the outcome of key uncertainty (risk event occurs or not) affects the value to the decision maker. We must specify the value functions to represent the outcomes of each action the key random variable. Further, to represent an evolving dynamic situation in which the available information changes over time, the value function will depend on the time period in which the decision maker chooses to take risk mitigating actions, if the decision maker should elect to mitigate the risks. We consider the cost associated with the risk mitigation action to be known and deterministic. We assume it has a fixed cost component c, and a variable cost g_t, that is a function of time, resulting in an additive value function,

$$v(t) = -c - g(t) \tag{4.1}$$

Values and equations specifically labeled as costs are reported as their magnitudes. To ensure appropriate representation of the monetary value to the decision maker, negative signs are added for $v(t)$ in equation 4.1. For simplicity of notation, $v_t = g(t)$ and $g_t = g(t)$. Within our problem formulation, we assume that the cost of risk mitigation is deterministic and that the risk event is fully ameliorated by the action taken.

Given this representation of costs, we must also specify equations to govern the evolution of the variable costs of risk mitigation. Similarly to the properties of the changes in the estimated probability of the risk event, the variable costs of risk mitigation for a one-period decision are context dependent. Therefore, similar to modeling the changes in probabilities throughout the time periods, we consider multiple functional forms to describe different ways in which these variable costs may change, including linear, quadratic, and exponential. In each case, we specify an initial value g_0 for time $t = 0$ and a final value g_k for time $t = k$, with $g_k > g_0$. The different shapes of the functions between these points represent different evolutions of these values over time. With this notation, the governing equations for the case of linear changes are

$$g(t) = g_0 + \frac{g_k - g_0}{k} t \tag{4.2}$$

For the case of quadratically increasing variable risk mitigation costs over time, the governing equation is

$$g(t) = g_0 + \left(\frac{g_k - g_0}{k^2}\right) t^2 \tag{4.3}$$

The third family of governing equations for the time-variable costs is exponential,

$$g(t) = g_0 e^{\ln\left(\frac{g_k}{g_0}\right) t/k} \tag{4.4}$$

The formulation of equation 4.4 is conducive to numerical analysis but introduces the constraint $g_0 > 0$. Because initial costs in time $t = 0$ should be predominantly weighted by the fixed cost, and to limit the number of required parameter specifications in the analysis, we specify the initial time-variable cost as 1% of the fixed cost, $g_0 = 0.01c$. The nonzero nature of g_0 also explains its inclusion in equations 4.2 and 4.3.

We must also consider the cost incurred if the risk event occurs and no mitigating actions have been taken. We model this cost as a deterministic cost, r, which represents a negative value to the decision maker. If no risk mitigation actions are taken and the risk event does not occur, the value is 0. If we assume that the available risk mitigation fully ameliorates the cost of the risk event, then the monetary outcome when risk mitigation is undertaken has the same outcome regardless of the occurrence of the risk event. The decision tree can then be simplified as shown in Figure 4.2.

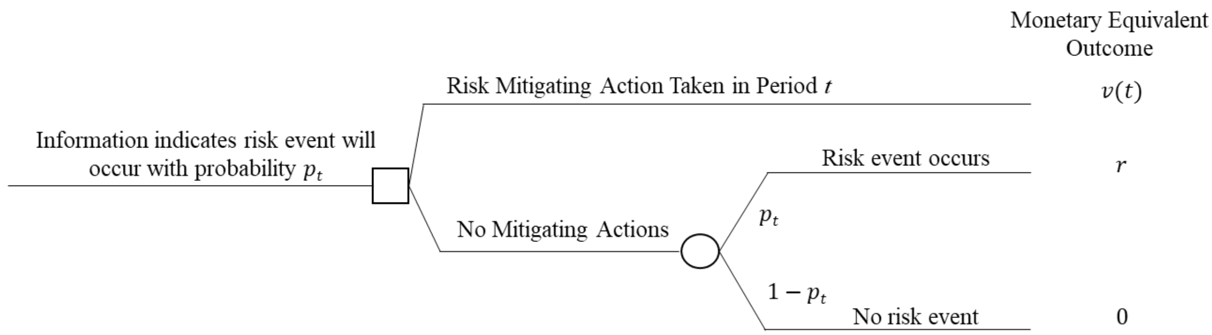


Figure 4.2 The single period, two-action decision tree when the decision maker accepts the probability from the information source.

Since uncertainty is an integral component of the analysis, we must consider preferences for a monetary equivalent value under uncertainty. We consider a risk averse decision maker that is rational and follows the axioms of normative decision making specified by von Neumann and Morgenstern (1947). We represent preferences under uncertainty with an exponential utility function of the form

$$u(x) = 1 - e^{-\gamma v} \tag{4.5}$$

where γ represents the constant absolute risk aversion and v represents a deterministic value represented as a monetary equivalent.

This utility function allows the analysis to consider the effect of risk preferences with a constant, absolute value for risk aversion.

We must also specify functional forms that govern how the estimated probability of the risk event occurring changes over time. Because these values and the way they change are anticipated to be highly context dependent, we consider multiple governing functional forms including linear, quadratic, and exponential. In each case, we will specify an initial value for time $t = 0$ and a final value for time $t = k$. These values are denoted p_0 and p_k, respectively, with the constraint $p_0 \neq p_k$ and bounds $0 < p_0 < 1$ and $0 < p_k < 1$; we do not model cases with probabilities of 0 or 1 as we assume there is no certainty on the occurrence of the risk event. The different shapes of the functions between these points will then represent different patterns of changes in these values over time. For $p(t)$, the initial and final values for the probability of the risk event are denoted p_0 and p_k. With this notation, the governing equation for the case of linear changes is

$$p(t) = p_0 + \frac{p_k - p_0}{k} t \tag{4.6}$$

with the constraint $0 \leq t \leq k$.

The governing equation for the case of quadratic changes in p_t depends on whether p_t is increasing or decreasing over time. In the case that p_t is increasing with time, the equation becomes

$$p(t) = p_0 + \left(\frac{p_k - p_0}{k^2}\right) t^2 \tag{4.7}$$

with the constraint $0 \leq t \leq k$.

Finally, the governing equation for the case of exponential changes in p_t is

$$p(t) = p_0 e^{\frac{\ln(p_k/p_0)}{k} t} \tag{4.8}$$

with the constraint $0 \leq t \leq k$.

With this problem formulation, many combinations of governing functions and variables are possible. We will consider all possible combinations of governing functions. For ease of reference, each combination of the governing functions for the change in time-variable risk mitigation costs and the change in the estimated probability of the risk event occurring will be assigned a case number. These combinations and case numbers are provided in Table 4.1.

Table 4.1 The governing equations used in each case

Case	**Governing Equation Functional Form** *g(t)*	*p(t)*
1	Linear	Linear
2	Linear	Quadratic
3	Linear	Exponential
4	Quadratic	Linear
5	Quadratic	Quadratic
6	Quadratic	Exponential
7	Exponential	Linear
8	Exponential	Quadratic
9	Exponential	Exponential

Within the analysis, there are several other parameters to consider. We must examine the effect of the cost of the risk event occurring without mitigation, the fixed risk mitigation cost, the maximum time-varying risk mitigation cost, the initial estimated probability of the risk event, the decision maker's risk aversion, and the length of the time horizon. We consider low ($r = 5{,}000$) and high ($r = 10{,}000$) risk event costs. To reduce the number of combinations of parameters, we consider low risk mitigation costs with $c = 500$ and $g_k = 5{,}000$, and high risk mitigation costs with $c = 1{,}000$ and $g_k = 10{,}000$. We consider low ($p_0 = 0.05$) and high ($p_0 = 0.50$) initial estimated probabilities of the risk event occurring. We consider low, moderate, and high risk aversion, modeled as $\gamma = 0.00003$, $\gamma = 0.0003$, and $\gamma = 0.001$. Finally, given the large number of parameter combinations to consider, and observing that the two different values of p_0 can provide insight to the effect of different time horizons, this analysis considers a single time horizon length of $k = 20$. We also only consider increasing $p(t)$, noting that decreases in $p(t)$ over time would increase the attractiveness of the 'no mitigation action' alternative.

Omitting the risk aversion parameter, these parameter specifications result in eight variations to consider for each case of governing functions. These variations are numbered in Table 4.2. To facilitate references to specific combinations of parameters, we refer to the case number, followed by a period and the specific parameter variation number. Case 1.1 refers to case 1 from Table 4.1 and parameter variation 1 from Table 4.2; case 1.2 refers to case 1 from Table 4.1 with parameter variation 2 from Table 4.2, and so forth.

Table 4.2 Variations of parameters for each case

Variation	$\boldsymbol{r}$	**Mitigation Cost** $\boldsymbol{c}$	$\boldsymbol{g_k}$	$\boldsymbol{p_0}$
1	5000	500	5000	0.05
2	10000	500	5000	0.05
3	5000	1000	10000	0.05
4	10000	1000	10000	0.05
5	5000	500	5000	0.50
6	10000	500	5000	0.50
7	5000	1000	10000	0.50
8	10000	1000	10000	0.50

To examine the effects of each case and the variation of the parameters for that case, we calculate the certain equivalent for each action in the two-action decision at each time period. The certain equivalent is a concept from decision analysis that provides the deterministic value for an uncertain deal that is tailored to a decision maker such that the decision maker is precisely indifferent between selecting the deterministic value and the uncertain deal (Howard and Abbas 2015). Because the problem formulation exclusively considers costs, the certain equivalents for each alternative will be negative, but the preferred alternative will be the one with the larger (less negative) certain equivalent. To best convey how the certain equivalents change over the time horizon, the results are presented in the form of line graphs. When presenting the results, we take advantage of the fact that the risk mitigation costs are modeled as being deterministic and therefore do not change with changes in risk aversion because there is no uncertainty. We can therefore reduce the number of figures by plotting certain equivalents for the 'no mitigating actions' alternative for each risk aversion coefficient on the same plot, with each of these three lines being compared to a single line displaying the cost of risk mitigation at the given time.

4.2 Results: Trusted Information Source

We first consider case 1, with linear evolution of both the time-variable risk mitigation costs and the estimated probability of the risk event occurring. The results for case 1 are shown in Figure 4.3. The results for cases 2 through 6, with linear evolution of the time-variable risk mitigation costs and quadratic evolution of the estimated probability of the risk event occurring, are shown in Figure 4.4 through Figure 4.8, respectively.

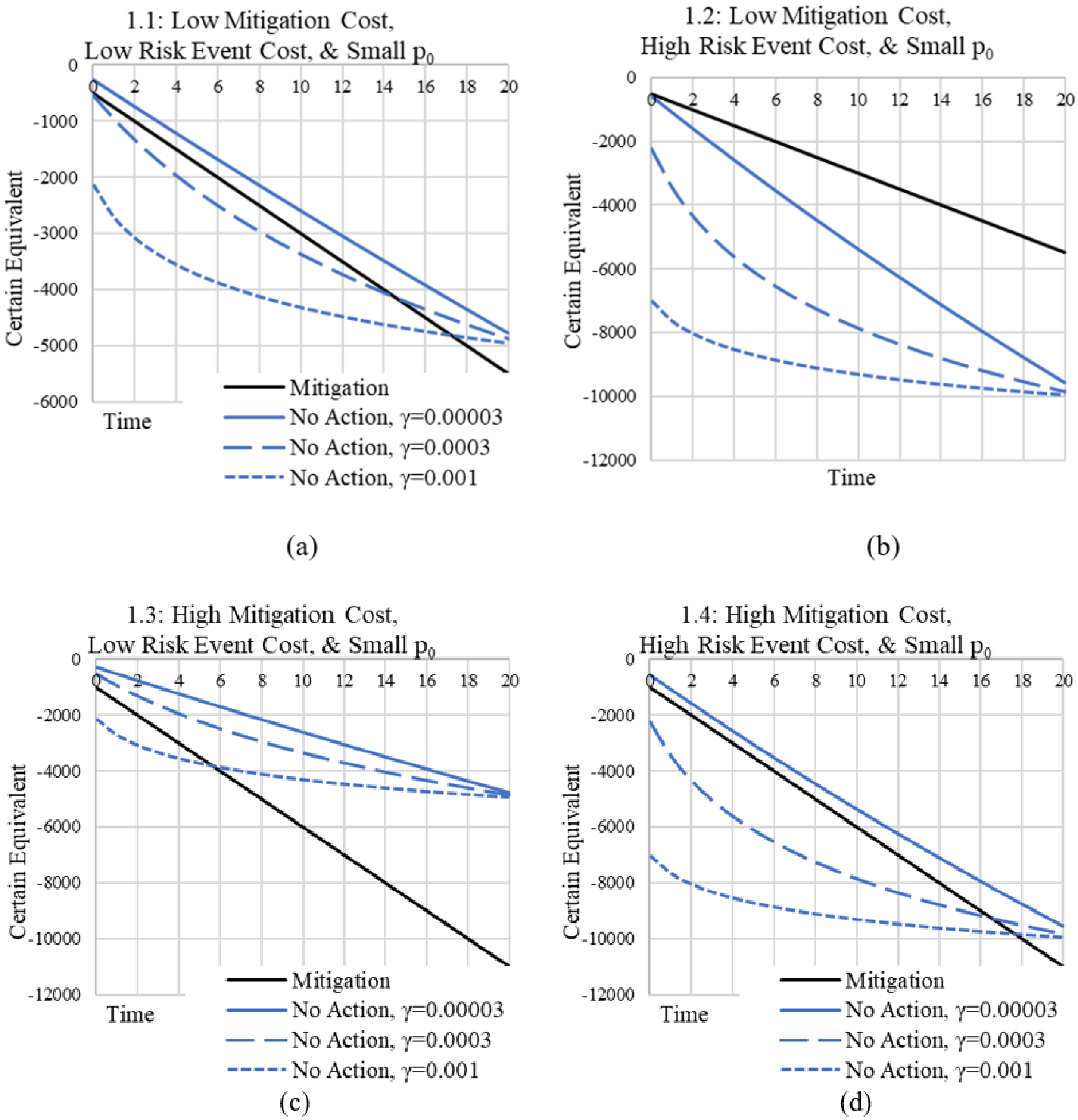


Figure 4.3 The certain equivalents for case 1 with variations on the parameters: 1.1 (a), 1.2 (b), 1.3 (c), 1.4 (d), 1.5 (e), 1.6 (f), 1.7 (g), and 1.8 (h)

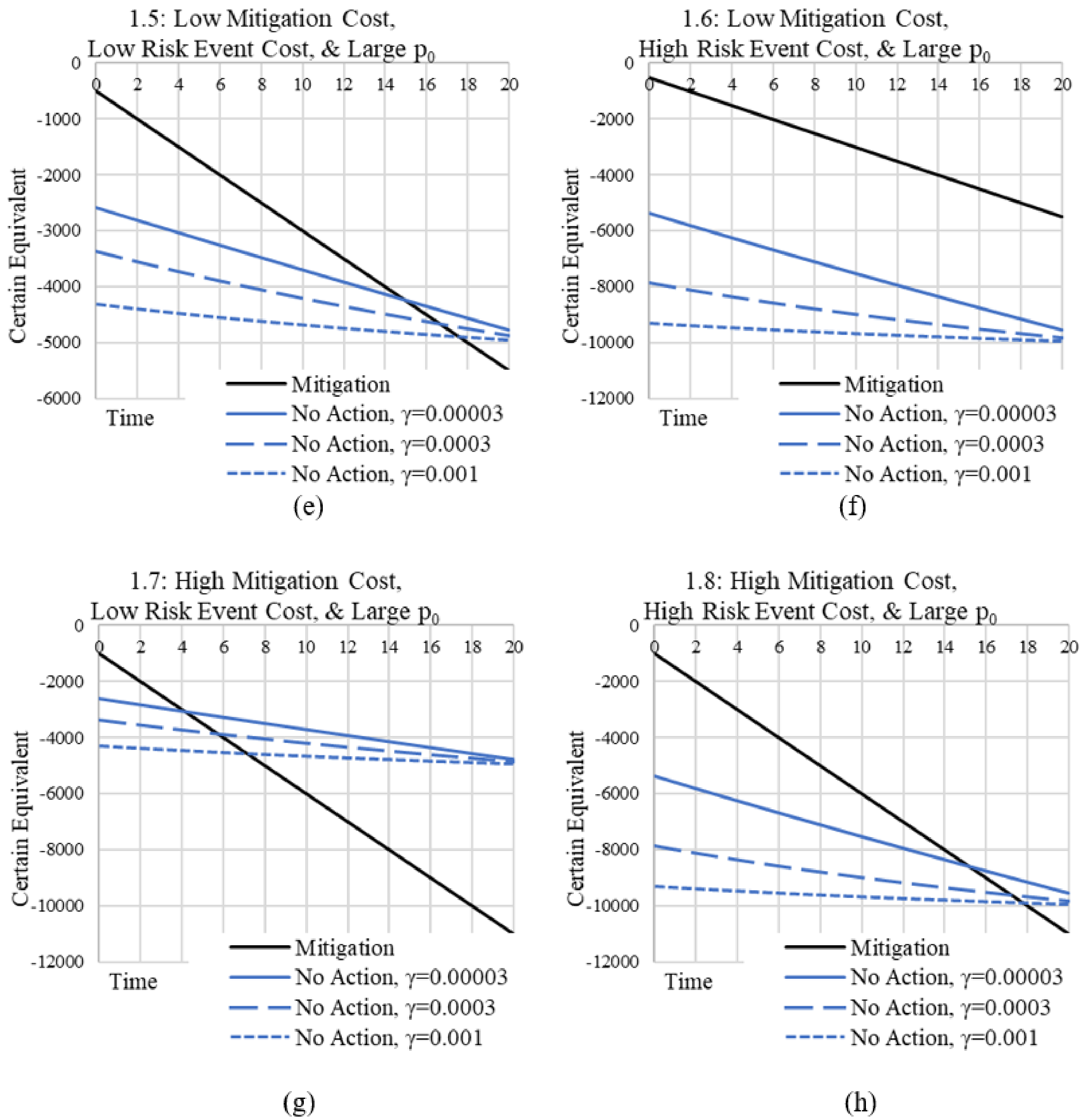


Figure 4.3 (cont.) The certain equivalents for case 1 with variations on the parameters: 1.1 (a), 1.2 (b), 1.3 (c), 1.4 (d), 1.5 (e), 1.6 (f), 1.7 (g), and 1.8 (h)

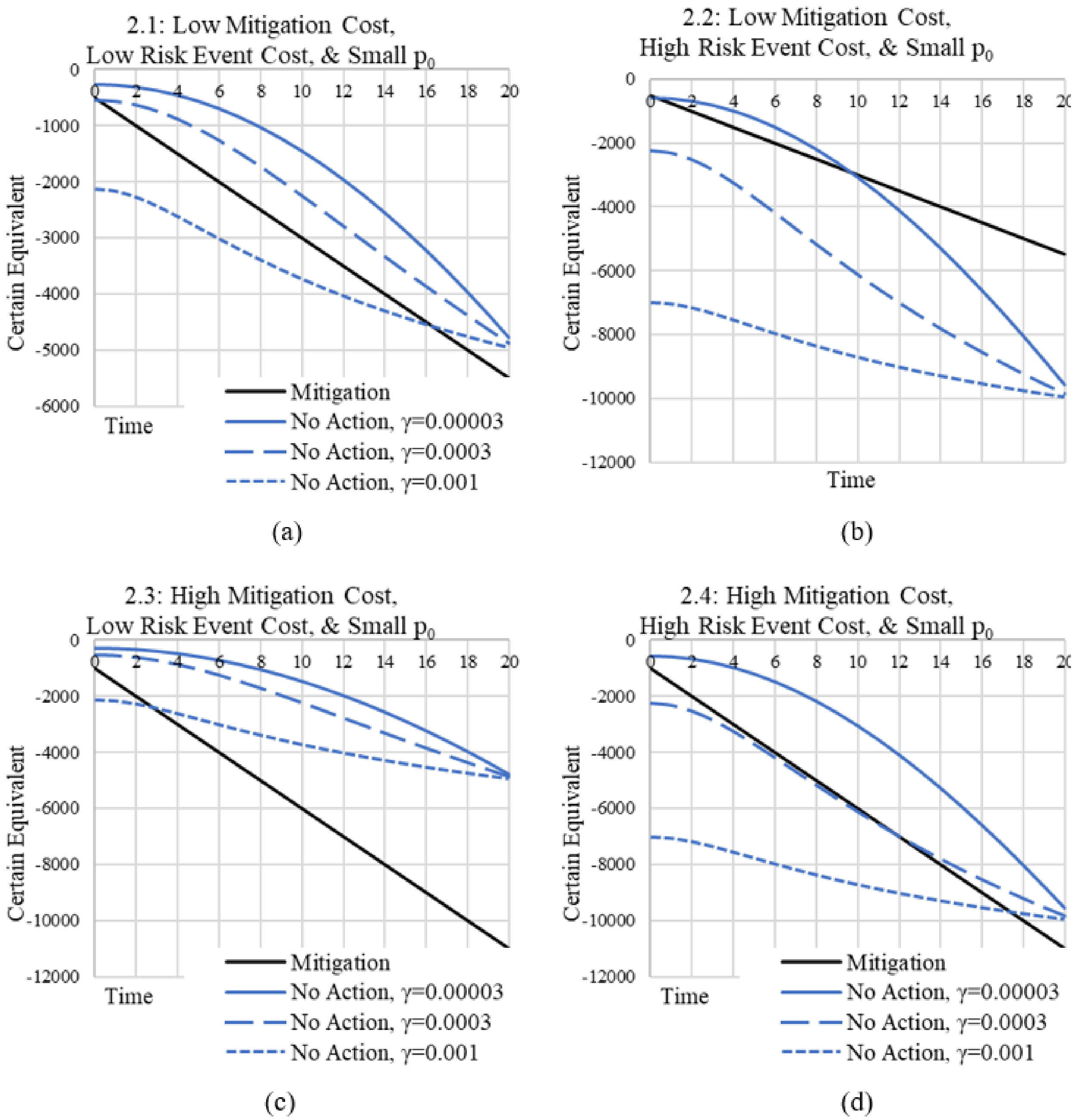


Figure 4.4 The certain equivalents for case 2 with variations on the parameters: 2.1 (a), 2.2 (b), 2.3 (c), 2.4 (d), 2.5 (e), 1.6 (f), 2.7 (g), and 2.8 (h)

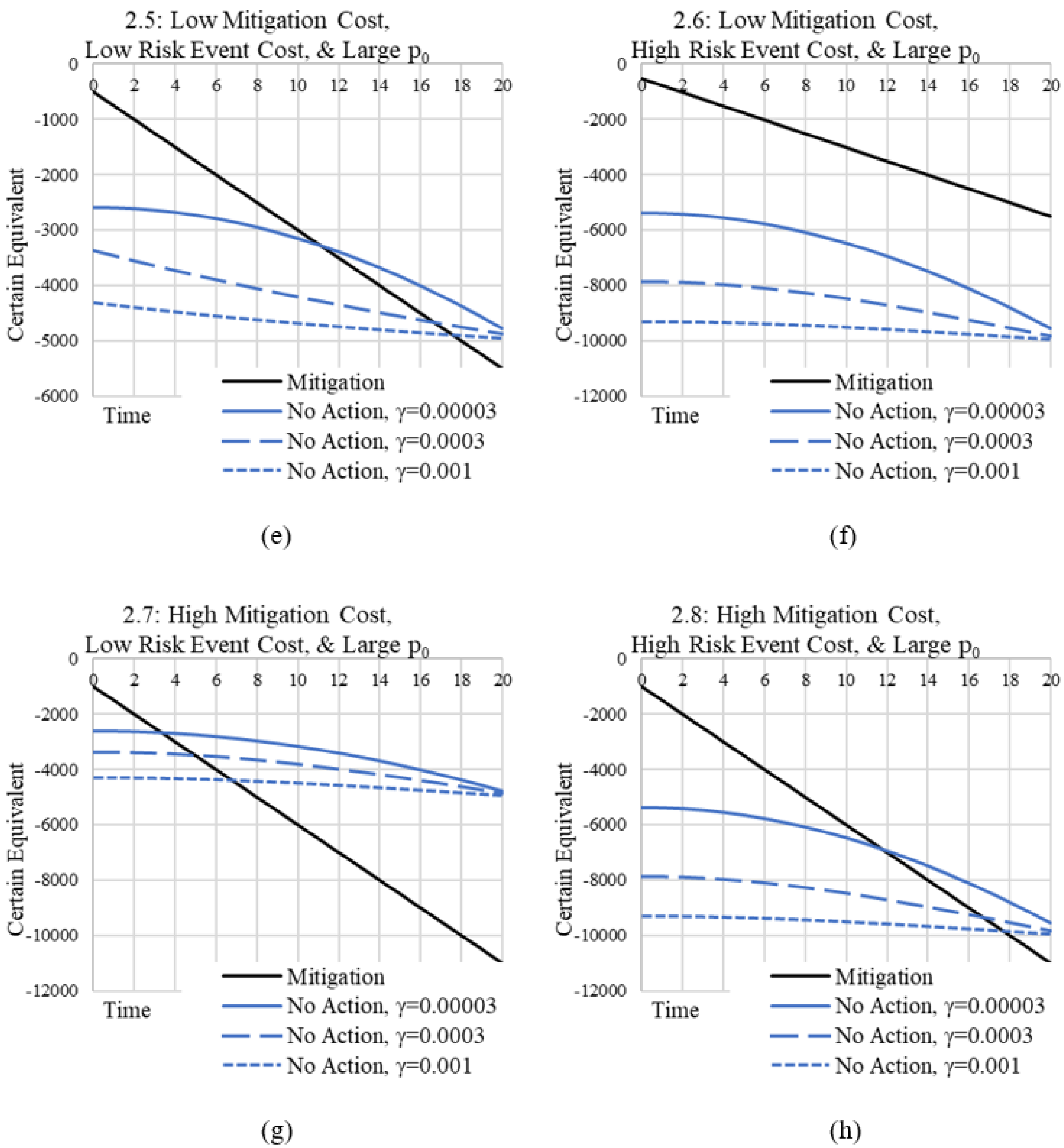


Figure 4.4 (cont.) The certain equivalents for case 2 with variations on the parameters: 2.1 (a), 2.2 (b), 2.3 (c), 2.4 (d), 2.5 (e), 1.6 (f), 2.7 (g), and 2.8 (h)

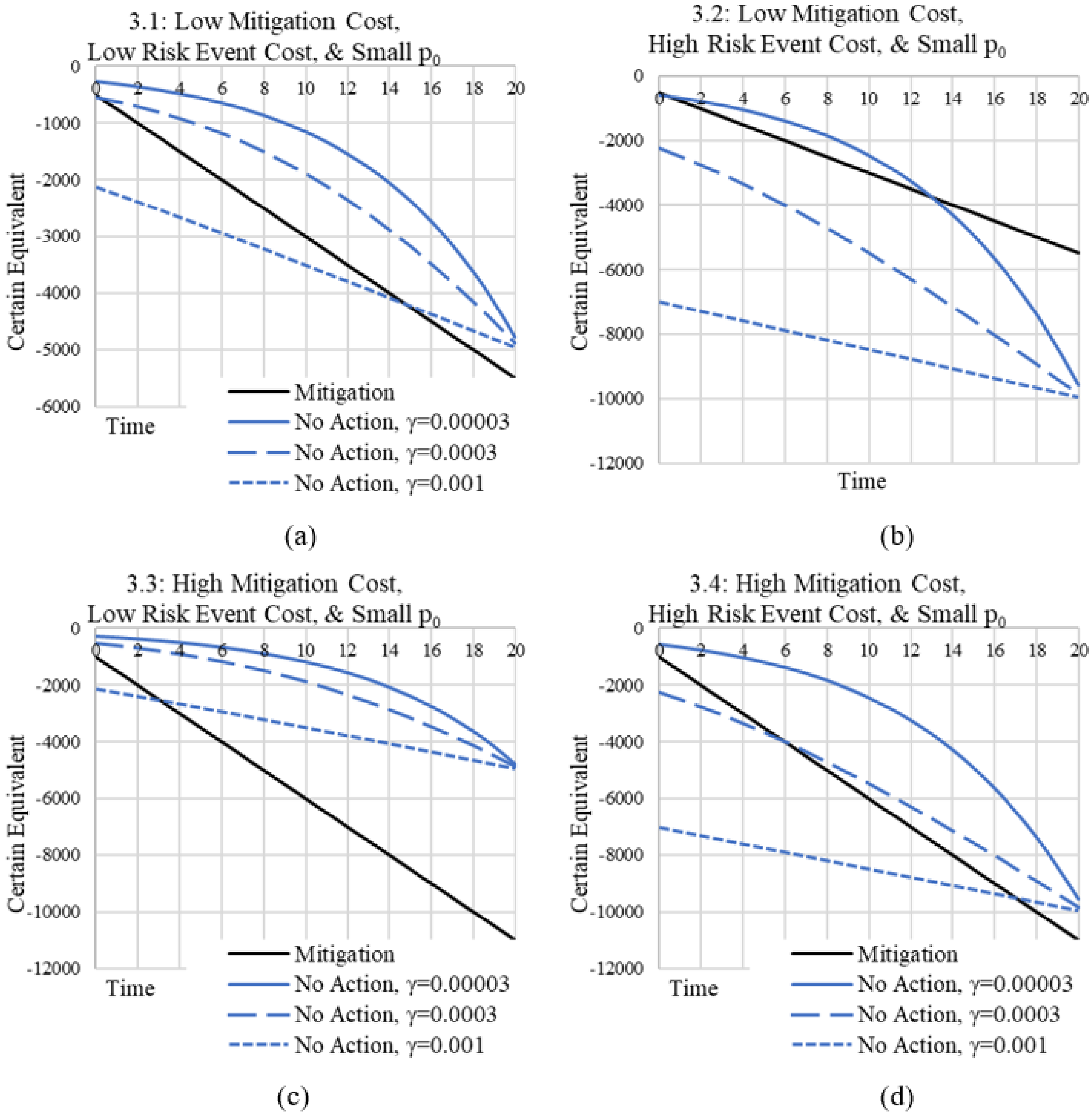
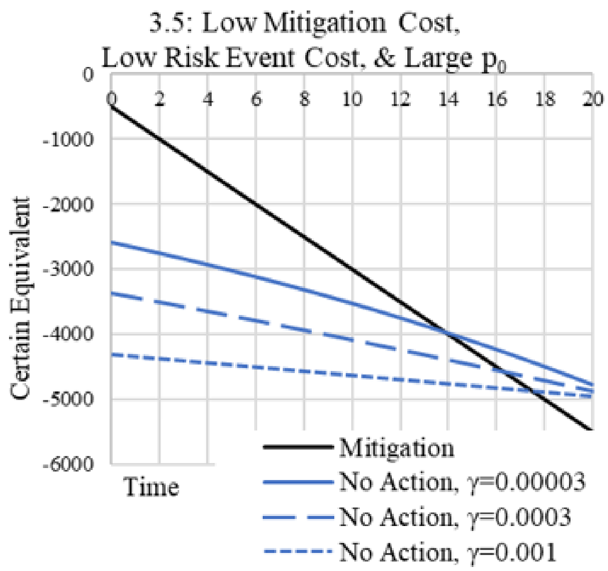
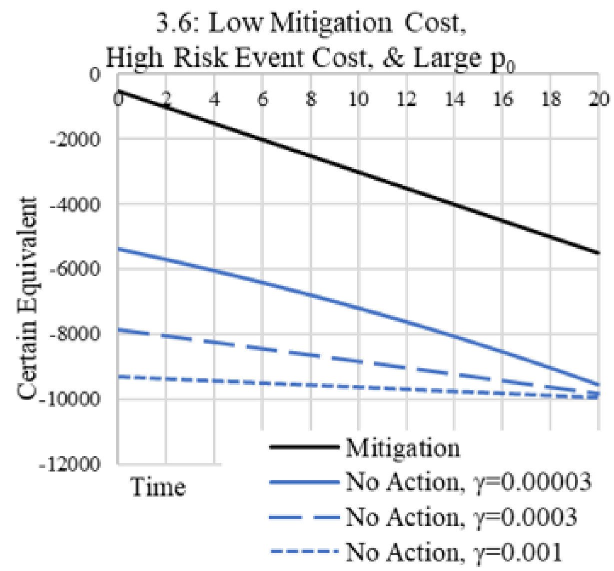


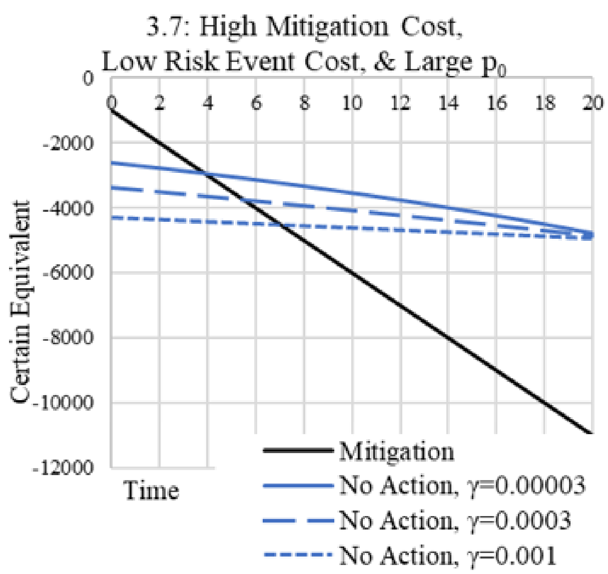
Figure 4.5 The certain equivalents for case 3 with variations on the parameters: 3.1 (a), 3.2 (b), 3.3 (c), 3.4 (d), 3.5 (e), 1.6 (f), 3.7 (g), and 3.8 (h)



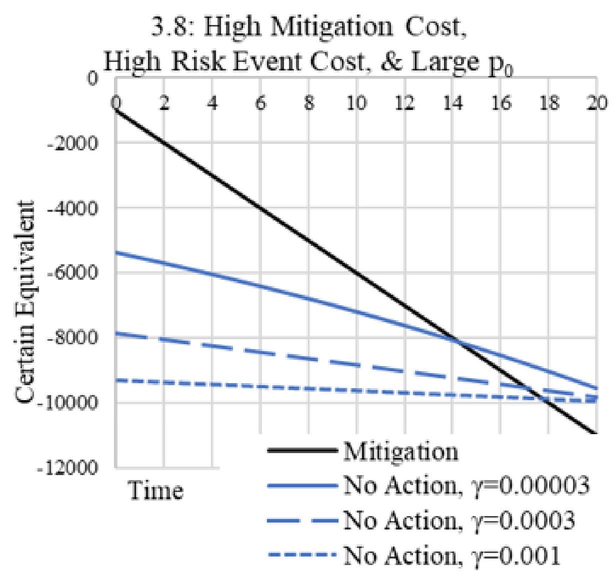
(e)



(f)



(g)



(h)

Figure 4.5 (cont.) The certain equivalents for case 3 with variations on the parameters: 3.1 (a), 3.2 (b), 3.3 (c), 3.4 (d), 3.5 (e), 1.6 (f), 3.7 (g), and 3.8 (h)

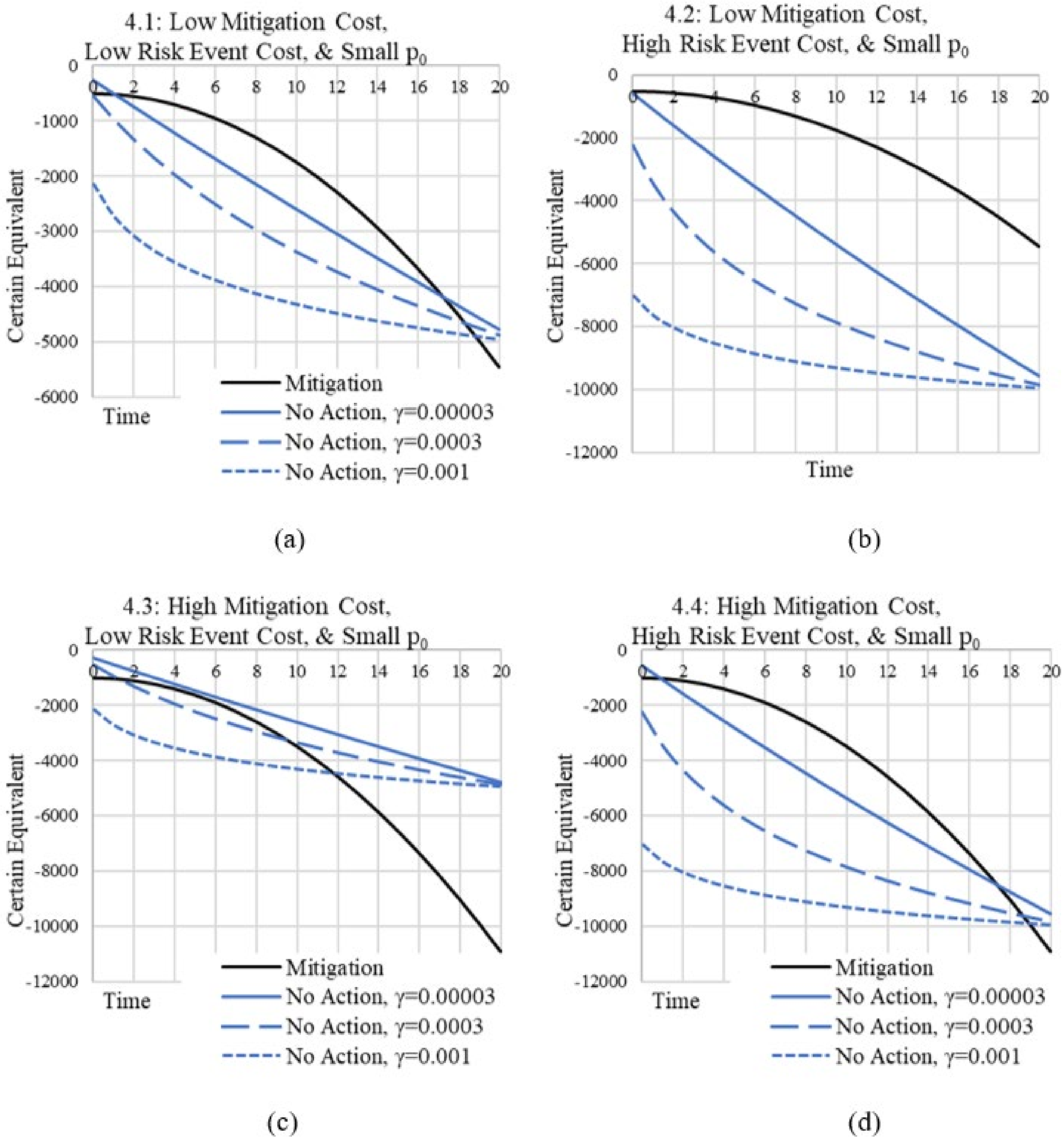
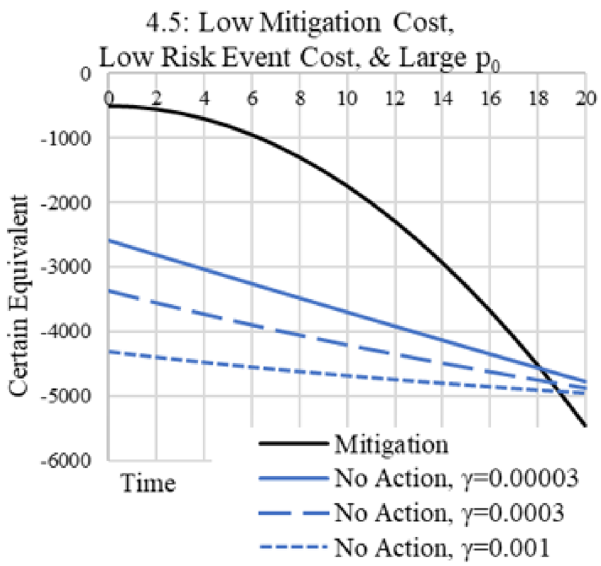
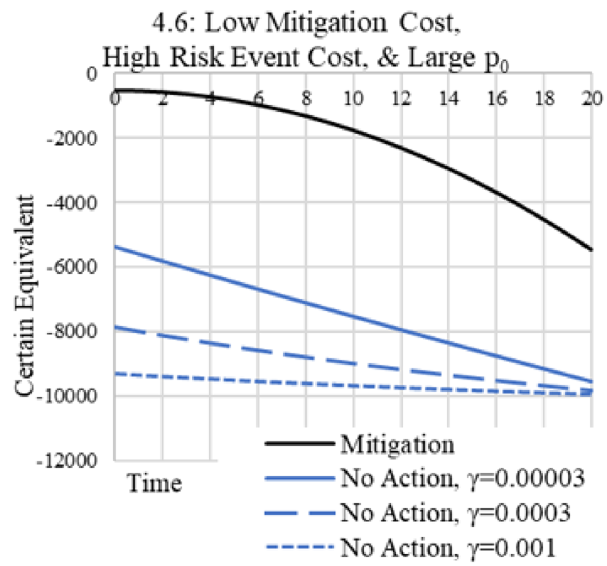


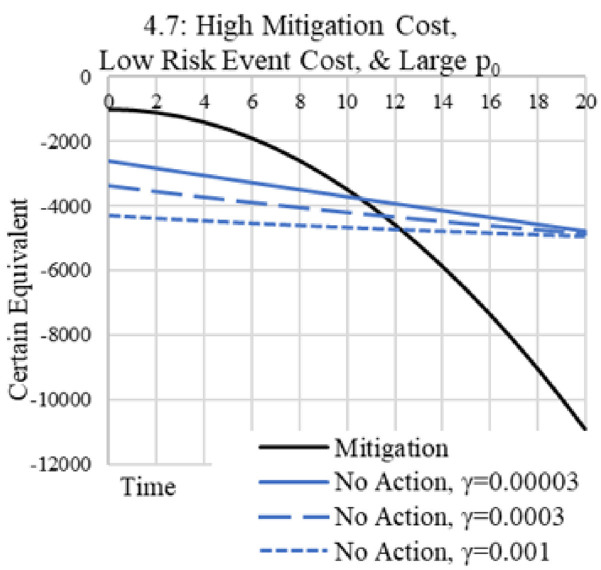
Figure 4.6 The certain equivalents for case 4 with variations on the parameters: 4.1 (a), 4.2 (b), 4.3 (c), 4.4 (d), 4.5 (e), 1.6 (f), 4.7 (g), and 4.8 (h)



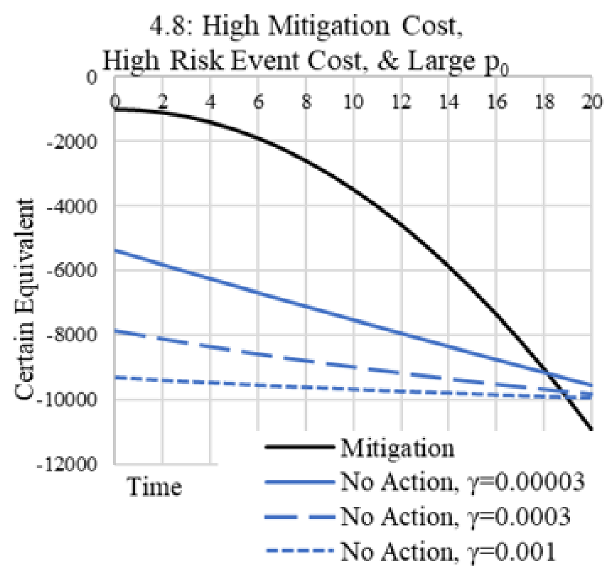
(e)



(f)



(g)



(h)

Figure 4.6 (cont.) The certain equivalents for case 4 with variations on the parameters: 4.1 (a), 4.2 (b), 4.3 (c), 4.4 (d), 4.5 (e), 1.6 (f), 4.7 (g), and 4.8 (h)

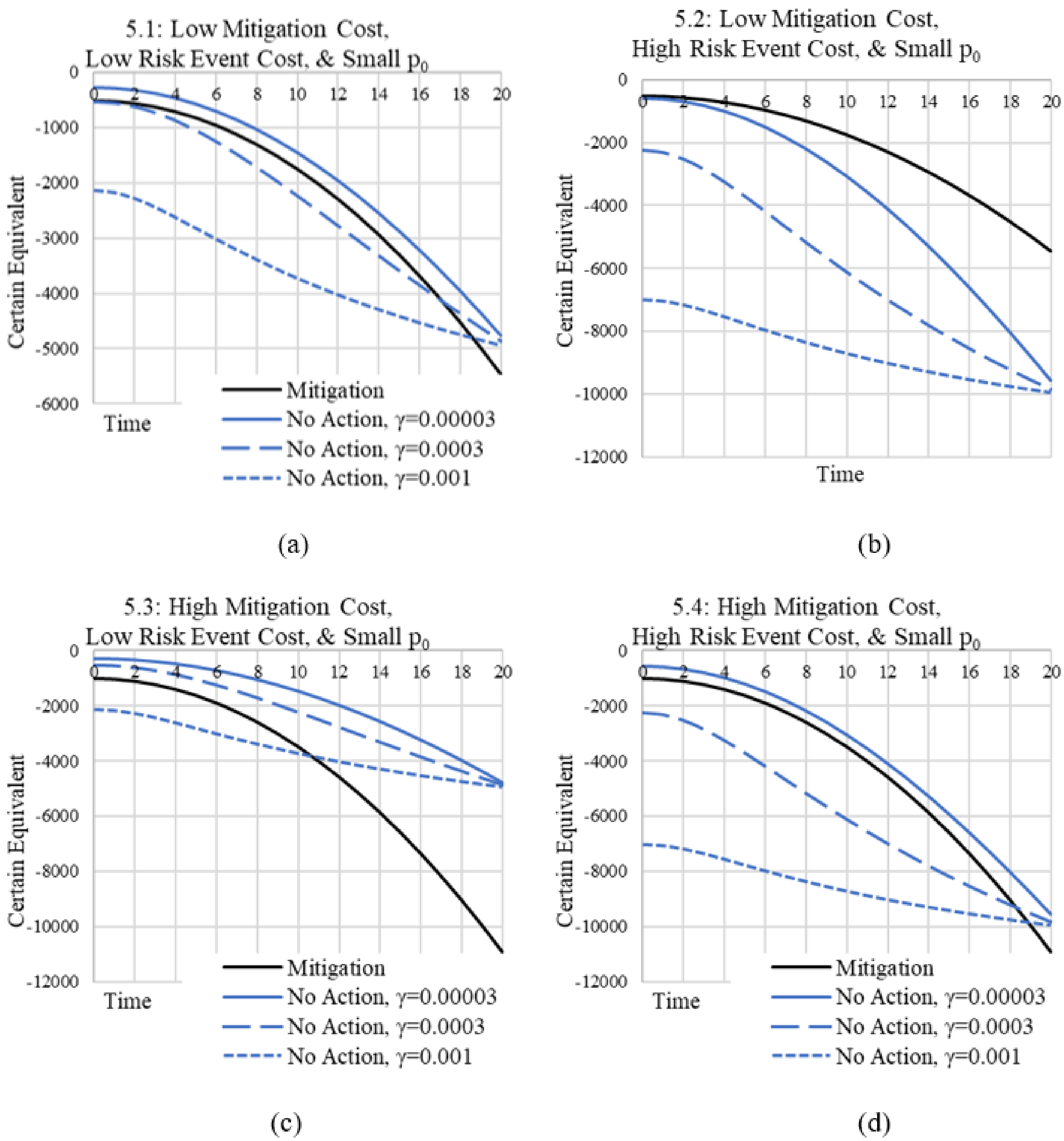


Figure 4.7 The certain equivalents for case 5 with variations on the parameters: 5.1 (a), 5.2 (b), 5.3 (c), 5.4 (d), 5.5 (e), 5.6 (f), 5.7 (g), and 5.8 (h)

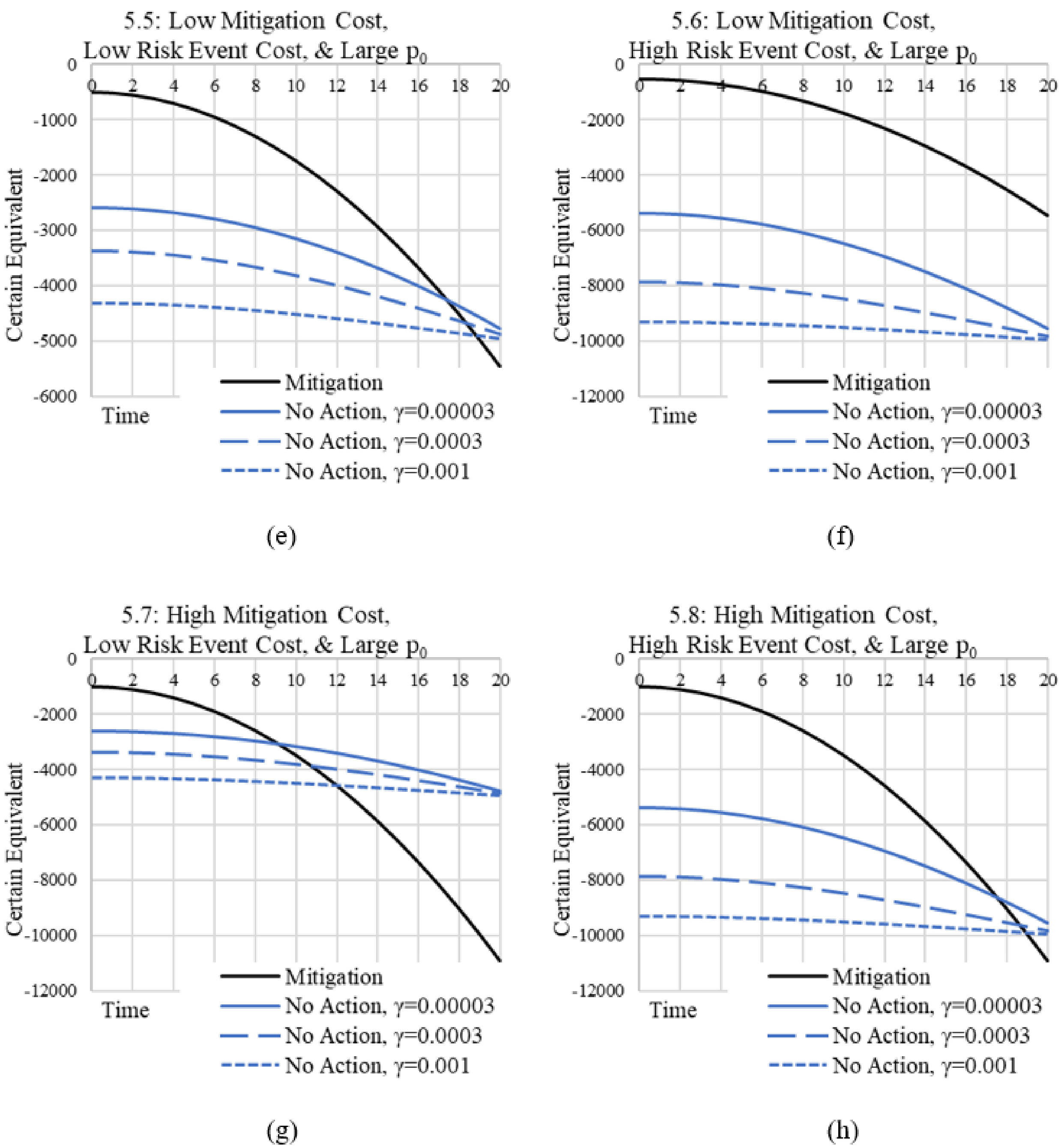
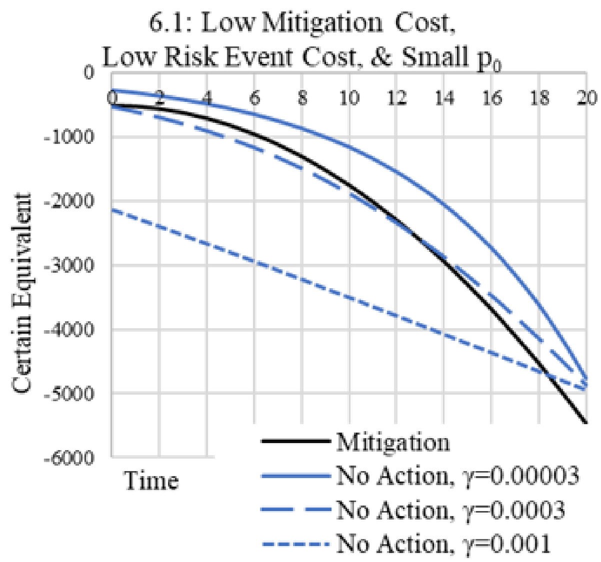
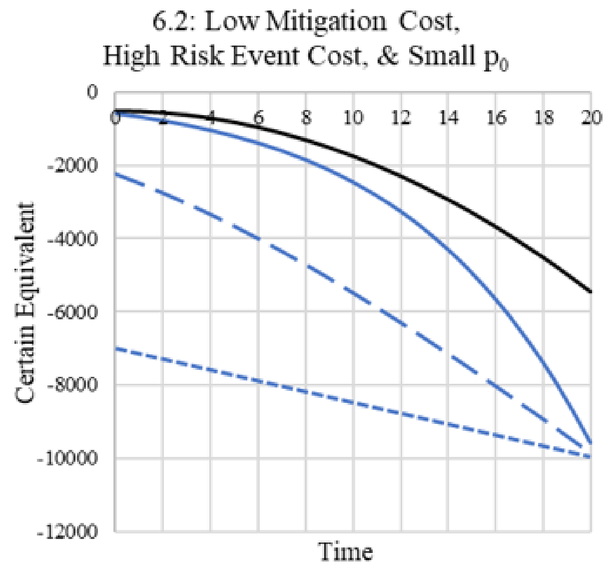


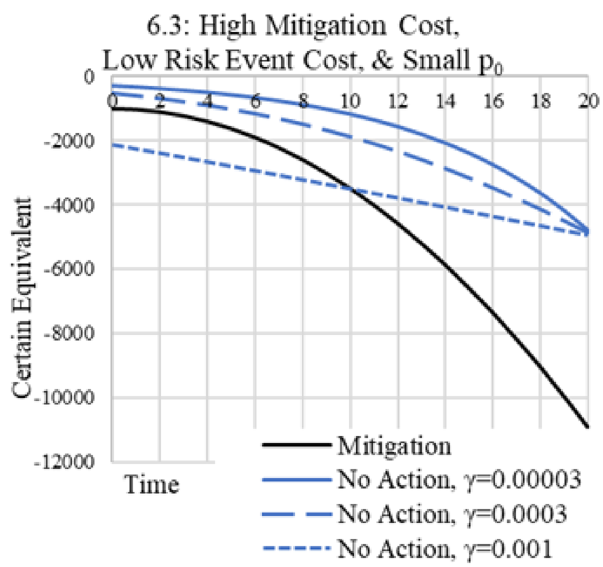
Figure 4.7 (cont.) The certain equivalents for case 5 with variations on the parameters: 5.1 (a), 5.2 (b), 5.3 (c), 5.4 (d), 5.5 (e), 5.6 (f), 5.7 (g), and 5.8 (h)



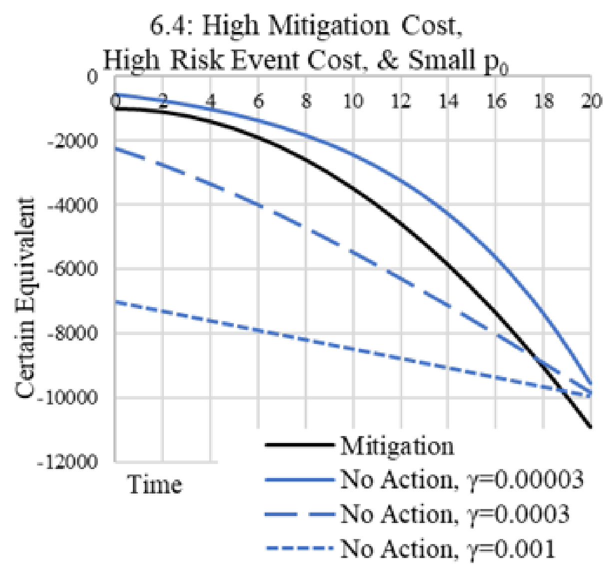
(a)



(b)



(c)



(d)

Figure 4.8 The certain equivalents for case 6 with variations on the parameters: 6.1 (a), 6.2 (b), 6.3 (c), 6.4 (d), 6.5 (e), 6.6 (f), 6.7 (g), and 6.8 (h)

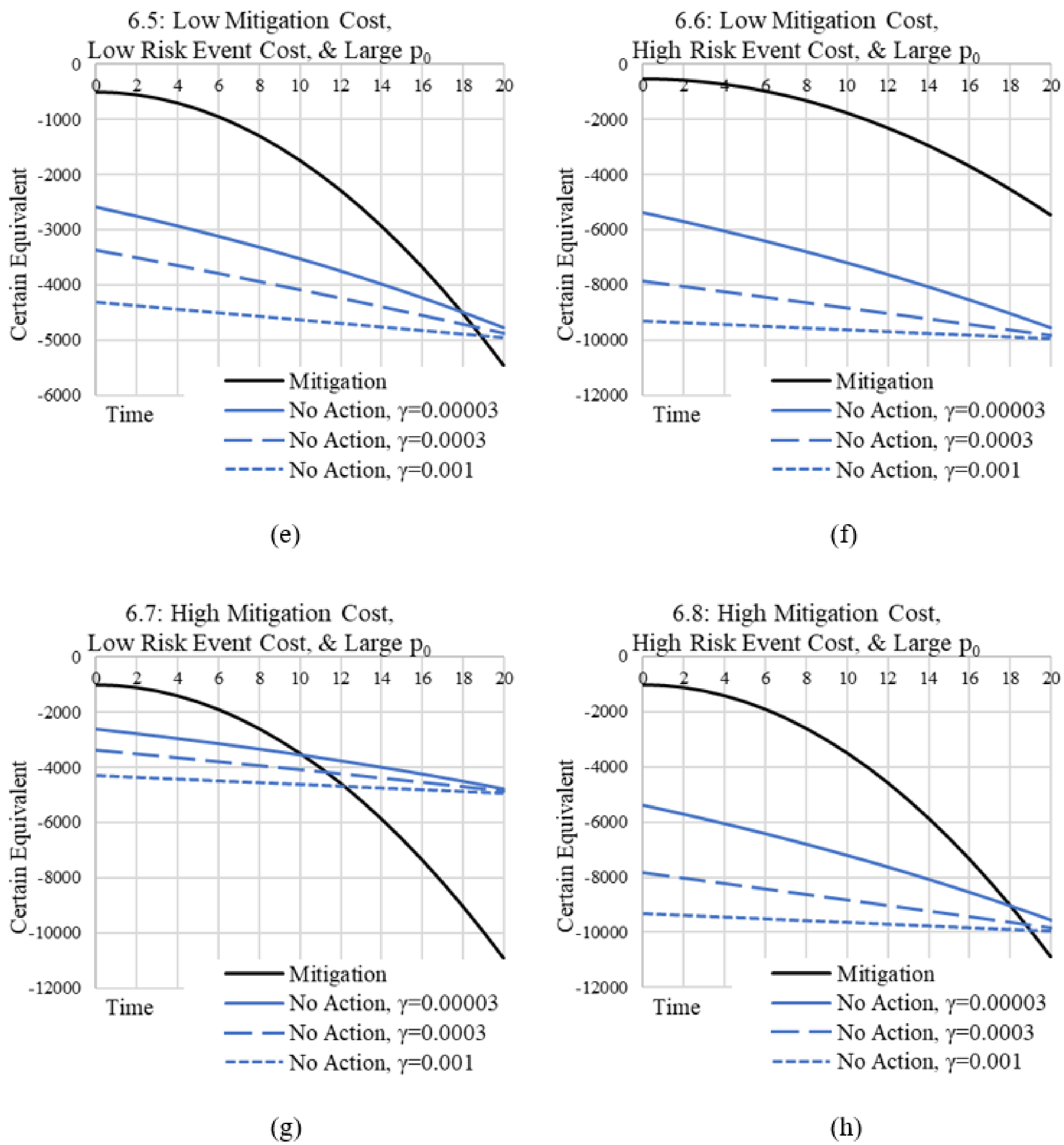


Figure 4.8 (cont.) The certain equivalents for case 6 with variations on the parameters: 6.1 (a), 6.2 (b), 6.3 (c), 6.4 (d), 6.5 (e), 6.6 (f), 6.7 (g), and 6.8 (h)

We observe that the results for cases 7 through 9, while not identical, follow similar trends as cases 4 through 6. To conserve space within the body of this report, we present these results within Appendix A, in Figure A.1, Figure A.2, and Figure A.3.

From the results in Figure 4.4 through Figure 4.8, as well as those in Figure A.1 to Figure A.3, we observe that for a risk event associated with high costs, the alternative 'take mitigating action' tends to dominant the 'no mitigating action' alternative, with some exceptions for the least risk averse decision makers and a small initial p_0. Similarly, we observe that a large initial p_0 consistently results in risk mitigation being the preferred alternative in early time periods. We suggest that extensions and future research focus on scenarios that involve a small initial p_0 and low risk event costs relative to the mitigation costs.

4.3 Extensions: Untrusted Information Source

The analysis is interested in the tradeoff between the accuracy of the prediction over time and reductions in the value available to the decision maker over time. However, the problem becomes more complicated in the event that the decision maker does not trust the information source. When analyzing this extension of the problem, we must also consider the ways in which a decision maker might adjust the probability estimates from the information source. We must specify some adjustment function, $a(p(t))$ that takes the probability estimate at time t, $p(t)$, and modifies it in some way. The resulting effect on the decision tree is illustrated in Figure 4.9. In Figure 4.9, the decision maker does not accept the estimated probability of the risk event as provided by the information source and instead implements an adjustment to the probability, denoted $a(p_t)$.

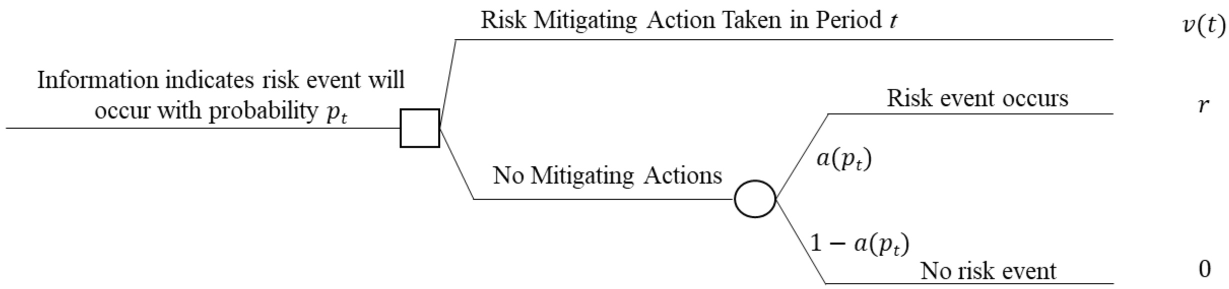


Figure 4.9 The single period, two-action decision tree when the probability from the information source is adjusted by the decision maker.

This extension adds degrees of freedom to the problem because there are many ways such an adjustment could conceivably occur. These adjustments that individuals make to probability estimates when they do not trust the information source represent a direction for future research that will be beneficial to the development of any decision support system.

4.4 Summary

This chapter explored single-period, two-action risk mitigation decisions where a decision maker must determine whether or not to act to mitigate a potential future risk event, such as an impending hurricane or other extreme weather event. We rely on decision analytic techniques including a decision tree framework to model the tradeoff between forecast accuracy over time and increasing costs of risk mitigation. Different functional forms—linear, quadratic, and exponential—were considered to describe the evolution of both the estimated probability of the risk event and the time-variable mitigation costs.

The results indicate that for high-cost risk events, taking mitigating action is generally the preferred strategy, particularly when the initial probability of the event occurring is high. The analysis also highlighted the impact of risk aversion, with more risk-averse decision makers favoring early mitigation even at higher costs. Cases with lower initial probabilities and lower event costs relative to mitigation costs present more nuanced decision tradeoffs, warranting further study.

This work suggests a few directions for future research. Identifying sources of empirical data to support methods to better understand and model the evolution of forecasts, and how and whether they improve over time, would be beneficial. Also, understanding how people perceive probability estimates from different information sources could be incorporated into the model to enable extensions to scenarios when an information source is not trusted. The work in this chapter provides insights to the tradeoffs of timing with changing estimates of risk event probabilities and changing costs, providing a useful initial step in the development of a decision support tool, but future work remains.

Chapter 5 Multiple Action Decisions to Mitigate Risk

Similar to the prior chapter, this chapter is again concerned with single time period risk mitigation decisions in which a risk event occurs within a single time period. However, we now consider the case in which the decision maker has multiple decision alternatives available and can make sequential decisions over multiple time periods about how best to mitigate the risk. These properties align with many situations encountered within supply and transportation networks. Within our work, we include a general framework for analysis of decisions within this context in which there is a tradeoff between forecast accuracy over time and value over time. We demonstrate how the framework can be applied through the analysis of an inventory decision, which serves as an illustrative example.

Inventory management is an important component of supply chain management and represents an important mechanism for mitigating the risk of disruptions within supply chains. These decisions also affect the volume of a product that must be shipped to a specific location and timing of those shipments, thereby impacting the transportation network. The newsvendor problem is a classic topic in the operations research literature (Arrow et al. 1951) with many variations (Qin et al. 2011). Researchers have examined the newsvendor problem and optimal product re-order levels in the case of an unknown demand distribution (Benzion et al. 2010; Katehakis et al. 2020) and with demand shocks (O'Neil et al. 2016). Other variations examined include multi-product inventory (Abdel-Malek and Areeratchakul 2007; Özler et al. 2009), stocking inventory at multiple locations (Yang et al. 2021; Govindarajan et al. 2021), stochastic lead times (Song et al. 2000; Wang and Tomlin 2009), and product substitutability (Zhang et al. 2021).

A distinguishing feature of our work is the consideration of the tradeoff between forecast accuracy and supply availability. We consider a single selling period with multiple time periods over which to observe signals and estimate demand (with increasing accuracy), and multiple time periods over which to order inventory (with decreasing likelihood of availability). This formulation reflects the experience of many retailers during the COVID-19 pandemic in which many factors contributed to supply disruptions and product shortages as companies could not obtain the desired inventory (Chowdhury et al. 2021). The consideration of uncertain supply availability relates this work to several studies in the literature, including Serel (2014), Kazaz and Webster (2015), Käki et al. (2015), Sayın et al. (2015), Ray and Jenamani (2016), Ma et al. (2016), and Zheng et al. (2023).

The remainder of this chapter presents the general framework for the analysis, the problem formulation for our variation of the newsvendor problem, and the results of sensitivity analysis.

5.1 General Problem Framework and Notation

We begin by outlining a framework to approach this type of problem. In this pursuit, we largely follow the three stages of decision analysis outlined by Howard (1968): deterministic, probabilistic, and informational. In this approach, the first stage is a deterministic analysis in which the decision scenario and its scope is defined, along with the available alternatives and relevant uncertainties. The second stage is the probabilistic analysis in which the probabilities are determined and preferences under uncertainty are specified. The third stage is informational analysis that examines what information is most useful to the decision maker. We follow these steps with the caveat that within our approach, we assume an element of time which makes the determination of the optimal timing of policies less clear. To emphasize this analysis, we add a stage between the probabilistic and informational stages that we call the sensitivity and policy analysis phase. This emphasis deviates from the representation by Howard (1968), in which sensitivity analysis was embedded in the other phases. This general framework is illustrated in Figure 5.1.

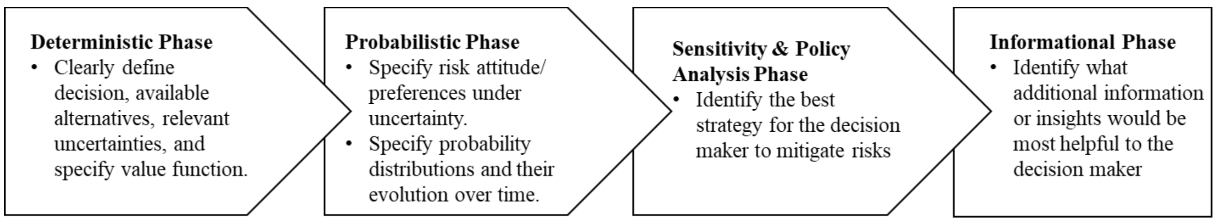


Figure 5.1 The general framework for the analysis.

Within our analysis, we focus on the sensitivity and policy analysis portion of the problem. By studying the best course of action with information accuracy increasing over time but the available alternatives decreasing, we can provide decision support to the decision maker as well as provide a means to provide insight to support a stronger analysis in the informational phase.

We assume the decision scenario is well-defined. The scenario involves an uncertainty with an associated random variable that impacts the value to the decision maker. The outcome of the uncertainty will be revealed in a future, known time window. This random variable represents an impact of the risk event. In the context of inventory problems, it is the stochastic demand. Action may be taken to mitigate the impact of the risk event across different time periods, but the total impact of risk mitigating actions can be represented by a single variable. In the context of inventory problems, the risk mitigation involves selecting an appropriate inventory level to meet the anticipated demand. We assume a value function can be specified that incorporates the impact of any random variable in addition to the action(s) taken by the decision maker.

Illustrative notation for this general framework will use variables selected for ease of interpretation within an inventory problem. We assume k total time periods. We assume the relevant uncertainty, D, has a probability distribution that changes over time. At time period t, the probability distribution over D is $f_D^t(d)$. The standard deviation is σ_D^t. We require that $\frac{d}{dt}(\sigma_D^t) < 0$. Any risk mitigating action taken in time period t can be represented by a scalar measurement and is denoted s_t. The total impact of mitigating actions at time t can be found as the sum of actions across all prior time periods, $S^t = \sum_{i=1}^{t} s_i$. Constraints on the actions are represented by a separate random variable, M, with observations in each time period denoted m_t. These variables place an upper bound constraint on the actions that may be taken by the decision maker, denoted as $s_t \leq m_t$. This constraint similarly has a probability distribution that changes over time and is denoted $f_M^t(M)$.

The value function can be specified and may include random variables. It is denoted $V(d, S^k)$. For this chapter, we assume a risk neutral decision maker. A unique characteristic of the risk neutral decision maker is that they value an uncertain deal by its expected value. Given some of the numeric complexities in the formulation of a newsvendor problem in which information is updated over time and product availability changes over time, this assumption improves the problem tractability. Thus, once we specify the value function, the decision maker is interested in the mean or the expected value of the value function for each alternative course of action.

Using this framework, we examine the tradeoff between forecast accuracy for an uncertainty of interest and the availability of risk mitigating alternatives under different conditions within the context of an inventory decision. First, we consider increasing forecast accuracy over time in isolation. Next, we consider both increasing forecast accuracy and stochastic availability of alternatives where the expected quantity of product available is decreasing.

5.2 Illustrative Example: An Inventory Decision

The newsvendor problem was introduced at the beginning of this chapter and serves as the basis for the deterministic phase of this analysis. A decision maker wants to maximize value by selling as many units of product as possible while having as few as possible leftover. Because the demand for the product is uncertain, this scenario represents a decision under uncertainty. It is a multiple action decision because the decision maker has many decision alternatives from which to select a course of action; each inventory level represents a different alternative. Within our formulation, each combination of inventory purchases at different time periods represents a different decision alternative. We use the newsvendor problem to illustrate issues within risk mitigation decisions broadly.

Within our analysis, we assume the following. The demand distribution is known for the current time period but not future time periods. Buying one unit of inventory costs b. The product is sold at price p. The cost per unit of having an insufficient inventory is c_u, where the subscript u is chosen to denote under-ordering. The cost per unit of having too much inventory is c_o, where the subscript o is chosen to indicate over-ordering.

Within a single time period problem, the optimal order quantity Q^*, for the risk neutral decision maker is found using the inverse of the demand distribution. Assuming a one period problem with a cumulative demand function $F_D(d)$ and inverse demand function $F_D^{-1}(d)$, the optimal order quantity is

$$Q^* = F_D^{-1}(\frac{c_u}{c_u + c_o}) \tag{5.1}$$

The ratio of underage costs to the sum of underage and overage costs is sometimes called the critical ratio given its central role in determining Q^*. This optimal order quantity is calculated to maximize the expected profit,

$$E[Profit] = p \cdot \min(Q, D) - b \cdot Q - c_o(Q - D)^+ - c_u(D - Q)^+ \tag{5.2}$$

where Q is the selected order quantity.

In the following two subsections, we consider how moving from a one-time period problem to a scenario in which the decision maker has multiple time periods over which to determine Q while estimated probability distributions over relevant uncertainties update in each time period, affect the optimal order quantity and expected value to the decision maker.

5.3 Increasingly Accurate Demand Forecasts

First, we consider the case of increasingly accurate demand forecasts. We model increasing accuracy in the demand distribution by specifying a decrease in the standard deviation of the demand distribution over time. We consider linearly decreasing standard deviations, $\frac{d}{dt}(\sigma_D^t) = \ constant$. Variations in the functional form of the decrease in the standard deviation is an opportunity for future research.

We observe that as σ_D decreases, the direction of change in the optimal order quantity depends on the relative size of c_o to c_u. In the case of $c_o < c_u$, the optimal order quantity will decrease due to the relatively larger penalty associated with over ordering. In this case, the increasingly limited availability of units to purchase will not have a limiting effect since the decision maker will already have ordered an optimal inventory quantity in the first time period that is greater than the updated value once the estimated probability distribution changes.

Ultimately, we are interested in the tradeoff between increasing forecast accuracy and decreasing available alternatives, we do not pursue this set of parameters further.

On the other hand, when $c_o > c_u$, the opposite is true. The optimal order quantity will increase as σ_D decreases, but this increase may be stymied by limited supply availability. The magnitude of the change in the optimal order quantity depends on the magnitude of the critical ratio. This effect is shown visually in Figure 5.2.

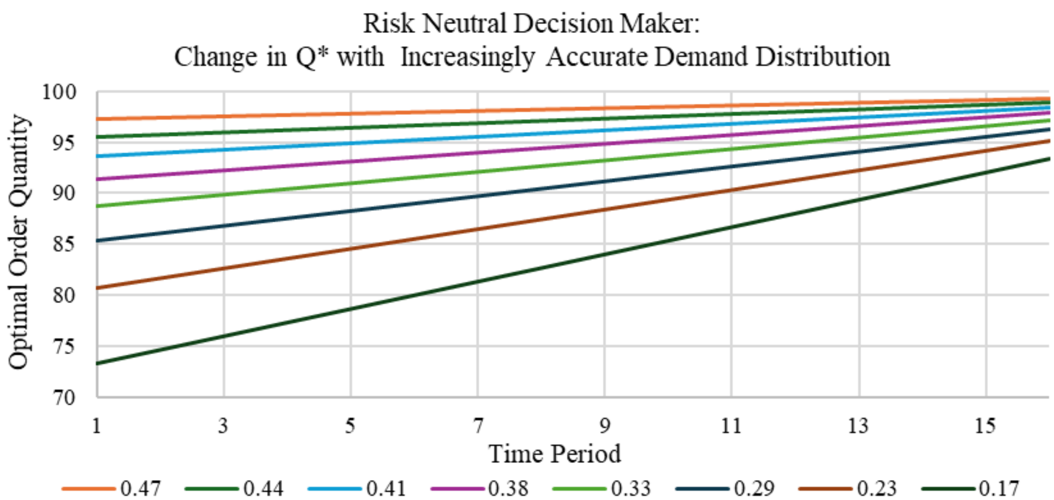


Figure 5.2 The changes in Q^* by critical ratio as demand forecast accuracy increases.

The calculations in Figure 5.2 use $\mu_D = 100$, $\sigma_D^1 = 20$, $\frac{d}{dt}(\sigma_D^t) = -1$, and $c_o = 10$. The underage cost c_u varies from eight to one to obtain critical ratios ranging from 0.47 to 0.17. As shown in Figure 5.2, when the critical ratio is smaller, indicating a larger difference between the underage and overage costs, the optimal order quantity is more sensitive to changes in the accuracy of the demand distribution.

5.4 Increasingly Accurate Demand Forecasts with Limited Product Availability

Next, we consider how changes in the availability of supply affect decision making. We assume the available supply of the product, or the maximum quantity available in the market follows a normal distribution with a constant standard deviation and decreasing mean over time. For each time period t, we denote the distribution $f_M^t(M)$. We assume that the mean decreases linearly with time, making $\frac{d}{dt}(\mu_M^t)$ a constant value. We truncate the distribution at 0.

To find the reduced value to the decision maker as a result of limited product availability, for each time period we must know the current expected inventory, $E_t[I]$, and the current optimal order quantity given the current demand forecast assuming no limitation in supply Q_t^*. Then, we calculate the probability that $E_t[I] < m_t < Q_t^*$ for each potential observation of M within time period t, denoted m_t. For each m_t, we must also find the associated expected profit when the order quantity is limited by m_t, enabling the calculation of the overall expected profit when supply is limited as specified by the model parameters.

We examine this problem numerically, considering the impact of both increasingly accurate demand forecasts and limited market availability of the product through sensitivity analysis. We begin by examining variations in the critical ratio of underage costs to the sum of underage and overage costs. For this initial examination, we use the demand and available supply parameters specified in Table 5.1 and vary the newsvendor problem parameters as specified in Table 5.2. We consider five different critical ratios and number each scenario 5.1.1 through 5.1.5.

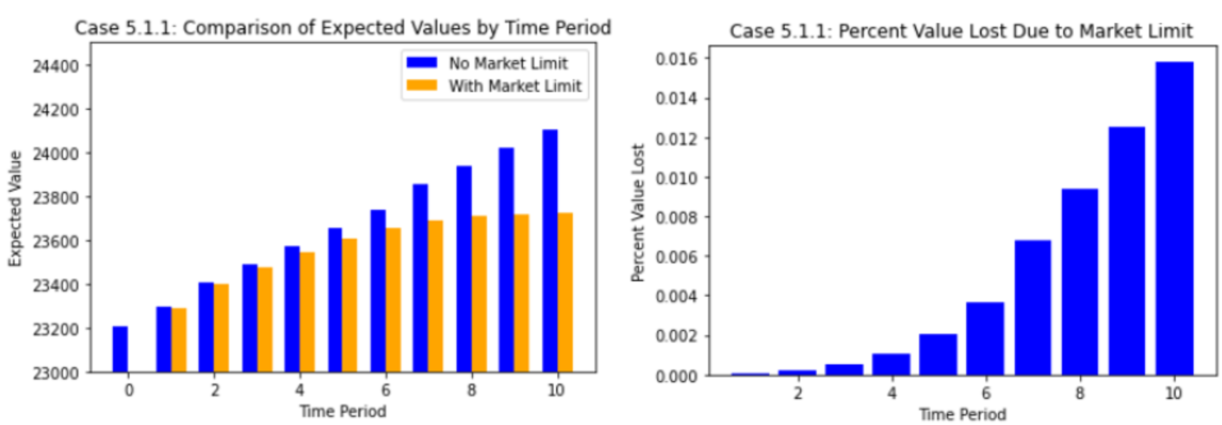
Table 5.1 The parameters that remain unchanged in the first five scenarios examined

Demand Parameters		Supply Limit Parameters		Newsvendor Parameters	
μ_D	1000	μ_M^0	1000	k	10
σ_D^0	200	σ_M	400	p	40
$\frac{d}{dt}(\sigma_D)$	-10	$\frac{d}{dt}(\mu_M)$	-100	b	15

Table 5.2 The parameters that change across the first five scenarios examined

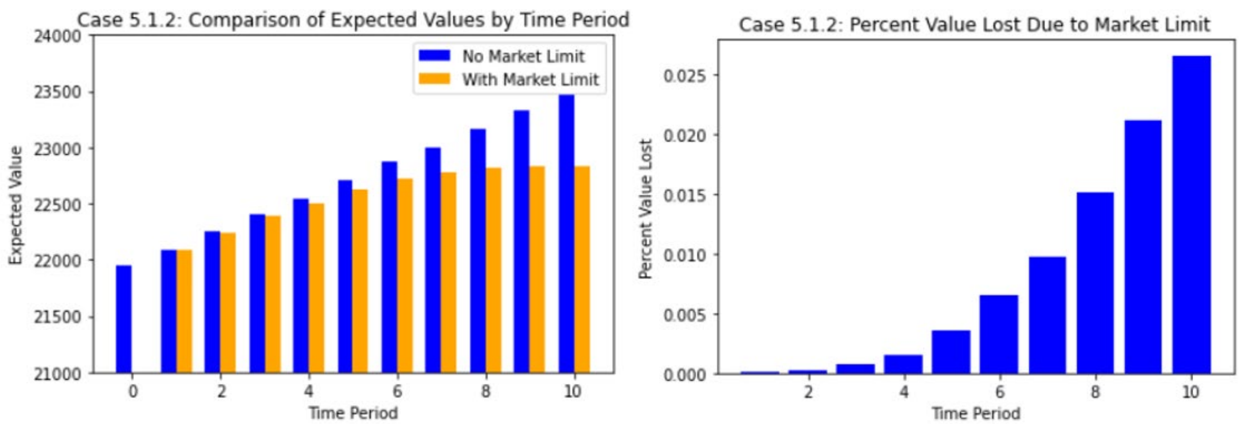
Case	c_u	c_o	$c_u/(c_u+c_o)$
5.1.1	3	5	0.375
5.1.2	2	5	0.286
5.1.3	1	5	0.167
5.1.4	0.5	5	0.091
5.1.5	0.25	5	0.048

The results for the five cases are shown in Figure 5.3 through Figure 5.7. They show that smaller critical ratios are associated with larger percentages of lost expected value.



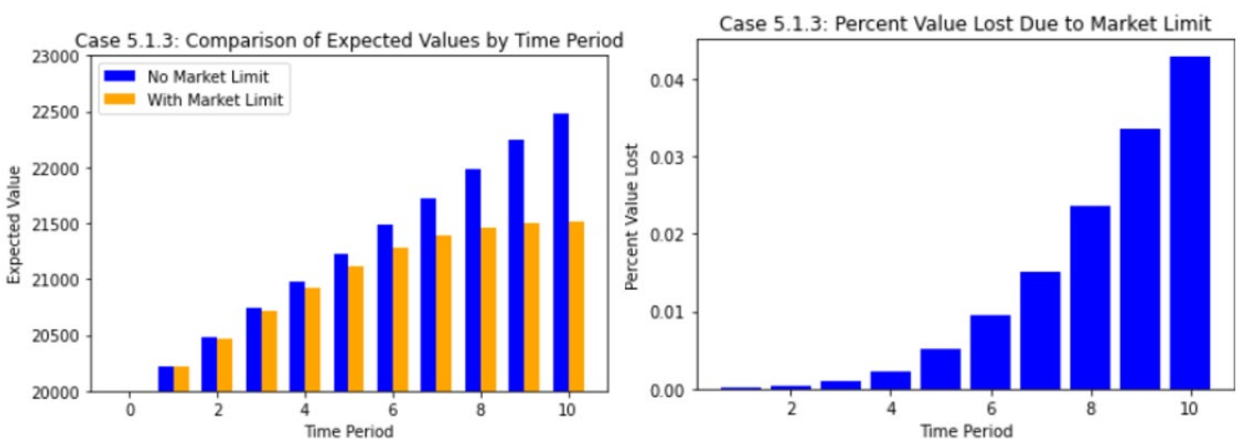
(a) (b)

Figure 5.3 Changes in expected value for case 5.1.1, shown as (a) the magnitude in dollars and (b) the percent value lost when supply is limited.



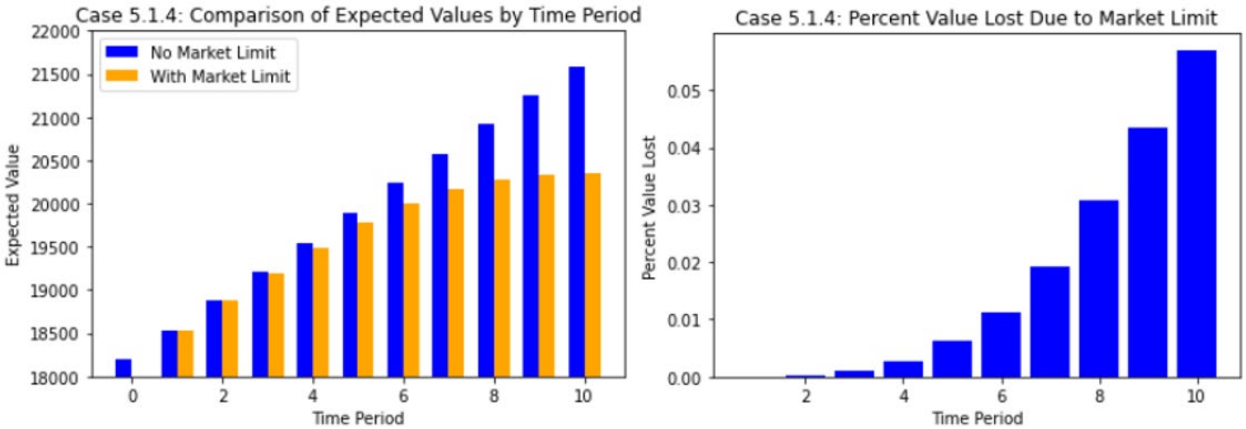
(a) (b)

Figure 5.4 Changes in expected value for case 5.1.2, shown as (a) the magnitude in dollars and (b) the percent value lost when supply is limited.



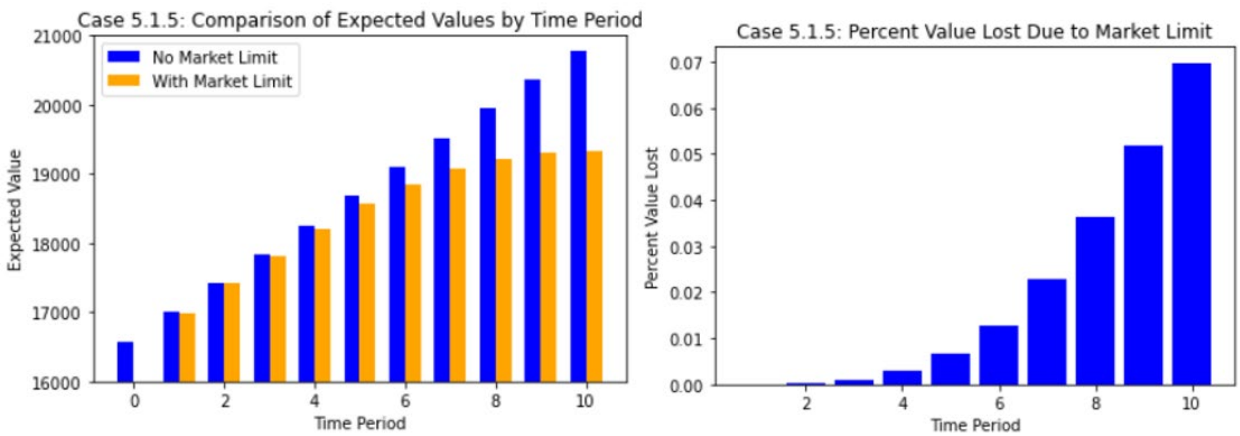
(a) (b)

Figure 5.5 Changes in expected value for case 5.1.3, shown as (a) the magnitude in dollars and (b) the percent value lost when supply is limited.



(a) (b)

Figure 5.6 Changes in expected value for case 5.1.4, shown as (a) the magnitude in dollars and (b) the percent value lost when supply is limited.



(a) (b)

Figure 5.7 Changes in expected value for case 5.1.5, shown as (a) the magnitude in dollars and (b) the percent value lost when supply is limited.

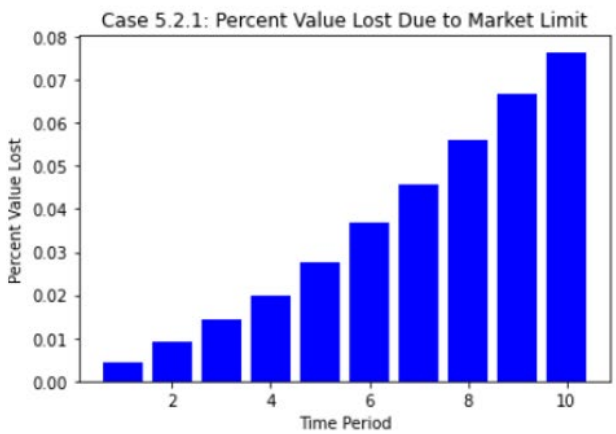
We are also interested in how changes in the properties of the limited supply of inventory affect decision making. We consider another set of five scenarios and modify the initial mean supply of inventory to be a multiple of the mean demand. We then reduce the mean supply of inventory by a step such that by the last time period, the mean is zero. We use $c_o = 5$ and $c_o =$

1, along with the same newsvendor parameters as the previous cases. Table 5.3 shows the initial distribution mean of the available supply for each scenario now considered, and the resulting time period decrement for each.

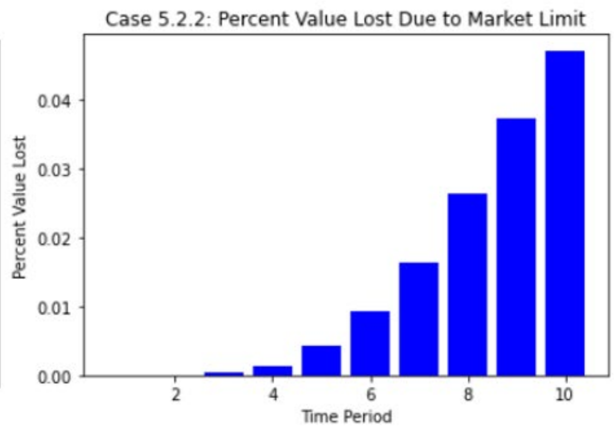
Table 5.3 The change in parameters describing available supply

Case	μ_D	σ_D^0	$\frac{d}{dt}(\sigma_D)$	μ_M^0	σ_M	$\frac{d}{dt}(\mu_M)$
5.2.1	1000	200	-10	1000	300	-100
5.2.2	1000	200	-10	2000	300	-200
5.2.3	1000	200	-10	3000	300	-300
5.2.4	1000	200	-10	4000	300	-400
5.2.5	1000	200	-10	5000	300	-500

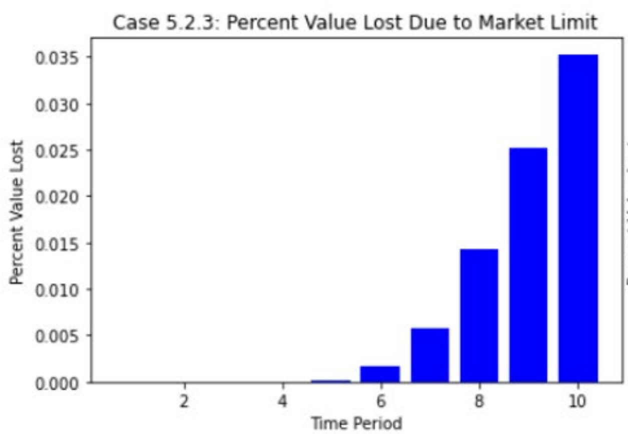
The effect of this change on the percentage expected value lost is shown in Figure 5.8(a-e).



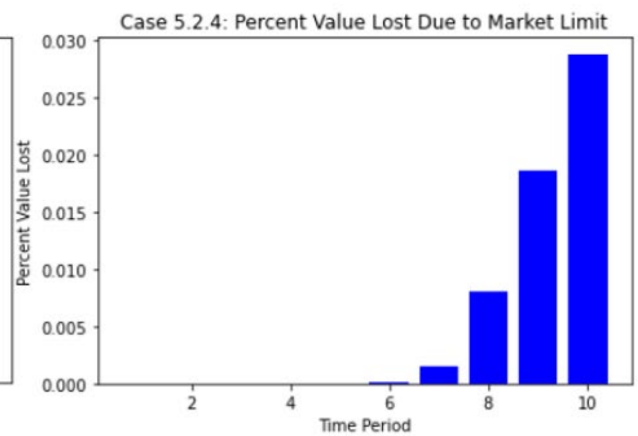
(a)



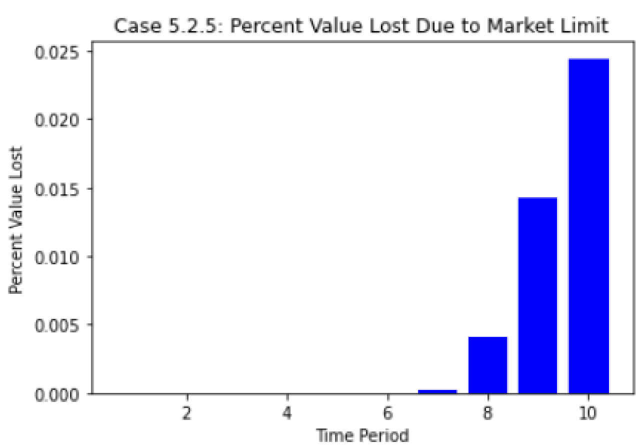
(b)



(c)



(d)



(e)

Figure 5.8 Changes in the percentage value lost for scenarios 5.2.1 (a) through 5.2.5 (e), showing increases in the initial supply but with faster reductions in availability.

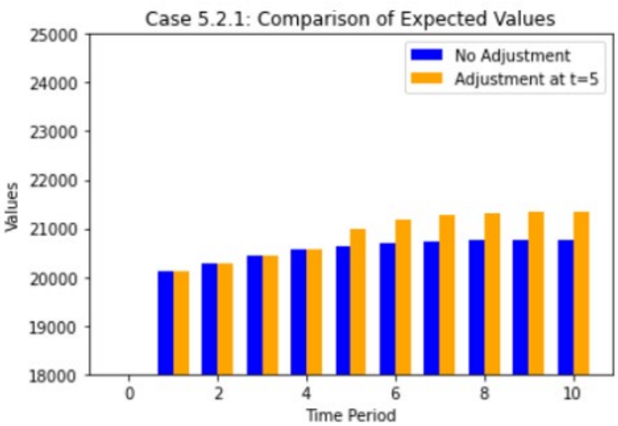
From these results, we observe that the availability of supply in the initial time periods plays an important role in determining the overall percentage value loss. The results also show how reductions in the availability of supply can have a large impact on the value observed by the decision maker.

5.5 Early Risk Mitigation

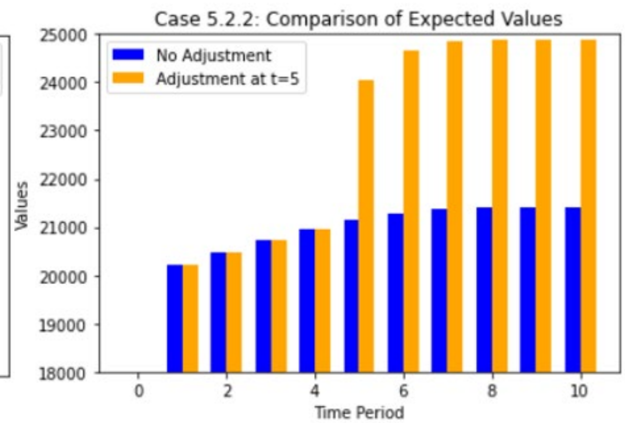
We consider the advantage garnered by a decision maker who observes changes in the marketplace in the early time periods and decides to increase their inventory holding proactively. Under some conditions, it might also be possible that tightened supply availability is correlated with high demand. If the decision maker believes there is reason for such a correlation to exist, then they may select a larger amount by which to increase their chosen inventory level.

To examine the advantages accrued to the decision maker who observes changes in the market early, we reexamine scenarios 5.2.1 through 5.2.5 in the case that the decision maker makes an adjustment to their strategy at time $t = 5$. We consider the case when the decision maker observes tightening supply in the market and uses this observation to update their belief about the demand distribution; we assume the decision maker increases their estimate of the mean demand μ_D by an amount equal to the initial standard deviation of the distribution, σ_D^0. Because we assume demand is normally distributed, this modification is equivalent to the decision maker determining that the initial (approximately) 84th percentile of the demand distribution actually represents the mean of the demand distribution. In other words, the decision maker believes the initial demand distribution underestimated the actual demand for the product. Given this updated estimate of the demand distribution, the decision maker will increase their desired inventory level according to equation 5.1, where the inverse demand distribution is updated to reflect the updated belief over the mean.

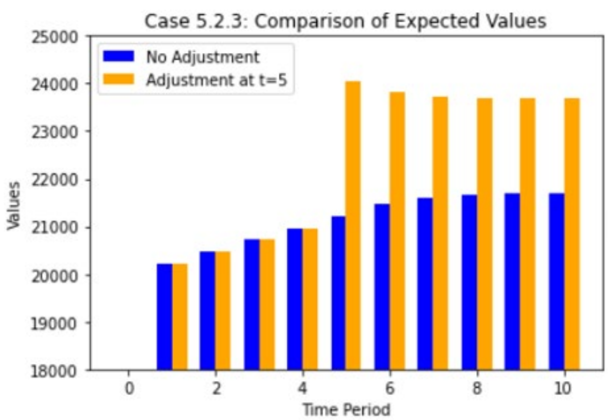
Care must be taken when calculating the resulting expected value from this adjustment to the inventory strategy. The expected value is calculated based on the decision maker's belief of the probability distributions. The use of two separate distributions would be similar to using two different systems of measurement when making a comparison. To ensure a fair comparison, we must be consistent in the selected parameters. Because we are using the initial situation as the baseline, we use the original problem parameters when calculating the expected value. In the adjusted strategy, the expected inventory quantity may also exceed the expected demand. In this case, the overage penalty will apply, penalizing inventory levels that are too large. For this analysis, we only consider the case of limited product supply and compare the two decision making strategies. The results for scenarios 5.2.1 through 5.2.5 are shown in Figure 5.9(a-e). In all cases, the expected value in the final time period is higher when the decision maker adjusts the inventory strategy at the midpoint in time after observing the changes in the distributions in the early time periods.



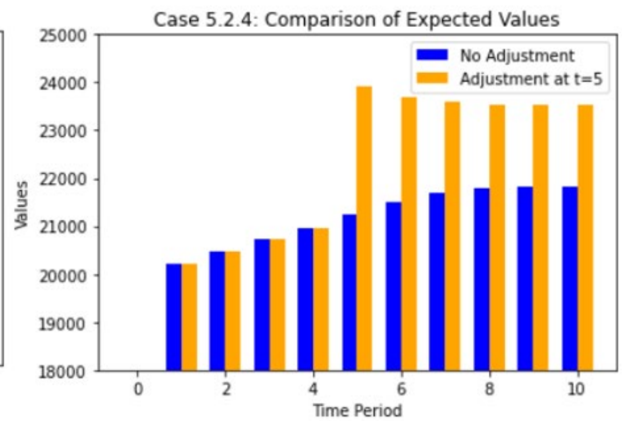
(a)



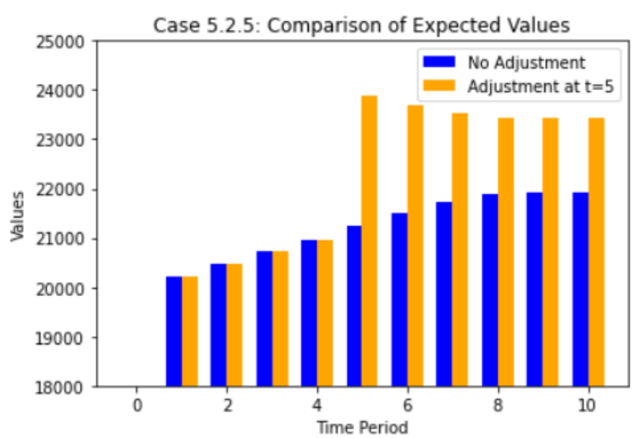
(b)



(c)



(d)



(e)

Figure 5.9 Comparison of the expected value with limited supply availability with and without an adjustment to strategy at time t=5, for scenarios 5.2.1 (a) through 5.2.5 (e).

5.6 Summary

This chapter explored multiple action risk mitigation decisions where the mitigating actions are taken sequentially over time. An inventory decision is used to illustrate the tradeoffs between increasing forecast accuracy and reductions in available decision alternatives over time. The results underscore the important role played by specifications of the decision maker's belief about factors relevant to the decision scenario. Differences in the parameters describing the reduction in available supply of the product result in markedly different expected values. Thus, differences in belief over how the market and available supply is changing will play important roles in changing what quantity of inventory is determined to be optimal.

This chapter has also examined the impact of early adjustments in risk mitigation strategy. If the decision maker notices early indications that the supply is tightening, and interprets that to indicate a higher demand, then the resulting shift in belief over the demand distribution enables the decision maker to avoid lost value due to the inability to source the product.

Although this chapter examines an inventory problem, the results suggest that the tradeoff between accuracy of probability estimates and changes in the availability of decision alternatives provides a rich environment for study. Given the different pull of these two effects, it is not immediately obvious in any given scenario what the optimal course of action should be, suggesting that these scenarios would benefit from enhanced decision support tools. This work provides a proof-of-concept for the need to examine this problem more closely. This work also underscores the importance of future studies that include the identification of available empirical data relevant to these types of situations and the development of models to reflect this situation in a variety of real-world settings.

Chapter 6 Conclusion

This work has examined the tradeoffs in risk mitigation decisions, beginning by reviewing them in the domain of supply chain and transportation networks and by identifying the relative time frame for the implementation and realization of the outcomes of those decisions. The remainder of the work focused on short term risk mitigation scenarios in which the decision maker would need to balance increasingly accurate information sources with fewer decision alternatives.

Key outcomes of the research include the development of a general framework for analyzing both one-time and sequential risk mitigation decisions. These frameworks lay the groundwork for dynamic decision support tools to improve the management of transportation systems with the goal of improving both efficiency and safety.

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Appendix A Additional Results on the Two-Action Decision Problem

This appendix contains additional results from the analysis of the one-period, two-action decision problem in Chapter 4 for when the decision maker accepts the probability estimates from the information source as provided. This appendix refers to the case numbers for each combination of governing equations in Table 4.1, followed by the combination parameter specifications listed in Table 4.2.

The results for case 7, with exponential time-varying risk mitigation costs and a linearly increasing estimated probability of the risk event occurring, are shown in Figure A.1.

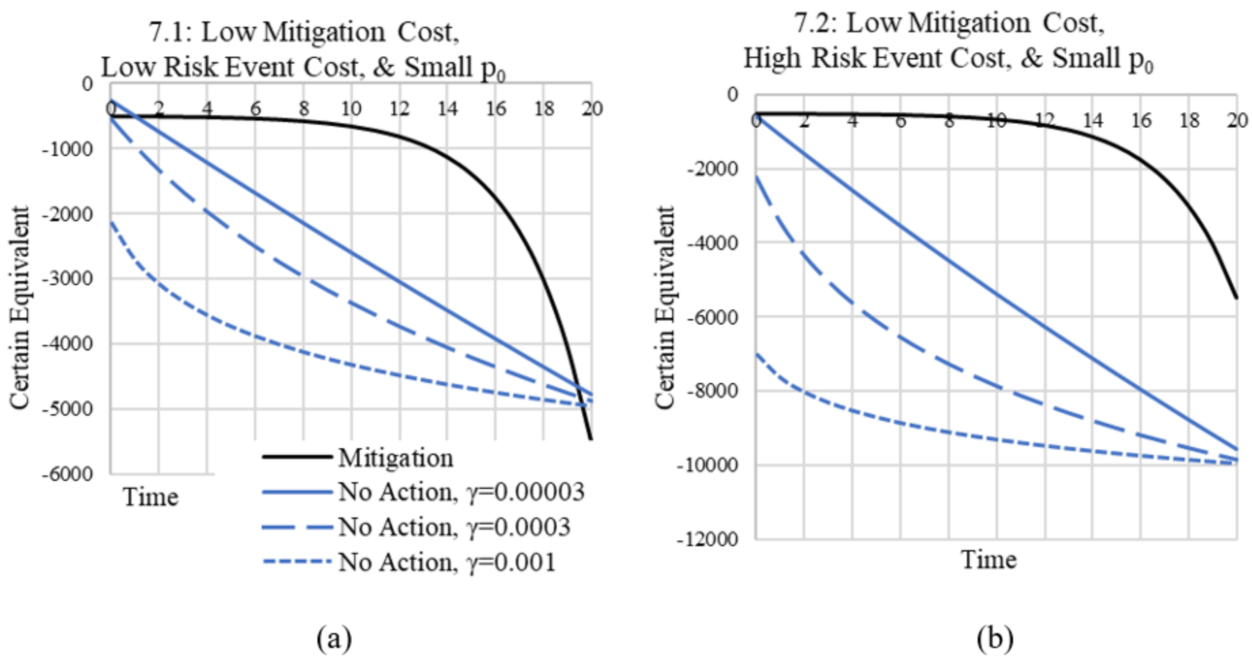
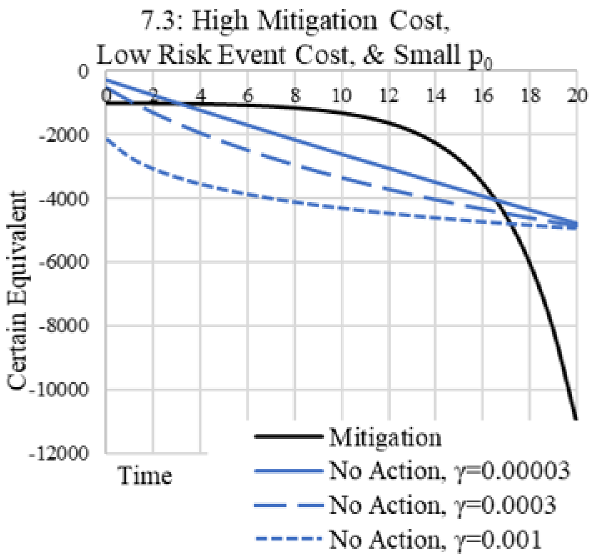
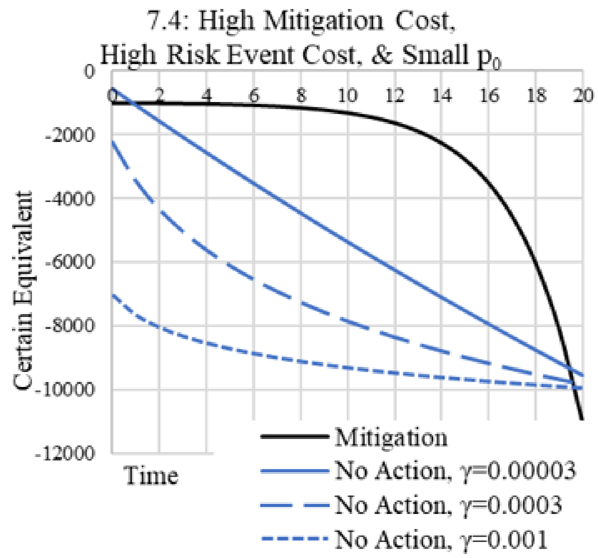


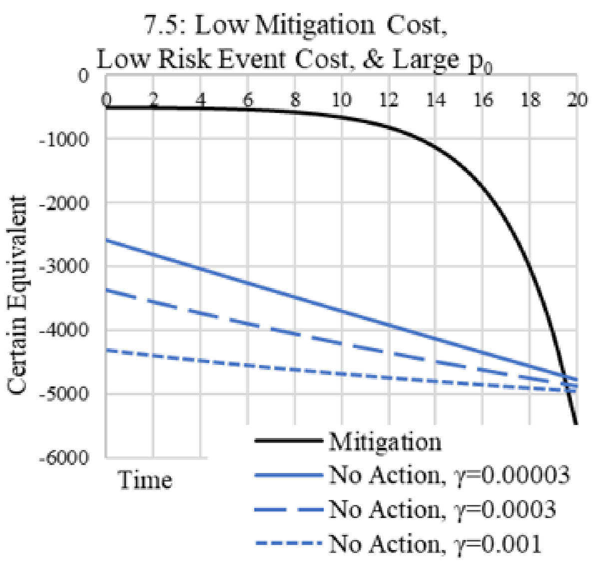
Figure A.1 The certain equivalents for case 7 from Chapter 4, with variations on the parameters: 7.1 (a), 7.2 (b), 7.3 (c), 7.4 (d), 7.5 (e), 7.6 (f), 7.7 (g), and 7.8 (h)



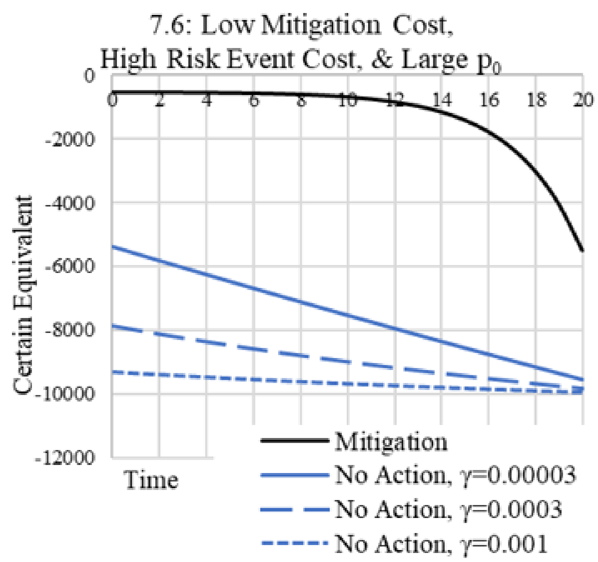
(c)



(d)

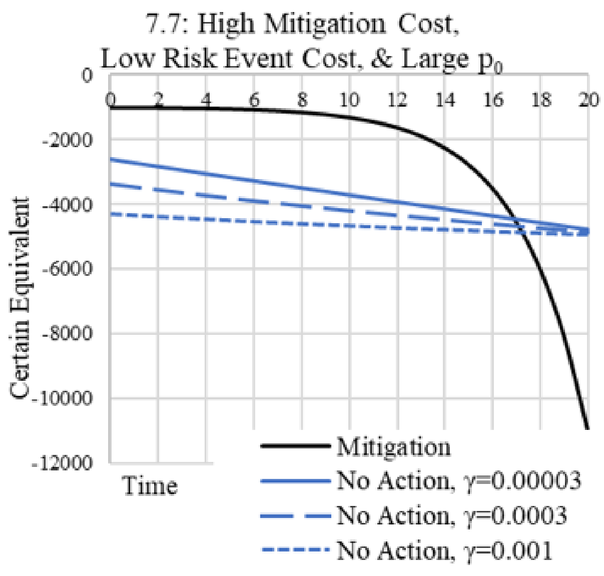


(e)

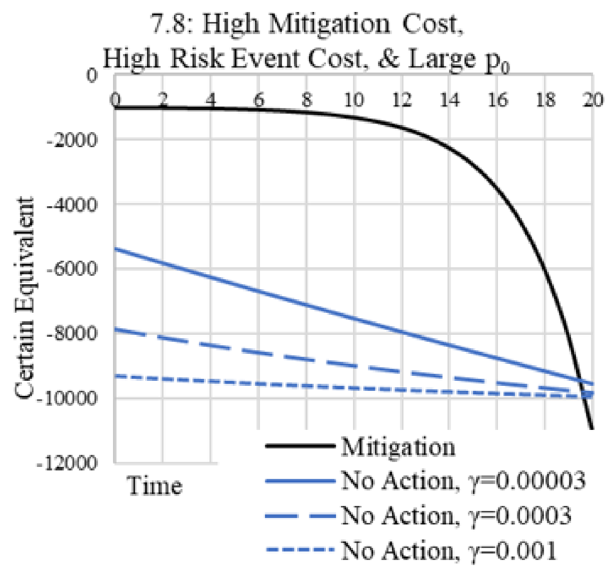


(f)

Figure A.1 (cont.) The certain equivalents for case 7 from Chapter 4, with variations on the parameters: 7.1 (a), 7.2 (b), 7.3 (c), 7.4 (d), 7.5 (e), 7.6 (f), 7.7 (g), and 7.8 (h)



(g)



(h)

Figure A.1 (cont.) The certain equivalents for case 7 from Chapter 4, with variations on the parameters: 7.1 (a), 7.2 (b), 7.3 (c), 7.4 (d), 7.5 (e), 7.6 (f), 7.7 (g), and 7.8 (h)

The results for case 8, with exponential time-varying risk mitigation costs and a quadratically increasing estimated probability of the risk event occurring, are shown in Figure A.2.

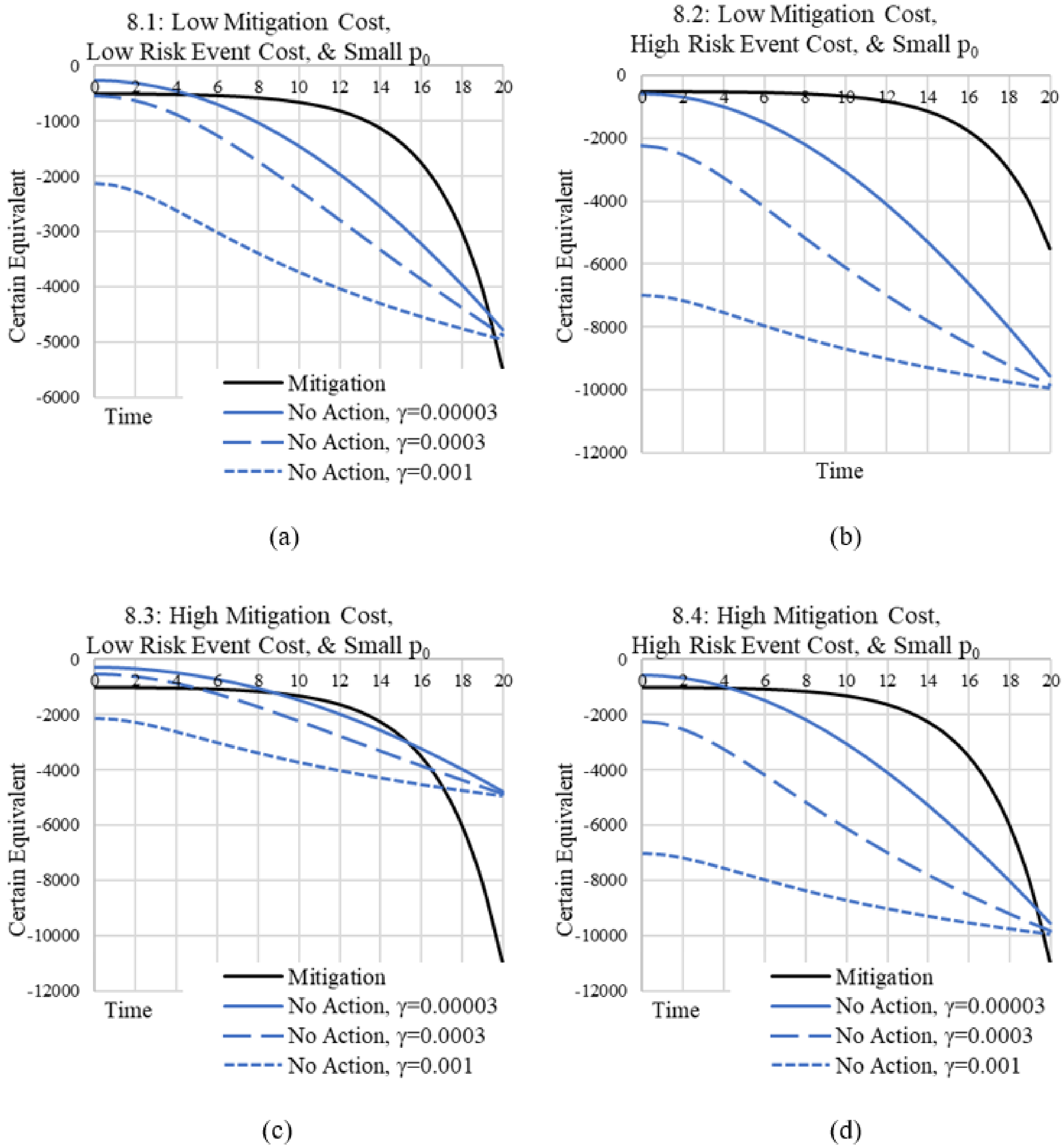
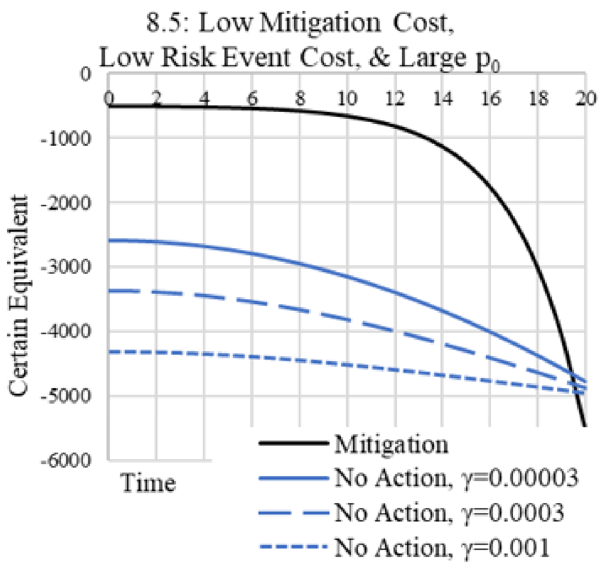
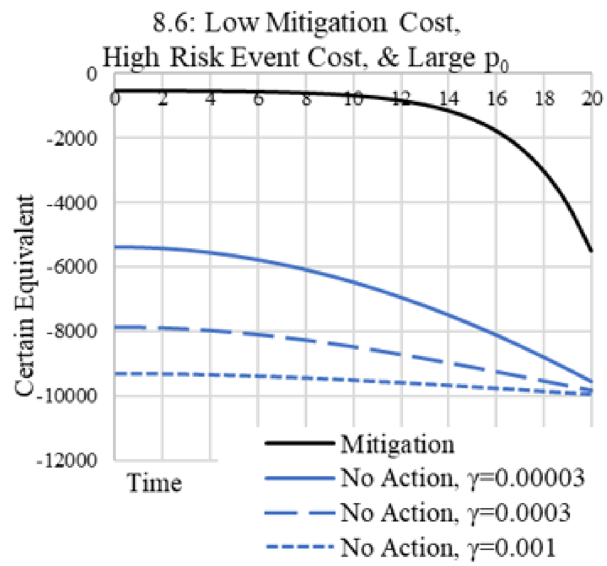


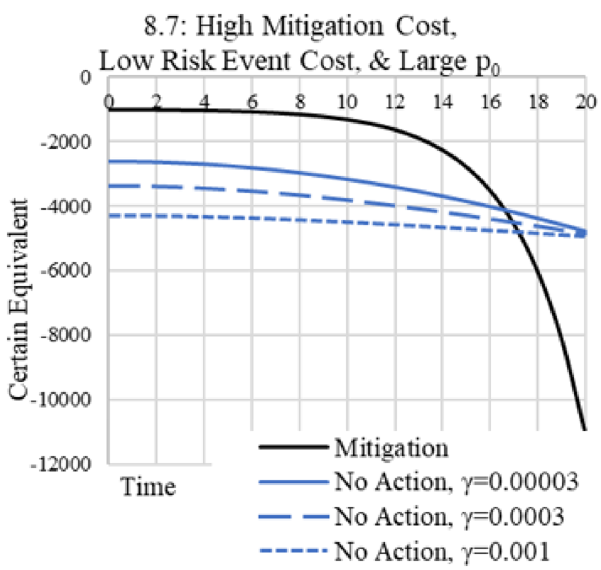
Figure A.2 The certain equivalents for case 8 from Chapter 4 with variations on th parameters: 8.1 (a), 8.2 (b), 8.3 (c), 8.4 (d), 8.5 (e), 8.6 (f), 8.7 (g), and 8.8 (h)



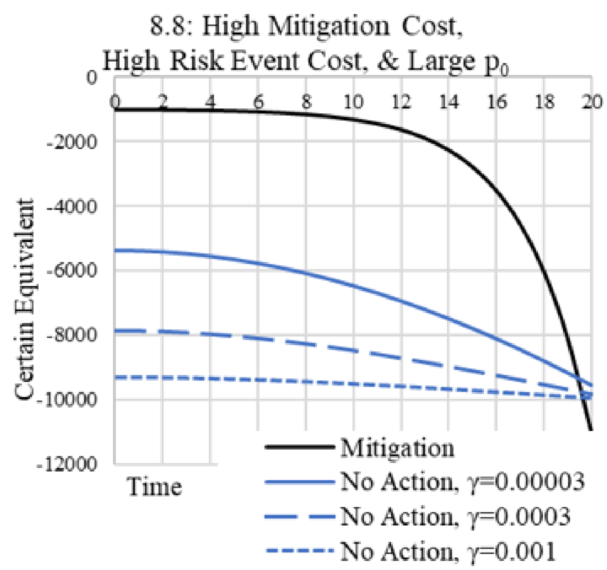
(e)



(f)



(g)



(h)

Figure A.2 (cont.) The certain equivalents for case 8 from Chapter 4 with variations on the parameters: 8.1 (a), 8.2 (b), 8.3 (c), 8.4 (d), 8.5 (e), 8.6 (f), 8.7 (g), and 8.8 (h)

The results for case 9, as presented in Chapter 4 with exponential time-varying risk mitigation costs and an exponential estimated probability of the risk event, are shown in Figure A.3.

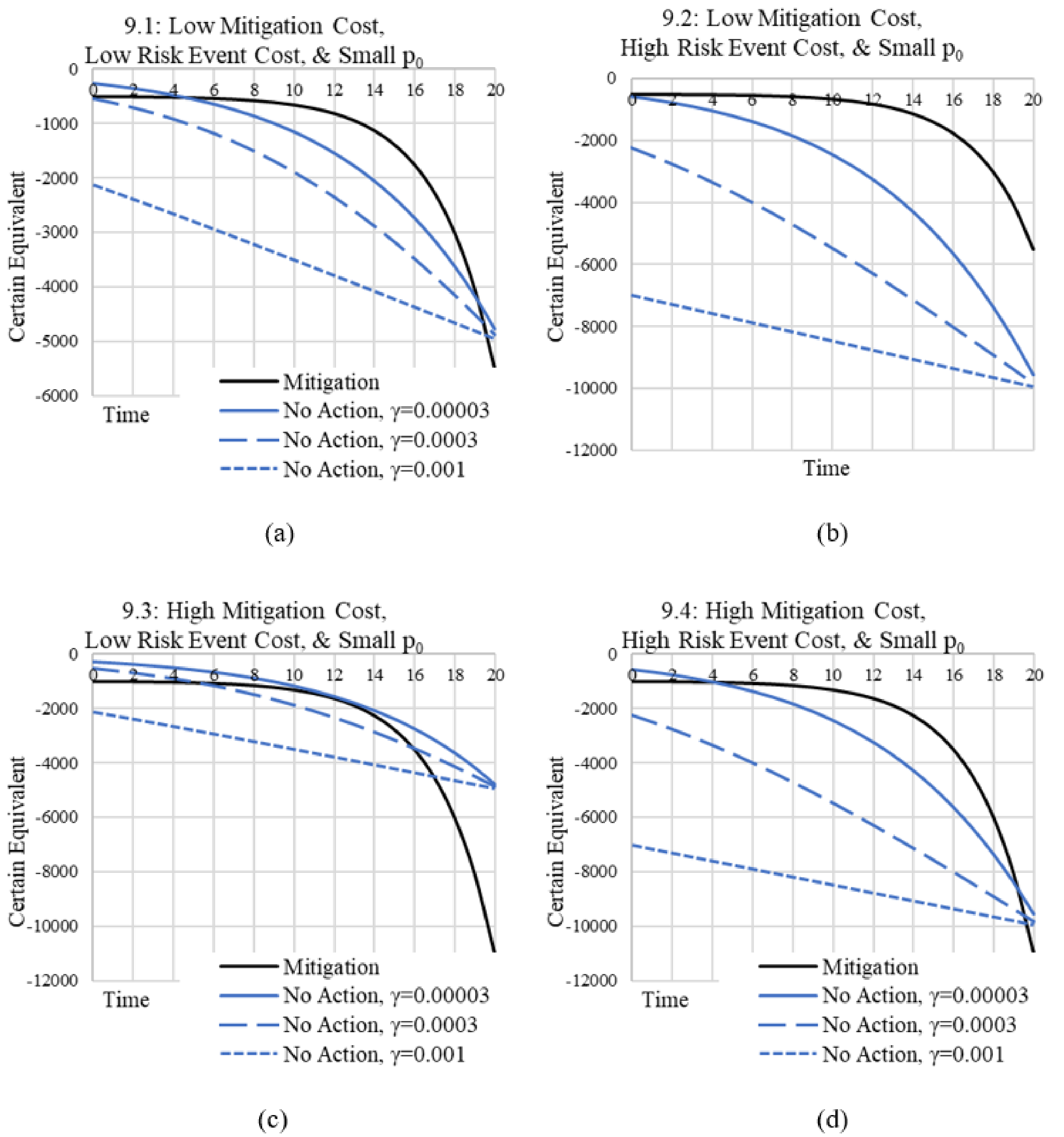


Figure A.3 The certain equivalents for case 8 from Chapter 4 with variations on the parameters: 9.1 (a), 9.2 (b), 9.3 (c), 9.4 (d), 9.5 (e), 9.6 (f), 9.7 (g), and 9.8 (h)

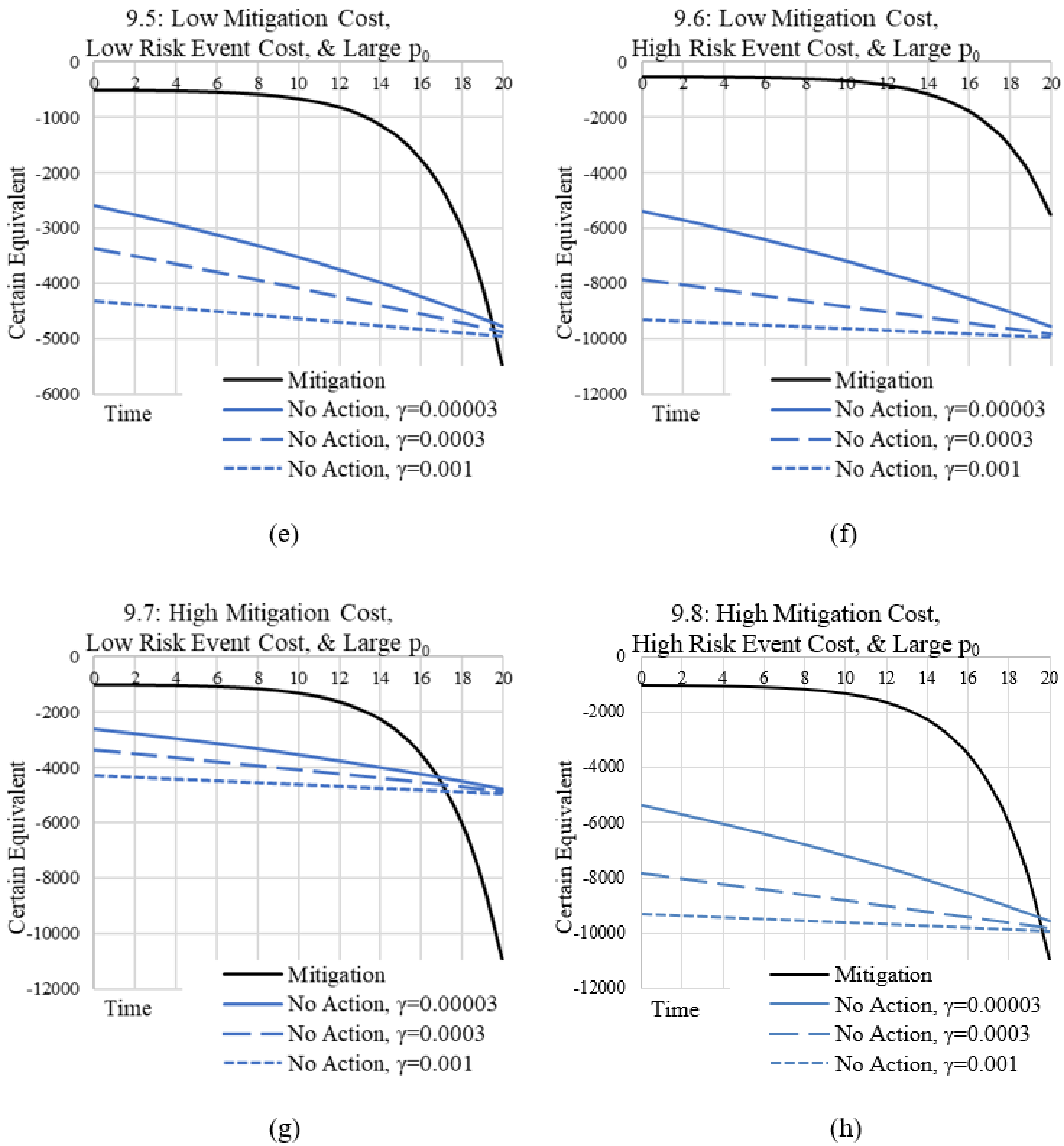


Figure A.3 (cont.) The certain equivalents for case 8 from Chapter 4 with variations on the parameters: 9.1 (a), 9.2 (b), 9.3 (c), 9.4 (d), 9.5 (e), 9.6 (f), 9.7 (g), and 9.8 (h)