

Tourism providers' reactions to decreased demand following a crisis

The impact of the Swine Flu on the tourism market: a panel data approach

Master Thesis

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AFFIDAVIT

I hereby affirm that this Master's Thesis represents my own written work and that I have used no sources and aids other than those indicated. All passages quoted from publications or paraphrased from these sources are properly cited and attributed.

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ABSTRACT

Crises and disasters can strongly affect the tourism industry and should therefore be managed correctly. As such, this MSc Thesis, first, ascertains whether tourism providers react according to theoretical suggestions by comparing theoretical tourism crisis management recommendations and behavior with real cases and, second, investigates whether the recent "Swine Flu" pandemic in 2009/2010 measurably and significantly affected tourism demand and, consecutively, tourism supply in a sample of seven cities evenly spread around the globe from 2007 until 2012. A panel regression approach indicates that, next to commonly considered factors, the influenza pandemic negatively affects tourism demand which, in turn, alters tourism supply.

TABLE OF CONTENTS

AffidavitI				
Abstra	AbstractIII			
List of	Tables	VII		
List of	Figures	VIII		
List of AbbreviationsXI				
1	Introduction	1		
2	Crises and Disasters: Definitions and Classification	4		
3	3 Theoretical Crisis Frameworks and Real Cases			
4	H1N1 Pandemic 2009/2010	17		
5	Tourism Market Modeling	21		
6	Methodology, Data and Modeling	25		
6.1	Methodology	25		
6.2	Data	29		
6.2.1	Source Market Aggregation	30		
6.2.2	Rooms Sold			
6.2.3	Gross Domestic Product			
6.2.4	Average Daily Rate – Destination			
6.2.5	Average Daily Rate – Competitors			
6.2.6	Consumer Price Index – Destination	.35		
6.2.7	Consumer Price Index – Competitors	.35		
6.2.8	Cases of Influenza H1N1	.35		
6.2.9	Dummy: Global Financial Crisis	.36		
6.2.10	Dummy: Olympic Games Beijing / Hong Kong	.36		
6.2.11	Dummy: Olympic Games London	.36		
6.2.12	Rooms Available			
6.2.13	Occupancy Rate			
6.2.14	Long-Term Interest Rate			
6.2.15	Short-Term Interest Rate			
6.2.16	Labor Costs			
6.3	Modeling	40		
6.3.1	Seasonality			
6.3.2	Variable Transformations	.40		
6.3.3	.3.3 Panel Effects			
6.3.4	Autocorrelation	.44		

6.3.5	Heteroskedasticity	ΔΔ	
6.3.6	Cross-Sectional Dependence		
6.3.7	Seemingly Unrelated Regressions		
6.3.8	Model Specification		
0.5.0		45	
7	Results	48	
8	Interpretation and Limitations	51	
8.1	Interpretation	51	
8.1.1	Gross Domestic Product	51	
8.1.2	Average Daily Rate – Destination (Demand)	52	
8.1.3	Average Daily Rate – Competitors	53	
8.1.4	Consumer Price Index – Destination	53	
8.1.5	Consumer Price Index – Competitors	53	
8.1.6	Cases of Influenza H1N1	53	
8.1.7	Dummy: Global Financial Crisis	55	
8.1.8	Dummies: Olympic Games	55	
8.1.9	Average Daily Rate – Destination (Supply)	56	
8.1.10	Occupancy Rate	56	
8.1.11	Interest Rates	56	
8.2	Limitations	58	
9	Summary and Conclusion	59	
10	Bibliography	62	
Appendices			
Apper	Appendix 1: Summary Tables and Statistics		
Appendix 2: Moving-Average Filter Scenarios			
Appendix 3: Development of MA Filtered Variables			
Appendix 4: Scatter Plots			
Appendix 5: Regression Sensitivity Checks and Variants			
Apper	Appendix 6: Regression Summary Table – standardized beta coefficients		

LIST OF TABLES

Table 1: Crisis Impact Classification based on Faulkner (2001)	6
Table 2: Variable codes and labels	29
Table 3: Source market aggregation by destination	32
Table 4: Pretest Stata commands and results by function	47
Table 5: Regression summary table	50

Table A.1: Variable description 74
Table A.2: Summary statistics – Barcelona
Table A.3: Summary statistics – Delhi 75
Table A.4: Summary statistics – Hong Kong
Table A. 5: Summary statistics – London
Table A.6: Summary statistics – Mexico City 77
Table A.7: Summary statistics – New York City77
Table A.8: Summary statistics – Rio de Janeiro
Table A.9: Regression sensitivity check – dummies: Olympic Games
Table A.10: Regression Variant – different lag/forward lengths 96
Table A.11: Regression Variant – root-root specification with lags
Table A.12: Regression summary table – standardized beta coefficients of the disjointed model 98

LIST OF FIGURES

Figure 1: Crisis and disaster management: a strategic and holistic framework (Ritchie, 2004). 10
Figure 2: Stakeholder roles within a destination tourism disaster management cycle as reported by tourism businesses two and a half years following a major forest fire disaster (Hystad, 2008)
Figure 3: Levels of crisis response
Figure 4: Schematic of the pandemic waves across the hemispheres (WHO, 2013, p. 40) 17
Figure 5: Pandemic (H1N1) 2009 laboratory confirmed cases and number of deaths as of 21 st January 2010 (BBC, n.d.)
Figure 6: Pandemic (H1N1) 2009 laboratory confirmed cases and number of deaths as reported to WHO as of 15 th August 2010 (WHO, 2010a, archived by the Wayback Machine)
Figure 7: Geographical representation of the cross-section dimension
Figure 8: Development of Rooms Sold (N _{jit}) by destination
Figure 9: Development of the Cases of influenza (H1N1 _{it}) by destination
Figure 10: Development of Rooms Sold (MA filtered) by destination
Figure 11: Scatter plot: Rooms Sold – Cases of Influenza with fitted values by destination 42
Figure 12: Scatter plot: Rooms Available (3 month forward) – Room Occupancy Rate with fitted values by destination

Figure A.1: Moving-average filter comparison for Barcelona	79
Figure A.2: Moving-average filter comparison for Delhi	80
Figure A.3: Moving-average filter comparison for Hong Kong	80
Figure A.4: Moving-average filter comparison for London	81
Figure A.5: Moving-average filter comparison for Mexico City	81

Figure A.6: Moving-average filter comparison for New York City
Figure A.7: Moving-average filter comparison for Rio de Janeiro
Figure A.8: Development of the Gross Domestic Product of the source market aggregation by destination
Figure A.9: Development of the Average Daily Rate at destination by destination
Figure A.10: Development of the Average Daily Rate at competing destinations by destination
Figure A.11: Development of the Consumer Price Index: destination/source market by destination
Figure A.12: Development of the Consumer Price Index: competitors/source market by destination
Figure A.13: Development of Rooms Available by destination
Figure A.14: Development of Rooms Available by destination, demeaned with group means. 86
Figure A.15: Development of the Room Occupancy Rate by destination
Figure A.16: Development of the Long-Term Interest Rate by destination, own illustration. Source: see Table A.1
Figure A.17: Development of the Short-Term Interest Rate by destination
Figure A.18: Development of the Unit Labor Costs by destination
Figure A.19: Scatter plot: Rooms Sold – GDP (3 month lag) with fitted values by destination 89
Figure A.20: Scatter plot: Rooms Sold – Average Daily Rate at destination with fitted values by destination
Figure A.21: Scatter plot: Rooms Sold – Average Daily Rate of competitors with fitted values by destination
Figure A.22: Scatter plot: Rooms Sold – Consumer Price Index: destination/source market with fitted values by destination
Figure A.23: Scatter plot: Rooms Sold – Consumer Price Index: competitors/source market with fitted values by destination

Figure A.24: Scatter plot: Rooms Available (3 month forward) – Average Daily Rate at destination		
with fitted values by destination		
Figure A.25: Scatter plot: Rooms Available (3 month forward) – Long-Term Interest Rate with		
fitted values by destination		
Figure A.26: Scatter plot: Rooms Available (3 month forward) – Short-Term Interest Rate with		
fitted values by destination		
Figure A.27: Scatter plot: Rooms Available (3 month forward) – Unit Labor Costs with fitted		
values by destination		

LIST OF ABBREVIATIONS

- ADR: Average Daily Rate
- CDC: Centre for Disease Prevention and Control
- CPI: Consumer Price Index
- ECDC: European Centre for Disease Prevention and Control
- FE: Fixed Effects
- **GDP: Gross Domestic Product**
- GFC: Global Financial or Economic Crisis
- GLS: Generalized Least Squares
- LM: Lagrange Multiplier
- LR: Likelihood-Ratio
- MA: Moving-Average
- OECD: Organization for Economic Cooperation and Development
- OCC: Average Occupancy Rate
- **RE: Random Effects**
- STR: Smith Travel Research
- **TC: Traveling Costs**
- WHO: World Health Organization

1 INTRODUCTION

Tourism is commonly categorized as part of the third economic sector – the service sector. Indeed, when determining the composition of a product based on good and service components, tourism products are typically found on the services end of the spectrum (e.g. travel, accommodation, guided tours, site visits, leisure activities). By its very nature, services cannot be stored or inventoried and, with the exception of information-based services, customers are required to be at the place of consumption (Lovelock & Wirtz, 2007). Thus, tourism is dependent on guests being present at the location of product consumption i.e. the destination or the route there. Indeed, if there are no guests at the destination, tourism companies cannot sell their products¹. This means that if guests are prevented from traveling to the destination, there is no demand for tourism products, consequently no sales and, as a result, lack of need for tourism services provision and bankruptcy.

A situation that severely affects tourism in such a way may be called a crisis. In an extreme case, a crisis would extinguish a whole industry – tourism in this context – at a destination. Yet, the ramifications of the event would not stop there. The interconnectedness of today's world and economy would result in complications and consequences for all directly and indirectly related businesses, sectors and industries. For instance, the lack of touristic activities like dining in a restaurant would affect said restaurant's suppliers and, in turn, the suppliers of the restaurant's suppliers and so on until the top of the supply chain. Hence, not only is the gastronomy sector affected, but also distributors, food processors, food producers and agricultural businesses. Of course, the consequential increase in unemployment due to the elimination of jobs all along the supply chain would precipitate other problems in different areas as well.

Naturally, crises are unlikely to result in such extreme situations. Rather, consequences on a smaller scale are more probable. However, even at such a level, businesses and their stakeholders will be negatively impacted. Therefore, it is imperative for practitioners and other interested parties to understand crises, their causes and consequences and how to manage best during troubling times.

Incidentally, the world is becoming more complex and, hence, more prone to disastrous events (Richardson, 1994). In addition, basic needs are found at the bottom of Maslow's Hierarchy and higher order needs at the top of the pyramid. Appropriately, tourism is found higher up in the

¹ Barring circumstances like advance payments at reservation without later consumption and money restitution.

Hierarchy of Needs. Thus, in this world with a rapidly growing number of crises (Paraskevas et al., 2013) and disasters and their consequences on demand, consumers have higher priorities i.e. basic needs, which they will strive to fulfill first before fulfilling their tourism related desires. Indeed, Gunter and Smeral (2016) suggest that crisis situations create uncertainties with consumers, to which they react by reducing international travels and substituting it with domestic tourism, necessities to fulfill basic needs and increased savings for emergencies.

One recent impactful crisis was the so-called "Swine Flu". This pandemic caused by the influenza strain H1N1 affected the world in 2009 and 2010 – soon after the global financial crisis (GFC) – and led to problems in multiple industries, among them the travel and tourism industry. In fact, health and safety are major concerns for tourists (Kozak et al., 2007). With the exception of Antarctica and many countries in Africa, most countries confirmed cases of and deaths due to the swine flu.

Faulkner (2001) mentions that few researchers have analyzed the impacts of crises or disasters on the tourism industry or their and governmental responses. The reactions of the tourism industry to economic or financial crises have been investigated mostly after the GFC at the end of the first decade in the 21st century (e.g. Alonso-Almeida & Bremser, 2013; Andraz & Rodrigues, 2016; Campos-Soria et al., 2015; Dragouni et al., 2016; Eugenio-Martin & Campos-Soria, 2014; Gunter & Smeral, 2016; Smeral, 2009a; Smeral, 2009b; Stylidis & Terzidou, 2014). On the other hand, crises and major events in general, as well as their consequences (for tourism), have also been studied and strongly investigated beforehand. The focus of those studies appears to be either research on the behavior of consumers i.e. investigations on demand-side reactions² or on proposed strategies or frameworks for crisis management and mitigation of negative impact. Other studies concentrate on the reactions of tourism service providers to crises. The object of supply-side research is usually one location, be it a country, region or city in the same or in a very similar environment.

Concerning tourism forecasting, demand modeling is clearly more prominent than supply modeling. Indeed, Song and Li (2008) assert that demand modeling and forecasting is an important area of study in tourism research. Despite the fact that supply forecasting can be of interest for policy makers and management organizations, statistical or econometric tourism supply modeling is rather absent in the literature, with the study by Smeral (2014) being a noteworthy exception.

² Yet, experts on tourism studies "[agree] that a better understanding of consumer behavior and attitudes to travel is needed in times of economic recession. [The] lack of knowledge about possible consumer responses to the [recent GFC] places great impediments in the way of forecasting its effects on the industry" (Sheldon & Dwyer, 2010, p. 4).

Similarly, studies about the H1N1 pandemic and its relation to tourism are quite scarce in the literature (e.g. Page et al., 2011). Thus, this thesis also aims to close this gap. In accordance with the existing studies on the pandemic and papers about the reaction to crises in general, which are both presented in subsequent chapters, the swine flu is hypothesized to have negatively affected the tourism industry and the tourism market.

This MSc Thesis focuses on the reaction of tourism providers to crises, investigates if real strategies, activities and procedures conform to theoretical concepts and empirically analyzes tourism providers' responses to a crisis. For this purpose, in the following sections this thesis tries to first define the term crisis, explain what a crisis is and how it can influence tourism supply (see Chapter 2). Afterwards, theoretical models and academic suggestions on crises are contrasted with analyses of real crises and tourism providers' behavior (see Chapter 3). The next steps are a brief description of the H1N1 pandemic 2009/2010 (see Chapter 4) and an overview of existing tourism demand and supply modeling (see Chapter 5). Then, the methodology and data used for the empirical study are described (see Chapter 6), which is followed by a report of its findings and results (see Chapter 7). Afterwards, the outcomes, consequences and limitations of the study are discussed and compared to previous research and suggestions in the literature (see Chapter 8). Finally, a brief summary and concluding remarks are provided (see Chapter 9).

2 CRISES AND DISASTERS: DEFINITIONS AND CLASSIFICATION

In order to understand more about the nature of crises, many authors have undertaken the task of defining what a crisis or a disaster is, what phases it is composed of, where it begins and where it ends. The English dictionary Macmillan (2007) defines a crisis as "an urgent, difficult, or dangerous situation" (p. 350) and a disaster as "something very bad that happens and causes a lot of damage or kills a lot of people" (Macmillan, 2007, p. 416). The definition of disaster is very similar to Macmillan's (2007) definition of catastrophe: "an event that causes a lot of damage or makes a lot of people suffer" (p. 224). Based on those definitions, disasters and catastrophes sound more serious than crises. The latter references only a dangerous situation, disasters and catastrophes, on the other hand, include a harsh outcome. In other words, a crisis does not have to result in a distressing consequence while disasters and catastrophes are only called such, if negative fallout occurs. This means that crises can, by definition, be defused and managed in such a way as to avoid negative consequences and ultimately, the transformation of a crisis to a disaster or a catastrophe. After this transformation occurs, responders have to deal with the fallout of the damaging event.

Faulkner's (2001) definitions of a crisis and a disaster, respectively, differ from a distinction based on the definitions found in dictionaries. Based on Selbst (1978, cited by Booth, 1993), Faulkner (2001) distinguishes those two terms by looking at the cause of the problem: if the situation is induced internally within an organization, for example through incompetent management, he proposes to use crisis. If external natural or human events have detrimental effects on a system, he uses the term disaster. However, Faulkner's (2001) distinction is in conflict with the common designation of events such as economic crises. Notwithstanding its name, an economic crisis is not an internally-induced problem of an organization, but rather prompted by an external influence. According to Faulkner's (2001) definition, from the point of view of, for example, companies, the economic crisis is a disaster, not a crisis, since "an enterprise...is confronted with sudden unpredictable catastrophic changes over which it has little control" (Faulkner, 2001, 2. The nature of disasters and crises, para. 3).

This example shows that defining a crisis can be problematic. Different authors, probably depending on contextual and environmental factors, may apply dissimilar or even contradicting definitions of the same words. A certain definition may be useful in a corresponding context, particularly when it is used by authors "to help improve their understanding of this phenomenon" (Ritchie, 2004, 3. Understanding crises and disasters, para. 1). However, the same words are often used differently across papers and hence with slightly disparate connotations. Hence, when one author uses the word crisis, it does not have to mean the same as when another author uses the same word, especially when definitions are cited but it is not clarified, which one is to be used. Overall, a crisis or disaster situation can be defined using the following components compiled by Faulkner (2001): "a triggering event, which is so significant that it challenges the existing structure, routine operations or survival of the organisation; high threat, short decision time and an element of surprise and urgency; a perception of an inability to cope among those directly affected; a turning point, when decisive change, which may have both positive and negative connotations, is imminent...characterised by `fluid, unstable, dynamic' situations" (2. The nature of disasters and crises, para. 11).

In relation to a company, this thesis will henceforth, besides where used differently by other authors or by common labels, use crisis for situations that are dangerous to an organization (or in the case of tourism destinations a group of organizations) and that may severely impact standard business practices and processes. If a crisis was not managed successfully, i.e. when the outcome of the situation is strongly negative, disaster or catastrophe will be used. For example, a tour operator affected by an economic crisis, who manages to survive without greater problems faces a crisis. If the organization is strongly negatively changed and has to, for instance, file for chapter 9 or chapter 11, it has faced a disaster.

However, crises, in addition to directly impacting tourism, may also affect tourism indirectly. Faulkner (2001) looks at crises from the point of view of tourism providers, where decreased demand is by itself a disastrous situation. In this case, a crisis situation can affect tourism demand directly, for instance events that decrease prospective guests' disposable income like financial or economic crises. Moreover, they can affect tourism demand indirectly through tourism supply and via problems at the destination, for example natural catastrophes or complications in an organization.

Table 1 shows the possible intersections between the party inducing or "at fault" for a crisis (row) and the source or cause of a crisis (column) or, in other words, impacts that create a crisis for the providers of a product. Needless to indicate, the table and its contents relate to the supply-side of tourism. The parties affected by an event, which in turn induce a crisis situation for tourism providers, are tourists and companies at the destination. In the first case, the demand side, the question to ask is why potential customers do not or cannot come to the destination. In the latter case, the supply side, it should be pondered, why tourism providers cannot provide adequate services or what impedes them in doing so, both as a precursor or precondition for reduced demand and shrinking occupancy. The cause for a crisis can be, in either case, internal or external. Here, internal refers to the decisions made by the respective party or otherwise self-induced situations. These range from simple income allocation decisions i.e. the preferences of consumers (for example related to uncertainty or safety) and substitutive products over technical MCAs³ to inept managerial organization. On the other hand, external refers to third-partyinduced and uncontrollable (but potentially influenceable) situations that are forced upon the parties. Examples for such cases are legal emigration, travel or immigration constraints, natural catastrophes at either the destination or the source market and economic, technical, legal or infrastructural obstacles. Nevertheless, no matter the reason for demand decreases, tourism providers have to deal with crises if they want to continue operations.

	Internal	External
	Budget constraints	Natural disasters (generating location)
D	Income allocation	Legal traveling constraints
Demand	Preferences	Infrastructural traveling constraints
	Substitutive products	
	Internal management prob-	Natural disasters (destination)
	lems	Economic obstacles
Supply	Technical problems	Legal obstacles
	Failure to adapt to change	Technical obstacles
		Infrastructural deficiencies ("infrastructural voids")

TABLE 1: CRISIS IMPACT CLASSIFICATION, OWN ILLUSTRATION BASED ON FAULKNER (2001)

Of course, external factors can influence internal factors, for instance when a company is mismanaged during a time of externally-induced issues. This is congruent with Heath's (1998, p. 9, cited by Ritchie, 2004) ripple effect: "the ability of a crisis to cause other crisis situations because these crises seem to fan outward" (3.3 Dealing with complexity, para. 2), which necessitates correct internal decision-making. Moreover, one crisis can be a result of more than one impact category.

Crises can undoubtedly exhibit multiple other characteristics that are not included in Table 1. In fact, Burnett (1998) created a crisis classification matrix based on threat-level, response options, time pressure and degree of control. Thereby, Burnett (1998) established levels of response by

³ Maximum Credible Accident

organizations. In addition, Ritchie (2004) summarizes categories of crises (and consequently disasters) by other authors and mentions different division criteria: level of uncertainty, the scale and geographical spread of a crisis, the time-aspect and duration of a crisis, the threat level, magnitude and prospective impact of a crisis and the degree of control and response options.

Furthermore, Faulkner (2001) and Ritchie (2004) mention the life-cycle models of crises. These frameworks try to depict the stages of a crisis so that managers can utilize the correct measures to respond in each phase. Obviously, determining the phase of a crisis or disaster and its characteristics can be difficult due to its complex nature and, in the case of large-scale crises, geographical diffusion (Ritchie (2004) provides an example, where different regions were in different stages of a crisis). Both authors (Faulkner, 2001 and Ritchie, 2004) delineate six phases of a crisis or disaster. At the beginning (1) is the pre-event stage, where actions to prevent disasters can be taken. This is followed by (2) the prodromal stage, when it is discernible that a crisis is going to happen. The third phase, (3) emergency, is when the event itself happens. Following the incident, (4) an intermediate phase bridges the time until (5) the long-term (recovery) phase when, in continuation of the previous phase, restoration activities are executed and the damage is repaired. The final phase (6) is called resolution, by which the crisis is over and the normal or new state is established.

Another possibility is to distinguish according to type of crisis i.e. whether the event is a natural catastrophe, an economic crisis, a demand crisis, a political crisis, etc. Most of the existing case studies analyze one of the abovementioned types of crises. In this case, research can focus on different aspects of the crisis, such as crisis management by organizations (e.g. Alonso-Almeida & Bremser, 2013; Anderson, 2006), preemptive organizational resilience (e.g. Sheppard & Williams, 2016), impact on demand (e.g. Campos-Soria et al., 2015; Stylidis & Terzidou, 2014) or crisis planning (e.g. Wang & Ritchie, 2012). In summary, there exist many different definitions and categorizations of crises and disasters.

Additionally, a wide range of behaviors regarding crises exists. Generally, it can be distinguished into pre-crisis, crisis and post-crisis behavior. Indeed, organization are, if they are not currently facing a crisis, separated from it by one degree since "any time you're (i.e. managers) are *[sic]* not in crisis, you are instead in a pre-crisis, or prodromal mode" (Fink, 1986, p. 7, cited by Faulk-ner, 2001, 2. The nature of disasters and crises, para. 5). Hence, tourism supply organizations have to try to anticipate and prevent, manage and survive crises, or, afterwards, deal with the consequences and fallout of a crisis. As our world becomes increasingly more complex and, ul-timately, more prone to disastrous events, these measures are especially important (Richardson, 1994).

3 THEORETICAL CRISIS FRAMEWORKS AND REAL CASES

This chapter first examines existing crisis and crisis management frameworks found in the literature and then reviews real crises studied by researchers in light of recommendations on how managers and organizations should act.

As per Faulkner's (2001) characteristics of a crisis, such situations are able to affect every part of an organization. Therefore, this topic has been thoroughly studied. In recent decades, researchers have started to also investigate the effect of disastrous situations on tourism from multiple angles. These studies can be roughly divided into general theoretical frameworks and suggestions regarding how to manage crises (e.g. Coombs, 1999; Faulkner, 2001; Fink, 1986; Parsons, 1996; Pauchant & Mitroff, 1992; Ritchie, 2004; Smeral, 2009a) and into empirical research or case studies on a specific crisis or a particular area or industry that is or was experiencing a crisis (e.g. Alonso-Almeida & Bremser, 2013; Anderson, 2006; Andraz & Rodgrigues, 2016; Blake & Sinclair, 2003; Speakman & Sharpley, 2012; Stylidis & Terzidou, 2014).

Most theoretical works appear to focus on crises in general and do not necessarily focus on tourism. Indeed, "little systematic research has been carried out on disaster phenomena in tourism, the impacts of such events on the tourism industry and the responses of industry and relevant government agencies to cope with these impacts" (Faulkner, 2001, 1. Introduction, para. 4). This, though, appears to have changed after the GFC in 2008, with more papers focusing on tourism related to the GFC and the GFC's impact on tourism and tourist behavior.

However, response and mitigation strategies depend on the specific type of crisis or disaster. In other words, depending on the party affected by a crisis and on how it is affected (for instance as categorized in Table 1), options to prepare and respond differ. For example, a crisis due to a natural catastrophe at the destination (immediate and direct physical effects) necessitates a different strategic approach and management than a crisis due to lack of demand (immediate effects on demand and only secondarily – the crisis – on tourism providers and organizations). Different destinations are exposed to different crises and disasters (Faulkner, 2001), which can be taken into account when planning for likely crises and the corresponding responses.

Principally, sociologically seen, according to Arnold (1980, as cited by Booth, 1993, pp. 102-103, as cited by Faulkner, 2001), there are four immediate behavioral phases to crisis situations: (1) individual and collective shock due to the unexpected event, which incites to action, (2) denial or defensive retreat, thus either trying to reject or escape the crisis, (3) acknowledgement and acceptance of the changes and (4) adaptation, learning, coping and rebuilding. Weng Chan (1995, as cited by Faulkner, 2001) also mentions four possible paths of actions that might be taken outside the initial incident: protection (prevention), accommodation (adaptation to suit disasters), retreat (relocation), nothing (no responses or actions).

General guidelines for disaster management (Cassedy, 1991; Drabek, 1995; Quarantelli, 1984; Turner, 1994) are summarized by Faulkner in his 2001 article in order to create a framework for tourism disaster management. While not necessarily focused on tourism, nor on crises, but rather focused on disasters (as defined and used by Faulkner (2001), hence externally induced critical situations), a broad outline of how tourism organizations should behave before, during and after the event(s) can be envisioned.

At all times, information has to be gathered, analyzed and disseminated. Indeed, the literature suggests to regularly collect new information, to assess possible risks and impacts for the short-term and the long-term, to assess the capabilities and resources of organizations and the community regarding disastrous events and to learn from past experiences, foreign and internal (or-ganizational learning).

The information should then be shared with likely-to-be-affected parties, for example through emergency media communication strategies, by educating the general public and by communicating information to horizontally and vertically aligned businesses and organizations. In order to be able to successfully communicate information to other organizations as to be sure that they understand what is expected of them, proper channels have to exist, preferably as part of formal relations (mutual aid agreements, joint plans and strategies) or other forms of involvement. In fact, it is suggested to have a common leader or disaster management team, in which all affected parties are involved, to create plans and strategies and to coordinate efforts.

On this subject, further suggestions concern the creation of flexible contingency and action plans, as well as modifiable strategies to avoid, mitigate or minimize disaster impacts. Regularly updated information aids in keeping these plans and strategies current and continually updated and periodical reviews help monitor the integration of new data and consider changes.

Drabek (1992, as cited by Faulkner, 2001) highlights the importance of warning systems with definite thresholds, so that responsible executives do not deny impact risks or probabilities of change and disasters. If recommended simulations, rehearsals, drills, tests and training regarding disaster appear to be insufficient, outside help might need to be enlisted. Furthermore, besides strategies regarding the disaster itself or the period before the event, plans for re-entry, resolution and recovery need to be established.

Ritchie (2004) used, among others, the phases identified by Faulkner (2001), as well as the above described disaster strategies to design a strategic and holistic crisis and disaster management framework for public and private tourism organizations (see Figure 1). While different characteristics of a crisis, for instance its duration, require different strategic approaches – and thus flexible crisis management – there appear to be similarities between the framework and the phases of a crisis (Ritchie, 2004). In the framework, Ritchie roughly assigns the various recommendations to the six phases by creating three main stages for strategic crisis management: a

crisis/disaster prevention and planning stage, a strategic implementation phase and a resolution, evaluation and feedback stage. (Tourism) organizations should incorporate and internalize the following recommendations for successful crisis management. Stage one includes planning and strategizing. Stage two deals with the evaluation and control of strategies, communication and collaboration during the crisis, as well as resource management. Stage three focuses on reentry, return to normality (or improvements), learning, response interpretation and judgement as well as changes wrought by the crisis.

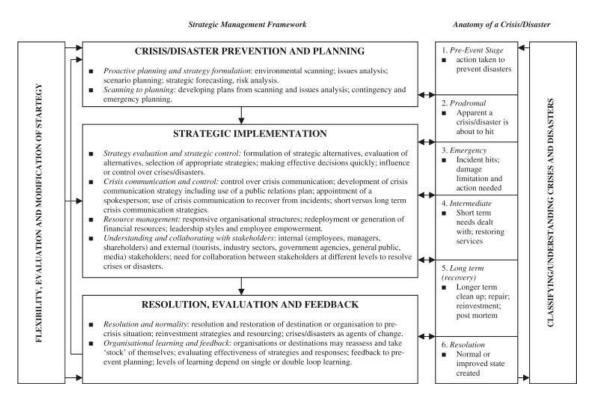


FIGURE 1: CRISIS AND DISASTER MANAGEMENT: A STRATEGIC AND HOLISTIC FRAMEWORK (RITCHIE, 2004)

In a study about the long-term lessons for tourism of a forest fire disaster (Hystad, 2008), the author determined that a tourism disaster management framework, which connects the various stakeholders is needed. In fact, different organizations can dispose of different resources and have different expectations regarding disaster management and thus require open communication and dialogue (Hystad, 2008). The framework displays four phases of a disaster (pre-disaster, disaster, post-disaster and resolution) and the respective roles of and connections between emergency organizations, tourism organizations and tourism businesses in each phase (see Figure 2).

Not explicitly mentioned in Ritchie's (2004) holistic and strategic framework is that high priority has to be placed on the safety of tourists, because, according to Faulkner (2001), tourists are in an unfamiliar environment and hence especially vulnerable to disasters.

Smeral (2009a) provides other recommendations that are directly addressed to tourism providers in relation to the 2008 GFC. The author advises tourism providers not to reduce marketing

expenditure but, if necessary, to cooperate in joint marketing initiatives. The main target group of marketing in trying times should be repeat visitors and those that live close to the destination, since guests tend to prefer "safe" and "riskless" locations with low chances of negative surprises, ergo destinations that are reachable by car and known to tourists. Moreover, guests wish for short-term flexibility and all-inclusive packages when booking, as well as a transparent price and product policy, which thoroughly presents the benefits of a product. Prices, though, should not be reduced significantly, in order to avoid difficulty in restoring prices to the previous price level, rather temporary special offers are suggested. In addition, service quality and consequently customer satisfaction should be improved by strengthening staff motivation. In addition to price and marketing considerations, a crisis offers chances for innovations, new concept tests, internal reforms and the identification of cost saving opportunities.

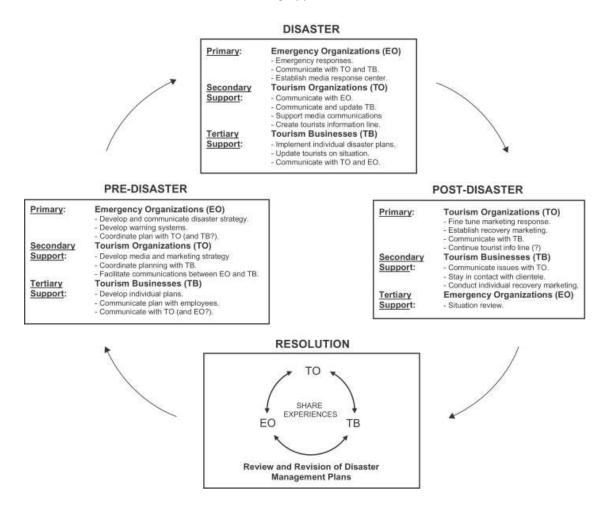


FIGURE 2: STAKEHOLDER ROLES WITHIN A DESTINATION TOURISM DISASTER MANAGEMENT CYCLE AS REPORTED BY TOURISM BUSINESSES TWO AND A HALF YEARS FOLLOWING A MAJOR FOREST FIRE DISASTER (HYSTAD, 2008)

In contrast to more traditional frameworks and models, Speakman and Sharpley (2012) investigated destination crisis management from a chaos theory perspective. They argue that general unvarying responses to crises are not adequate due to the unpredictable and heterogeneous nature of crises. Instead, when a crisis does not follow the established life-cycle framework, "different responses according to the specific character of the crisis and individual destinations" (p. 74) are required. Hence, as preparation for possible crises, the authors suggest organizations to strive to create a culture of flexibility, innovation, learning and change. Then, at the beginning of a crisis, existing marketing activities are recommended to be reduced (or even suspended) so that the new situation is characterized by appropriate, truthful and accurate communication, information and decision flows. After emerging from a chaotic state, systems tend to "self-organize" and re-order themselves without previous and conscious planning. This presents an opportunity for organizations to creatively improve upon the pre-crisis situation. Moreover, managers can act as facilitators for re-ordering the situation, as "island[s] of stability" (p. 71). For this purpose, communication platforms and cooperative relationships are necessary prearrangements.

Further responses to a chaotic crisis are, for example, marketing activities, such as reduced price vacations, value-added special offers, familiarization trips for journalists and tour operators and increased attention to the domestic market or taking advantage of government assistance, such as incentives for foreign investment, tax relief, increased funding for national DMOs or the invigoration of domestic tourism. After the crisis, joint marketing efforts to restore the destination's image and increase tourism flows are suggested.

Other studies have come to various additional conclusions, for instance Hajibaba et al. (2016), who employed a conjoint analysis to research the cancellation habits of tourists and possible strategies to mitigate problems arising from this issue. They assert that upgrading guests to luxury accommodations far from crisis centers is guests' preferred solution. Another example are Paraskevas et al. (2013), whose study uses the Critical Incident Technique⁴ and examines crisis knowledge management and stresses the importance of knowledge in tourism crisis management. In her study on the Australian tourism industry, Anderson (2006) highlights the significance of work-time flexibility in relation to the continued retention of veteran staff members who are more capable of delivering high-quality service than new staff, who are also in need of propaedeutic training. In addition, due to the negative influences of unfavorable economic conditions on tourism demand, it is also necessary to consider the loss aversion, liquidity constraints and precautionary savings of tourists (Smeral, in press), as well as the ramifications and implications of these factors, when making marketing decisions.

Figure 3 displays the various levels of crisis response by which tourism providers can expect to be affected. It thereby summarizes the abovementioned models, frameworks, strategies and actions – as suggested by the literature – in order to successfully persevere through times of

⁴ Participants are asked to "recall and describe a crisis they experienced in their organizations and then for their insights on what was learnt from the crisis" (Paraskevas et al., 2013, Research Design, para. 4).

crises. At the center, the figure depicts the single tourism provider within the context of its destination and close to emergency organizations, which can be within or outside of the organizations, as well as the outside government.

As detailed in the previous part of this chapter, the literature suggests appropriate, truthful and accurate information, communication, knowledge and learning flows between and within all actors and, if appropriate, other stakeholders (cf. also Stylidis & Terzidou, 2014) and that organizations be ready to enlist outside help, i.e. from the government and emergency organizations external to the destination. Moreover, establishing proper and formal channels or platforms for connections, communication and cooperative relationships is recommended. (Joint) leadership and facilitators (stabilizers) should be appointed. Flexible (and coordinated) strategies, plans, contingencies, re-entry and recovery actions for the various phases of crises should be created. Creating warning systems and holding drills, tests, simulations and trainings, as well as fostering a culture of flexibility, learning, innovation and change are also suggested. These latter values can further be exploited for the recovery phase after a crisis in order to implement improvements and reforms. The focus of the joint (and appropriate to the new situation) marketing efforts, strategies and activities should be transparency and the promotion of safety and should lie with loyal repeat customers.

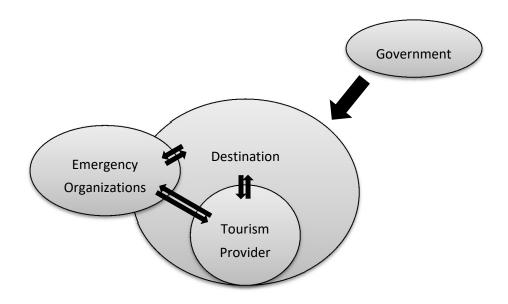


FIGURE 3: LEVELS OF CRISIS RESPONSE, OWN ILLUSTRATION

At the level of a single firm, further suggestions are concerning the reduction (or suspension) of existing marketing and its adaptation to the current situation – overall marketing expenses should not be reduced – the focus on service quality and customer satisfaction, the targeting of domestic and geographically close source markets (see also Andraz & Rodrigues, 2016) and the price policy (no strong reduction in prices, instead the creation of temporary special offers). The government, as help coming from the outside, can further aid the destination and single tourism

providers by creating incentives for foreign investment, institute tax reliefs and increasing funding for DMOs and by invigorating domestic tourism.

With these suggestions on how to behave in face of a crisis, a question arises, namely, whether research, which investigates crises from a positive point of view, validates that real behavior conforms with such suggestions or not.

In the case of the hotel industry in Madrid, Spain, with regards to the GFC, Alonso-Almeida and Bremser (2013) discovered that hotels with a loyal customer base and a strong brand image which focused on providing a high-quality service and increased their marketing expenditure did very well, while hotels, which implemented measures against quality and a strong image, cut costs and, as a consequence, had to reduce prices, performed the worst. These results are in line with findings suggested by the literature. However, the study hardly investigated factors at levels other than the single hotels; hence, no information about the compliance with suggestions like joint marketing or cooperation is available.

Anderson (2006) qualitatively analyzed interviews with members of the Australian tourism industry regarding a series of shocks in Australia at the beginning of the new millennium. Her findings positively highlight communication, focus on quality and organizational learning and negatively present planning, preparation, contingencies etc. Indeed, the interviews showed that staff was kept informed (internal communication), that organizations learned from (past) crises and are ready to use that knowledge and that staff was retained, in other words tourism providers did not favor short-term cost savings over long-term high-quality service. However, no preparations and no up-to-date or appropriate policies to guide organizational responses were available to access when needed.

The studies by Blake and Sinclair (2003) and by Goodrich (2002) both look at the aftermath of the September 11 terrorist attacks on the World Trade Center in the USA. The former study reports responses by the government, such as sector-specific subsidies, tax reductions, various credits, compensations and benefits to airlines, increases in security spending, tax credit for domestic travels and funding for marketing campaigns. The latter study furthermore highlights that the president and other politicians acted as marketers for the tourism industry by encouraging domestic tourism. In addition, Goodrich (2002) presents some actions taken by hospitality and tourism businesses, including their increased spending on surveillance cameras and security personnel, the rise of national advertising campaigns and the creation of special offers like reduced room rates, free breakfast or discounts on entertainment. Both articles show the influence of government aid rendered to the tourism industry. Moreover, Goodrich's (2002) article reveals that tourism businesses increased marketing expenditure for closer markets and used the lure of temporary special offers, while at the same time emphasizing and increasing safety for their guests.

A dichotomy can be seen in the tourism industry of Crimea. Ivanov et al. (2016) investigated the impacts of the entry of Crimea into the Russian Federation on the local tourism industry and discovered that hotels and travel agencies behaved differently. In this case, hotels decreased their prices but were unable to cut their costs (as a consequence, the authors believe that they shifted some of their activities into areas of the shadow economy). Also, it appears that hotels deemed their relationships with suppliers and partners important. On the other hand, tourism agencies decreased their costs – by, for example, retrenching employees – but did not reduce their prices. At the same time, the tourism agencies increased their marketing activities. Thus, in some cases, tourism businesses followed expert opinion on how to behave (mainly travel agencies) and in other cases they did not (mainly hotels).

A negative example, where the tourism industry went against recommendations as construed by the literature, is the case of the Irish tourism industry during and after the GFC and the European crisis as described by O'Brien (2012). Even before the crisis, guests regarded Irish tourism as having a low price-value ratio, since Irish tourism providers apparently did not focus on qualitatively high service, nor on customer loyalty and satisfaction. Furthermore, this destination took longer to realize that a crisis was happening and hesitated in formulating responses. Moreover, there was no policy alignment between public and private organizations. In fact, state tourism agencies were more proactive than and were unable to influence the private sector into following a joint direction. While the state tourism agencies implemented flexible worldwide marketing campaigns, the government was disinclined to face the negative situation and the hotel industry focused on mere survival instead of growth; on equilibrium instead of change.

Besides assembling recommendations for tourism providers in light of the chaos theory, Speakman and Sharpley (2012) also analyzed the Mexican tourism during the recent influenza H1N1 crisis. Both good and bad actions were undertaken by the Mexican tourism industry. On the one hand, Mexico had a strong brand image before the crisis, diversified tourism products, started a new (domestic) marketing campaign, created tailor-made special offers, performed joint marketing and the government allocated more resources to tourism and changed immigration policy to facilitate tourism inflow. On the other hand, at the start of the crisis Mexico was unprepared due to the lack of plans for health crises and it was not flexible, innovative or adaptive, which led to making controversial and hasty decisions and releasing scientifically unconfirmed information to the media, which aggravated the already negative press coverage.

These few studies show that, while some recommendations for tourism crisis management are actually implemented in reality, many more are not. Especially preliminary planning, better understanding and stronger management of crises are needed in tourism, as well as cooperation between the various actors affected by a crisis. However, this is only a small sample of cases and does not cover every situation. A more thorough and varied analysis with additional examples, which is beyond the scope of this thesis, is suggested as consecutive avenue of research. Another limitation is the incomplete information within the studies: the studies cover only a part of the

expert suggestions and not all of them, hence these studies do not give a complete picture of the relationship between "what should be done" and "what is effectively done" during times of crises.

4 H1N1 PANDEMIC 2009/2010

This chapter aims to provide a brief overview of the swine flu pandemic, in order to have contextual knowledge surrounding the crisis.

Humanity has been affected by diseases for millennia, with even the collapse of the Roman Empire being possibly linked to a plague (CDC, 2015). One disease that is pervasive on Earth is influenza – in fact, the flu was the most studied virus disease until the emergence of HIV (Potter, 2001). While smaller outbreaks happen almost every year in some countries (seasonal influenza), pandemics occur roughly every 10 to 50 years due to new influenza virus subtypes (Potter, 2001).

One possible cause for pandemics is the transformation of animal influenza viruses to human influenza viruses, for example in the case of the avian or the swine flu (WHO, 2014). According to the WHO (2010b), "[a] pandemic is the worldwide spread of a new disease [...] [against which] most people do not have immunity." The most infamous influenza pandemic was the Spanish Flu in the years following WW1, which caused between 20 to 50 million deaths worldwide (WHO, 2014). Incidentally, it is the same virus subtype, H1N1, albeit a different strain, as the swine flu in recent years. Normally, in the case of the seasonal flu, deaths are highest among the elderly. The 2009/2010 pandemic, on the other hand, mostly killed or severely affected younger people, regardless of their health (WHO, 2010b). Since 2010, the strain of H1N1 that caused the pandemic has been in circulation as a seasonal flu (WHO, 2014) and is now being called A(H1N1)pdm09 (WHO, 2011).

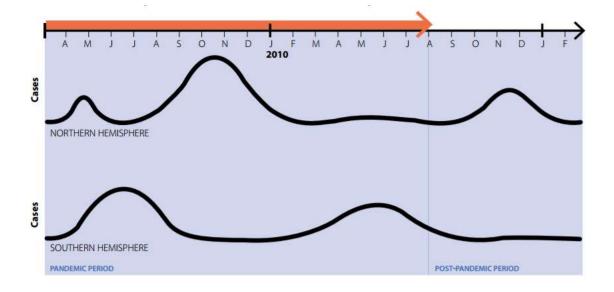
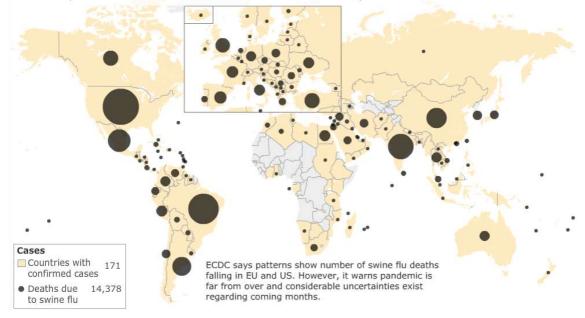


FIGURE 4: SCHEMATIC OF THE PANDEMIC WAVES ACROSS THE HEMISPHERES (WHO, 2013, p. 40)

In 2013, the WHO issued a publication concerning the evolution of the swine flu pandemic 2009/2010, which details the spread of the disease across the planet. Figure 4 shows the H1N1

flu cycle during and after the pandemic for the northern and southern hemisphere, respectively. According to the document (WHO, 2013), the first cases of an influenza-like illness in Mexico were reported on the 12th of April 2009. In the following two weeks, the USA's CDC (Centre for Disease Prevention and Control) confirmed cases of H1N1 virus infections. By April 27th, Mexico, the USA, Canada and Spain had declared laboratory-confirmed cases of the swine flu. On that day, two days after a *public health emergency of international concern* had been declared by the WHO Director-General Dr Margaret Chan, the WHO confirmed that this influenza warranted a declaration of a phase 4 pandemic alert. Phase 4 is described as follows: "Human to human transmission of an animal or human-animal influenza reassortant virus able to sustain community-level outbreaks has been verified" (WHO, n.d.-e).



21 January 2010: EU disease monitor scales down crisis response

Figure 5: Pandemic (H1N1) 2009 laboratory confirmed cases and number of deaths as of 21st January 2010 (BBC, n.d.)

Two days later, on 29th April, 148 laboratory-confirmed cases in 9 countries had been reported to the WHO and the Director-General of the WHO raised the level of influenza-pandemic alert to phase 5: "The same identified virus has caused sustained community level outbreaks in two or more countries in one WHO region⁵" (WHO, n.d.-e). As a consequence, in the following months, antiviral medicines were distributed, consultations convened and guides published. By the end of May 2009, Africa was the only continent without any reported cases of H1N1 infections and deaths were still limited the Mexico, Canada and the USA.

⁵ The six WHO regions are: African Region, Region of the Americas, South-East Asia Region, European Region, Eastern Mediterranean Region and Western Pacific Region.

On 11 June 2009, the level of influenza pandemic alert was raised from phase 5 to phase 6, where "[i]n addition to the criteria defined in Phase 5, the same virus has caused sustained community level outbreaks in at least one other country in another WHO region" (WHO, n.d.-e). Indeed, all continents⁶ were reporting cases of H1N1 infections and by 1 July deaths had been reported in Northern and Southern America, Australia, South-East Asia and Europe (UK and Spain). Due to the immense number of cases at that time, laboratories were not able to test all cases and stopped reporting less severe cases.

At the beginning of September 2009, around 200 countries and overseas territories reported cases of influenza: in four months, H1N1 had spread to almost all countries on the globe. However, many countries were not able to correctly report the number of fatalities as they lacked the capacity for testing in laboratories and only thusly confirmed fatalities were reported to the WHO. Nevertheless, as of 8 November 2009, more than 6250 deaths had been reported in relation to the swine flu. Moreover, during December 2009, 87% of all viruses tested were the H1N1 influenza strain responsible for the pandemic.

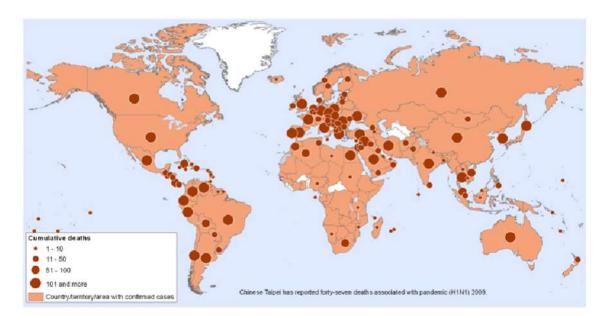


FIGURE 6: PANDEMIC (H1N1) 2009 LABORATORY CONFIRMED CASES AND NUMBER OF DEATHS AS REPORTED TO WHO AS OF 15TH AUGUST 2010 (WHO, 2010A, ARCHIVED BY THE WAYBACK MACHINE)

One year after the first cases had been detected, another influenza virus – the seasonal A(H3N2) – replaced H1N1 as the most commonly detected virus in some countries of the southern hemisphere. However, H1N1 still strongly affected healthy younger adults, while groups-at-risk were mainly infected with seasonal flus. By August 2010, H1N1 was no longer the dominant virus, yet there would still be a significant number of infected cases during the winter season. Instead, a

⁶ Excluding Antarctica

mix of seasonal influenza viruses circulated in the world. Thus, on 10 August 2010, Dr Chan declared that the swine flu pandemic had moved into the post-pandemic phase, where: "[I]evels of influenza activity have returned to levels seen for seasonal influenza in most countries with adequate surveillance" (WHO, n.d.-e).

Figure 6 shows the final situation regarding the 2009/2010 pandemic at the beginning of the post-pandemic phase including affected countries and cumulative deaths.

5 TOURISM MARKET MODELING

In this chapter, an overview is given of tourism market modeling, what is currently being and has already been researched in this regard, what some pertinent results of previous studies are and how this field relates to and handles crisis events and situations.

Song et al. (2011) state that more than 500 studies on tourism demand modeling have been published since the 1960s. According to Song and Li (2008), such mostly quantitative studies can be divided into non-causal and causal models. The former methods consist of time series that model or forecast tourism demand, either ex post or ex ante. The latter choose from a plethora of econometric methods to identify causal relations between tourism demand and variables influencing it.

The authors (Song & Li, 2008) also mention that the new millennium has produced more diverse forecasting methodologies. Some prominent methods used by researchers to model or forecast tourism demand time series after the year 2000 (Song & Li, 2008) are variations of the ARIMA models (AutoRegressive Integrated Moving-Average) and GARCH models (Generalized Autoregressive Conditional Heteroskedastic). Methodologies such as naïve 1 (no change), naïve 2 (constant growth rate), simple autoregressive and exponential smoothing models, were mostly used to evaluate other models' forecasting accuracy. Popular methodologies with an econometric focus, identified by Song and Li (2008), include the autoregressive distributed lag model (ADLM), the error correction model (ECM), the vector autoregressive (VAR) model and the time varying parameter (TVP), as well as variations and improvements thereof. Moreover, tourism forecasters have started employing artificial intelligence (AI) models, such as the artificial neural network (ANN), the rough set approach, the fuzzy time series method, genetic algorithms (GA) and the support vector machine (SVM). Of course, other models have emerged or gained more importance since the paper (Song & Li, 2008) was published, for instance ETS (Error-Trend-Seasonal or ExponenTial Smoothing), seasonal naïve or Bayesian estimation, such as BVAR, which was found to outperform other models under certain conditions (Gunter & Önder, 2015).

Based on previous research, Scholtz et al. (2012) identified the factors that most powerfully influence the tourists' demand for tourism products in a destination or country. These determinants were identified as income, relative prices, traveling costs, exchange rates, marketing expenses, travel motivation, supply factors and qualitative factors, such as age and holiday entitlements that influence time available for travel. From a broader point of view, evidence suggests that there is a time lag between economic cycles and tourism demand cycles (Gouveia & Rodrigues, 2005).

Some papers employing econometric methods go one step further and additionally evaluate the forecasting performance of the methods utilized. Comparing these evaluations, Song and Li (2008) discovered that there is no one model that consistently outperforms other models in

terms of forecasting accuracy. Depending on the subject(s) studied, the situational considerations and the variables incorporated and excluded in the model, different approaches deliver superior or inferior results with dissimilar forecasting accuracies.

Song and Li (2008) found that panel data regression models, despite being suitable for tourism demand modeling (see Modeling), were used in only 3.3% of the studies investigated – that is in 5.6% of articles containing econometric approaches. Song and Li (2008) further stated that the method's tourism forecasting ability had not yet been studied. When compared with other fore-casting methods, Baltagi (2008) found that homogeneous panel data estimators, which have common parameters across the cross-sectional entries, performed better than heterogeneous panel data estimators, which vary across individuals. However, Baltagi's (2008) findings have yet to be applied to tourism forecasting, where panel data models are seldom used.

While none of the panel analyses in Song and Li's (2008) review of recent research focus their investigation on crisis situations, in general "economists made considerable efforts to develop demand models and to estimate the effect of specific events (impact analysis) such as 9/11, SARS, megaevents, wars, terrorist attacks, etc" (Smeral, 2009a, p. 1) and lately also for financial and economic crises, especially the GFC in 2008 (Hall, 2010; Smeral, 2009a; Smeral, 2009b). Researchers, including Araña and León (2008) as well as Blake and Sinclair (2003) and Carlsen and Hughes (2008), Eugenio-Martin, Sinclair and Yeoman (2005) as well as Mao, Ding and Lee (2010), have specifically studied tourism demand related to terrorist attacks or natural disasters. A few other studies that analyzed crises or incorporated crises into an analysis are reported in the following paragraphs.

Andraz and Rodrigues (2016) analyzed the resilience of Portugal's tourism generating countries to external shocks. They conclude that economic cycles and tourism flows are related to each other and as a result economic shocks have negative impacts on tourism demand, as measured in overnight stays. In fact, "[r]ecession periods dictate tourism contractions, while economic expansions are reflected in persistent increases of tourism flows" (Andraz & Rodrigues, 2016, p. 6). Andraz and Rodrigues (2016) also assert that different crises result in different reactions by tourism markets.

The research done by Campos-Soria et al. (2015) focused on the economizing strategies of tourists during the global financial or economic crisis. They corroborated previous studies regarding the likely behavior of tourists in times of economic distress, namely that tourists rather economize on holiday expenditure (how to cut-back) than take fewer holidays (cutback). Indeed, Campos-Soria et al. (2015) found that tourists mostly reduced the length of their stay and sought out cheaper accommodation.

Regarding the same topic, the economic crisis, Eugenio-Martin and Campos-Soria (2014) were the first to research the cutback decision of tourists and the factors that such decisions are based

on: different preferences for tourism expenditure in heterogeneous countries can be linked to home-country climate conditions, GDP and GDP growth.

In addition, Smeral (in press) provides evidence that income elasticites of demand in tourism differ depending on the overall economic environment, i.e. they vary across the business cycle. Loss aversion, liquidity constraints and precautionary savings are suggested as the main reasons for this behavior.

Song et al. (2011) focused on the impact of the GFC on demand for hotel rooms in Hong Kong. Their results show that the income level of tourists' home countries, the price of hotel rooms and the word-of-mouth effect most strongly affect hotel room demand.

The same location, Hong Kong, was studied by Wu et al. (2010) in regards to infectious diseases and their impact on hotel occupancy rate. Unexpected disease outbreaks – H5N1 bird influenza (avian flu) and SARS (Severe Acute Respiratory Syndrome) – were found to have significant negative impacts on the Hong Kong hotel industry.

Uniting many of the topics mentioned in the above studies, Page et al. (2011) considered the impacts of both the GFC and the Swine Flu on demand for tourism in the United Kingdom. They divided changes in tourism demand based on how strongly tourist arrivals were affected by the GFC and Influenza H1N1, respectively. Page et al. (2011) found evidence that, indeed, both crises had measurable negative impacts on tourism demand for the United Kingdom.

The previously mentioned studies demonstrate that crisis situations can have significant and measurable effects on tourism demand. In fact, the conclusions of these studies show that different crises necessitate different responses by the tourism industry and that tourism flows are related to economic cycles and factors, but also influenced by other shocks. These results make it necessary for interested and affected parties to consider crises when making decisions.

Markets consists not only of demand, but also of supply. Hence, also the latter has to be taken into consideration. However, unlike tourism demand, tourism supply modeling and forecasting is rarely done. A search for publications using the two scientific search engines⁷ Google Scholar (scholar.google.com) and sciencedirect (www.sciencedirect.com) yielded no results. Regarding supply planning, it is rarely modeled because it is seen as an investment problem and a real estate business problem (E. Smeral, personal communication, 19th December 2016). Indeed, only one article, which as part of forecasting the city hotel market modeled – in addition to

⁷ Google Scholar alone already lists results from many other databases, including sciencedirect, hence it was considered redundant to repeat the same queries on the few other available search engines or databases.

tourism demand – tourism supply and provides a supply function (Smeral, 2014), was discovered. Smeral's (2014) article is described in more detail in chapter 6.1, Methodology.

In contrast to demand or supply analyses, a recent study (Perles-Ribes et al., 2016) investigated the effects of crises on tourism destination competitiveness. In the empirical analysis, global market share was used as the explained variable to determine the competitiveness of Spain based on various economic indicators. Another study by Barrows and Naka (1994) evaluated hospitality stock returns in the USA based on macroeconomic factors and found that especially restaurant stocks were able to be explained by these variables. These studies show that tourism market studies are not constricted to modeling only demand or supply, but that there are broader applications of forecasting methods.

6 METHODOLOGY, DATA AND MODELING

This chapter describes, first, the methodology used for the quantitative analysis and the rationale behind it; second, the data used – sources, transformation, strengths and weaknesses; and, third, the pre-tests and reasoning behind the chosen model specifications.

6.1 Methodology

The impact of a demand-induced crisis on tourism providers is to be analyzed specifically focusing on the example of the H1N1 pandemic 2009/2010 (the so-called "swine flu") for the six years from 2007 until 2012 (as to include effects of the 2008 GFC). To this end, a system of two equations is necessary. The first equation tries to estimate the impact of the pandemic on tourism demand; the second equation tries to link tourism demand with tourism supply.

A basis for the design of these equations serve the standard tourism demand (Equation 1) and standard tourism supply (Equation 2) models from Smeral's (2014) paper on the forecasting of the city hotel market. Since it cannot be argued that the swine flu was the the only reason for changes in touristic activity and changes in demand the only reason for adjustments of supply, these additional standard variables, as reported below, have to be included in the model.

$$N_{ji} = f(Y_j, ADR_{ji}, ADR_{jc}, CPI_{ji}, CPI_{jc}, TC_{ji}, TC_{jc}, Q_i)$$
(1)

Equation 1 shows how tourism demand can be explained with constant prices and exchange rates from the source market (j) to the destination (i) in terms of overnight stays (N_{ji}), which is a function of the tourists' countries' GDP or income (Y_j), the average daily rate per bed night sold of the destination (ADR_{ji}) and of competing destinations (ADR_{jc}) in relation to the tourists' country of origin, the consumer price index to capture the costs for various products and services of the destination (CPI_{ji}) and of competing destinations (CPI_{jc}) in relation to the source market, the traveling costs (TC_{ji} and TC_{jc}, respectively) and varied qualitative factors (Q_i) (Smeral, 2014; also cf. Song et al., 2011).

$$B_i = f(ADR_i, OCC_i, F_i)$$
(2)

On the other hand, Equation 2 illustrates how the supply of beds (B_i) can be explained with the average daily rate (ADR_i), the bed occupancy rate (OCC_i) and shift factors (F_i), such as construction and labor costs, interest rates and expected capital gains in a destination (Smeral, 2014).

In order to be representative of the crisis in general as well as to aid in reducing the risk of local characteristics influencing the results, a small number of destinations across the globe has been chosen for analysis. Specifically, due to the source of crucial data being the research company

STR Global (www.strglobal.com), which focuses on city tourism and hospitality, cities were chosen to compare the effects on tourism supply of the demand-based crisis that resulted from the H1N1 influenza.

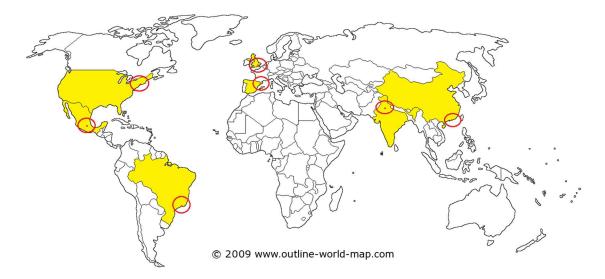


FIGURE 7: GEOGRAPHICAL REPRESENTATION OF THE CROSS-SECTION DIMENSION. RED DOTS APPROXIMATE THE SEVEN CITIES' LOCATIONS, OWN ILLUSTRATION BASED ON WORLD MAP (N.D.)

The exact cities chosen were identified as the foremost city destination (by foreign arrivals) in their respective country based on 2009 rankings according to the strategic market researcher Euromonitor International (www.euromonitor.com). The countries, in turn, were chosen based on two reasons. First, the locations were chosen based on their broad distribution in terms of geographical location. In other words, all majorly affected continents (Europe, Asia, North America and South America) were planned to be represented. Second, the locations were chosen based on how early and how severely a country had been affected by the swine flu. In other words, based on first reports of illnesses and on the number of cases and deaths (BBC, n.d.). The assumption is made that tourists cognitively associate cities with their respective country, for example, if they hear about a pandemic in Mexico, tourists' decision to travel to Mexico City is influenced by the fact that Mexico City is located in Mexico.

Two countries were chosen per continent and one city per country for eight cities in total, namely Hong Kong in China, Delhi in India (Asian representatives), New York City in the United States of America, Mexico City in Mexico (North American representatives), London in the United Kingdom, Barcelona in Spain (European representatives), Rio de Janeiro in Brazil and Buenos Aires in Argentina (South American representatives). Buenos Aires was subsequently dropped from the sample, because data was not obtained, leading to a sample of seven cities in seven countries and on four continents.

These two above-identified dimensions – months as the time dimension and the seven cities as the cross-sectional dimension – are a clear case of panel data⁸, an approach seldom used in tourism demand modeling. For that reason, the full model is estimated to be as follows:

$$\begin{cases} N_{jit} = f(Y_{jt}, ADR_{it}, ADR_{ct}, CPI_{jit}, CPI_{jct}, Q_{it}, H1N1_{it}) \\ B_{it} = f(ADR_{it}, OCC_{it}, F_{it}) \end{cases}$$
(3)

The modified demand function (Equation 3) is similar to the standard tourism demand model (Equation 1). However, unlike Equation 1, Equation 3 does not include traveling costs $(TC_{ji,jc})$ because they are difficult to obtain or estimate (Dwyer, Forsyth & Dwyer, 2010). Additionally, there is no generally agreed upon definition and traveling costs might, together with overall price indices, cause multicollinearity issues (Song et al., 2009, as cited by Gunter & Önder, 2015).

Moreover, due to the nature of the data procured from STR, the ADR variables are not included as ratio between the ADR of the tourists' home countries and the destinations or competing destinations, respectively, and instead as simple measurements of expense for tourists (cf. Song et al., 2011). Dummy variables are used to account for demand or supply changes due to non-recurring events (Song et al., 2011) and are included as part of the qualitative factor (Q_i). Events included are the GFC (2008M09 – 2009M04), the Olympic Games 2008 in Beijing and Hong Kong (horse riding) (2008M08) and in 2012 in London (2012M07, 2012M08). Finally, the impact of the swine flu (H1N1_{it}) is included as an independent and exogenous variable (Page et al., 2011). Since the effects of the pandemic are the focus of this study, the other variables, which are included in the model, also serve as control variables in order to obviate an omitted variable bias.

The modified supply function (Equation 4) is also similar to the standard tourism supply model (Equation 2). The shift factors (F_i) included are long-term interest rates, short-term interest rates and, to some extent, labor costs.

In both equations, *i* as subscript represents one of the seven city-destinations, the subscript *j* represents the corresponding source markets and the subscript *c* the matching competitors (for ease of computation and lack of data, the respective competitors are determined to be the other six cities). Both functions are additionally enhanced with a time factor (*t*) to represent the longitudinal nature of the model – one period indicates the passing of one month for a total of 72 months or six years.

⁸ The presence of panel effects and, thus, the appropriateness of panel data estimation is tested in chapter 6.3 Modeling.

The next chapter describes the source market aggregation used for the analysis before it details the individual variables, their transformations, the source of these variables and their strengths and weaknesses.

6.2 Data

In the following paragraphs, after a section regarding the source markets (*j*) used for the model, the data and variables for the analysis are described. Each of the two dependent and thirteen explanatory variables considered for the full model are reported in light of the data's origin and initial characteristics, followed by a description of the transformations necessary in order for the data to fit the model and caveats regarding limitations and weaknesses. For further details, see Appendix 1: Summary Tables and Statistics.

Variable Code	Label
N _{jit}	Rooms Sold
Y _{jt}	Gross Domestic Product
ADR _{it}	Average Daily Rate – Destination
ADR _{ct}	Average Daily Rate – Competitors
CPI _{jit}	Consumer Price Index – Destination/Source Market
CPI _{jct}	Consumer Price Index – Competitors/Source Market
H1N1 _{it}	Cases of Influenza H1N1
d_GFC	Dummy: Global Financial Crisis
d_OGHK	Dummy: Olympic Games Beijing / Hong Kong
d_OGL	Dummy: Olympic Games London
B _{it}	Rooms Available
OCC _{it}	Occupancy Rate
LT_r _{it}	Long-Term Interest Rate
ST_r _{it}	Short-Term Interest Rate
LC _{it}	Labor Costs

TABLE 2: VARIABLE CODES AND LABELS

Table 2 associates the variable codes from Equations 3 and 4 with their respective labels and outlines the structure for this chapter.

Note that ADR_{it} is only listed and described once although it is included twice in the model – in the demand function (Equation 3) and in the supply function (Equation 4). Moreover, unless data is missing, every variable includes data for each of the seven cities and for each of the 72 periods.

Transformations beyond the basic data preparations are included in the chapter Modeling. Factors to be taken into consideration for this purpose are seasonality, lagged effects and non-linear effects (Smeral, 2014).

6.2.1 Source Market Aggregation

Four variables depict the situation in or regarding the generating countries of the city destinations. Since it would not be feasible to gather data for every single source market, the respective top five foreign source markets have been identified and their data used for further analysis. Henceforth, these five collective source markets together will be referred to as source market aggregation for a destination and are reported below.

6.2.1.1 Barcelona

The top five foreign source markets for Barcelona were identified as the five countries with the highest number of arrivals or bednights to Barcelona in the years 2007 until 2012 according to TourMIS (Tourism Marketing Information System; www.tourmis.info). These countries are Italy, the UK, the USA, France and Germany. When referring to Barcelona's source market aggregation, these five markets are specified. They represent, on average throughout the years, 61% of total foreign bednights and 59% of total foreign tourist arrivals.

6.2.1.2 Delhi

For Delhi, the top five foreign source markets in 2010 were, according to the Tourism survey in the State of Delhi by order of the Indian Ministry of Tourism (2010), the USA, the UK, Germany, Australia and Japan. They constitute 50% of total foreign tourists in Delhi in 2010 and they are assumed to be the top five foreign generating countries for the other years between 2007 and 2012 too.

6.2.1.3 Hong Kong

Hong Kong data was not publicly available for the necessary years. Thus, the top five foreign source markets were identified based on 2013, November 2014 and November 2015 data (Citrinot, 2014; Hong Kong Tourism Board, n.d.). In all three cases, the USA, Mainland China, South Korea, Japan, Singapore and Taiwan were the countries generating the most tourist arrivals. Due to its status, Taiwan was not considered. The People's Republic of China, on the other hand, is economically distinct from Hong Kong (it is, after all, a Special Administrative Region) and was hence included. In 2013 (Citrinot, 2014), those five countries represented 77% of total

foreign tourist arrivals to Hong Kong and are assumed to be valid as top source markets for previous years as well.

6.2.1.4 London

London's source market aggregation was identified in a similar manner to Barcelona, that is via TourMIS data for the six years. Over these years, on average 43% of total foreign tourists arrived from the USA, France, Germany, Italy and Spain.

6.2.1.5 Mexico City

No data for Mexico City was directly available, hence Mexico as a whole is considered as proxy for the city destination. According to the Tourism Promotion Council of Mexico (n.d.-a), the top five foreign source markets for the year 2014 were the USA, Canada, the UK, Colombia and Spain. Indeed, they constituted 52% of total foreign tourist arrivals. Eleven percent of total international tourist arrivals were to the Federal District (*Distrito Federal*) (Tourism Promotion Council of Mexico, n.d.-a, n.d.-b). The assumption of an even distribution between the country and the city and the assumption of similar source markets in different years were made to justify those five generating countries as source market aggregation for Mexico City.

6.2.1.6 New York City

For New York City, the top five foreign source markets vary slightly over the six years. They include the UK, Canada, Germany, France, Brazil and Italy (New York City and Company, 2015). Brazil was omitted due to a lack of data, hence the former four countries and Italy were chosen for New York City's source market aggregation. These five countries represent, on average, 38% of international visitors to NYC between 2007 and 2012.

6.2.1.7 Rio de Janeiro

The Brazilian Study on International Tourism Demand 2007-2013 (Brazil Ministry of Tourism, 2014, p. 40) reports on the source markets for Rio de Janeiro. On average, 41% of total international tourists arrived from the USA, France, the UK, Germany and Italy. While Argentina had a higher ranking than Italy, it was not considered for the source market aggregation due to a lack of data.

6.2.2 Rooms Sold

The variable coded N_{jit} serves as proxy for tourism demand and is, next to rooms available, one of the two dependent variables in the model. It gives the number of rooms sold by the destination to the source markets over time as collected by STR and as communicated in its trend reports (STR, 2017a-g). There are no missing values, hence 504 entries across the seven cities for 72 months each have been available for analysis.

Since STR does not collect data for all hotels, results may be influenced by the hotels included (or not included) in the sample. The assumption is that STR data works as representative sample of the locations' real data. This assumption has been tested for Barcelona and Hong Kong.⁹

City	Source Market Aggregation	% of total foreign tourists
Barcelona	USA, UK, Germany, France, Italy	59%
Delhi	USA, UK, Germany, Japan, Australia	50%
Hong Kong	USA, China (PRC), South Korea, Japan, Singapore	77%
London	USA, Germany, France, Italy, Spain	43%
Mexico City	USA, UK, Canada, Spain, Colombia	52%*
New York City	UK, Germany, France, Italy, Canada	38%
Rio de Janeiro	USA, UK, Germany, France, Italy	41%

TABLE 3: SOURCE MARKET AGGREGATION BY DESTINATION, OWN CALCULATIONS

*VALUE FOR MEXICO (COUNTRY)

In the case of Barcelona, rooms sold as received from STR have been correlated with monthly data on "[b]ednights in hotels and similar establishments in city area only" by total foreign and domestic markets as retrieved from the database of TourMIS (Tourism Marketing Information System; www.tourmis.info). The result suggests a very strong and significant correlation between the STR sample and overall data from TourMIS with p=0.94. The remaining difference can be explained with the dissimilar variables used for the correlation (bednights vs rooms sold), the different sample location (city area only vs greater Barcelona) and also the different sample size.

In the latter case of Hong Kong, the data from STR has been correlated with monthly data from official Hong Kong statistic reports (Hong Kong Census and Statistics Department, n.d.) for all hotels in Hong Kong. Since rooms available and rooms sold are not included in the reports, the former value has been calculated as the number of rooms multiplied by the days in a month and the latter as rooms available multiplied by the occupancy rate. Rooms sold between STR data and official Hong Kong statistics are, as for Barcelona, significantly and almost perfectly correlated with ρ =0.96.

⁹ Sufficient data for such a reliability check was not available for the other city destinations.

These correlation tests reveal that the assumption that STR data is a representative sample for rooms sold in these two destinations holds. It is possible to conclude that the same is true for the other five destinations. The results for rooms available and the occupancy rate are reported in their respective sections.

Moreover, STR provides its own solution regarding this collection bias (cf. STR, 2017a-g): the company first analyzes guidebook listings and hotel directories for information on hotels that do not provide data, second groups reporting and non-reporting hotels based on price level and geographic proximity and third estimates the figures for non-responding hotels based on data on nearby responding hotels with similar price levels.

Furthermore, visual inspection of the variable reveals no implausible outliers (cf. Figure 8). The observable seasonality is, as previously mentioned, expected and the effects due to, presumably, the GFC and the pandemic are visible (downward trend) in 2009. For graphs depicting the deseasonalized development of the variables, see Appendix 2: Moving-Average Filter Scenarios.

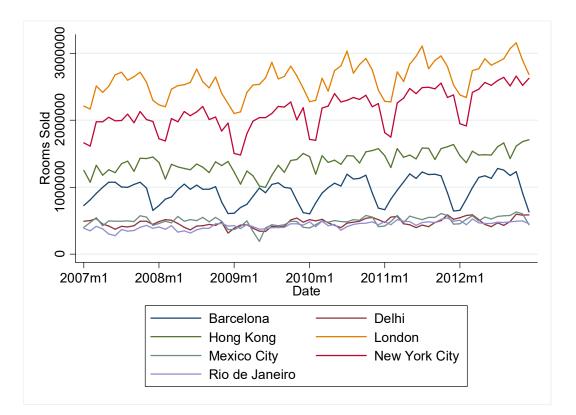


FIGURE 8: DEVELOPMENT OF ROOMS SOLD (N_{JIT}) BY DESTINATION, OWN ILLUSTRATION. SOURCE: STR (2017A-G)

6.2.3 Gross Domestic Product

Since cities constitute the cross-sectional dimension of the model, business travelers have to be taken into consideration. Hence, GDP is more appropriate as a measure for the income of tourists (Smeral, 2009a, 2014). This first explanatory variable, coded Y_{jt}, shows the total GDP of the source market aggregation (see section 6.2.1) for each city destination in monthly and million US dollars at constant prices (2010). Data for GDP was not available in that format for all countries, hence own calculations were used to derive the final numbers.

The basis for the calculations was the quarterly and seasonally adjusted GDP using the expenditure approach in national currencies and with current prices (OECD, n.d.-b; Federal Reserve Bank of Atlanta, 2016) for the countries identified to be part of any source market aggregation: the USA, France, Germany, Italy, Spain, the UK, Canada, Colombia, South Korea, Japan, China and Australia. Data for Singapore was available at 2010 market prices only (Singapore Department of Statistics, n.d.).

As a first step, the GDP in national currencies in billions or millions were all converted to US dollars. Monthly foreign exchange rates (Federal Reserve Bank of St. Louis, n.d.) were averaged and the resulting quarterly foreign exchange rates were used to convert the quarterly GDP from current national currencies to current US dollars. Simple multiplication brought the entries to the same scale. As a second step, monthly Consumer Price Indices (OECD, n.d.-b) with base year 2010 were averaged to quarterly CPI values and employed to transform the current GDP into constant GDP¹⁰ in order to account for inflation. In the case of Australia, only quarterly CPIs were available (OECD, n.d.-b) and for Singapore available annual CPIs were assumed to be valid for twelve months each (The World Bank, n.d.). As a third and final step, the quarterly and constant GDP in US dollars was divided by three to receive monthly figures (Gunter & Önder, 2015).

These now correctly available values for the GDP for every important source market for each month were subsequently grouped by destination and totalized in order to obtain values that represent the total GDP of the individual city's source market aggregation (cf. Table 3), which is appropriate to use in the model. For ease of interpretation and calculation, the GDP in the dataset has been recalculated to million US dollars.

6.2.4 Average Daily Rate – Destination

The explanatory average daily rate for the destination (coded as ADR_{it}) is one of the variables accounting for differences in price levels between the source markets, the destination and its competitors. The nominal values in US dollars were converted to constant (2010) values by using, similar as with the GDP, the CPIs (OECD, n.d.-b) of the respective destination. Since the ADR is also obtained from STR, the same caveats and assumptions as for Rooms Sold apply.

¹⁰ Constant GDP₂₀₁₀=GDP_t × $\frac{CPI_{2010=100}}{CPI_{t}}$; subscript *t* denotes the current period

6.2.5 Average Daily Rate – Competitors

This variable, ADR_{ct}, represents the average daily rate of a destination's competing destinations as weighted average. The weights are the respective proportion of tourists from the destination's source market aggregation traveling to its competitors. In other words, the variable is the sum of the six competitors' ADR_{it} weighted by the percentage of tourists from the destination's source market aggregation traveling to the corresponding competitor out of tourists from the destination's destination's source market aggregation traveling to all its competitors.

The numbers and, consequently, shares of tourists were taken for the year 2009 and the weights kept equal for all six years. In the cases where 2009 data was not available for a city, the respective country's growth or decline (The World Bank, n.d.) was used as proxy to calculate the destination's number of tourists for 2009. Moreover, since not all destinations published numbers on tourists arriving from each source market of the other destinations, values that were not available have been assumed to be insignificant and, hence, negligible.

6.2.6 Consumer Price Index – Destination

Also embodying a relative price level, the variable coded as CPI_{jit} serves as a connection between price levels at the source market aggregation and the destination and is calculated as fraction of the destination's CPI (CPI_{it}) over the source market aggregation's CPI (CPI_{jt}). While CPI_{it} is simply the monthly consumer price index of the country where the destination is located with base year 2010 (OECD, n.d.-b), CPI_{jt} is calculated as a weighted average of the source markets' CPIs. The weights are the proportion of a source market's GDP over the sum total GDP for the source market aggregation. Only quarterly CPIs for Australia (OECD, n.d.-b) and only annual CPIs for Singapore (The World Bank, n.d.) were available. They were each assumed to be valid for three and twelve months, respectively.

6.2.7 Consumer Price Index – Competitors

CPI_{jct} is, in contrast to CPI_{jit}, the result of dividing the CPI of the destination's competitors (CPI_{ct}) by the source market aggregation's CPI (CPI_{jt}) and represents the relative price level between the competing destinations and the generating countries. CPI_{jt} for CPI_{jct} is equal to CPI_{jt} for CPI_{jit}. CPI_{ct}, on the other hand, is calculated identically as ADR_{ct} and is, thus, the weighted average of the competing destinations' CPI with the base year 2010 and the weights being the respective share of tourists from the destination's source market aggregation traveling to its competitors.

6.2.8 Cases of Influenza H1N1

The present variable modifies the standard tourism demand model and is included to explain the changes in rooms sold due to monthly numbers of cases of the swine flu at the destination (H1N1_{it}). This impact caused by the pandemic is captured via the number of reported cases per country per week and summarized to monthly figures¹¹ (WHO, n.d.-b). While the pandemic lasted, officially, from April 2009 until August 2010, data outside this period is used to cover the entire analyzed time from 2007 until 2012 (cf. Figure 9).

Data on the swine flu, although taken from the WHO, is often only an estimate due to the fact that reporting countries were not required to test and report individual cases after July 2009, which led to official figures understating the real numbers of cases (WHO, n.d.-d). Additionally, many deaths were not attributed to the H1N1 virus, because these cases were never tested or recognized as a result of the swine flu (WHO, n.d.-d). However, since news media did assumably not have a more detailed source of information during those times, it should be safe to assume that the number of cases used in the model corresponds to the impact of swine flu on tourism demand.

6.2.9 Dummy: Global Financial Crisis

The dummy variable, coded as d_GFC, takes into account the ramifications of the Global Financial Crisis, as seen already in Figure 8. It takes a value of 1 in the months from September 2008 until April 2009 and 0 otherwise (cf. Figure 9).

6.2.10 Dummy: Olympic Games Beijing / Hong Kong

Another event that might have influenced the number of tourists traveling to Hong Kong are the Olympic Summer Games in Beijing in August 2008, which include the equestrian competitions that happened in Hong Kong. Hence, this dummy variable (d_OGHK) takes a value of 1 for that month and 0 otherwise.

6.2.11 Dummy: Olympic Games London

A second dummy variable for Olympic Summer Games, this time in London, is coded as d_OGL and takes a value of 1 for July and August 2012 and a value of 0 otherwise.

¹¹ Cases for weeks with more than two days in a neighboring month were divided in half and equally allocated to both months.

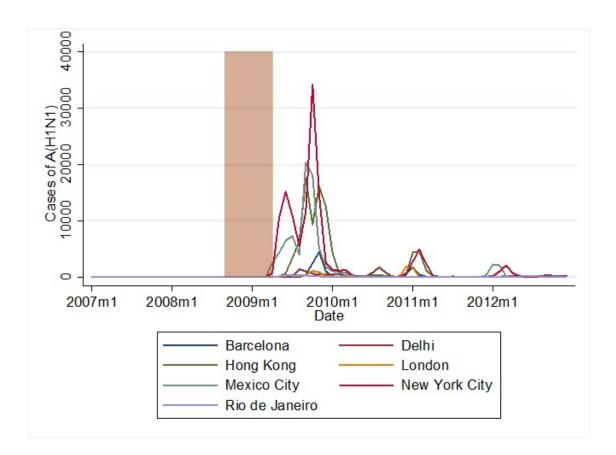


Figure 9: Development of the Cases of influenza (H1N1 $_{\rm ff}$) by destination, own illustration. Source: WHO (n.d.- c)

THE SHADED AREA CORRESPONDS TO THE MONTHS WHEN THE DUMMY FOR THE GFC TAKES VALUE OF 1

6.2.12 Rooms Available

The rooms available variable, coded B_{it}, contains data for tourism supply and is, besides rooms sold, one of the two dependent variables in the model. It gives the number of rooms available at a destination over time as collected by STR and as communicated in its trend reports (STR, 2017a-g). There are no missing values, hence 504 entries across the seven cities for 72 months each have been available for analysis.

Just as rooms sold, the reliability of data from STR has to be considered. For rooms available, the assumption of STR data being a representative sample was tested only for Hong Kong.¹² Since data for rooms available is not directly included in the reports (Hong Kong Census and Statistics Department, n.d.), the number of rooms was multiplied by the days in a month in order to receive comparable data. As with rooms sold, the correlation is significant and very strong

¹² Sufficient data for such a reliability check was not available for the other city destinations.

with p=0.98, which implies that STR data for rooms available is able to represent and approximate the real situation in Hong Kong and, thus, likely to be the case in the other destinations too. The results for the occupancy rate are reported in the subsequent section.

6.2.13 Occupancy Rate

The room occupancy rate (OCC_{it}) is calculated as a fraction of rooms sold (N_{jit}) over rooms available (B_{it}) (STR 2017a-g, own calculations) and is used to, partially, explain the number of rooms available at a destination. Together with the average daily rate at the destination (ADR_{it}), it serves as connection between the two equations in the model and, hence, indirectly links the impact of the swine flu (H1N1_{it}) to the tourism supply. To make calculations simpler, the occupancy rate is given as percentage points instead of in percentages in the model.

As with rooms available, the reliability of the occupancy rate was checked only for Hong Kong.¹³ The data for overall occupancy rate is available in the Hong Kong statistics reports (Hong Kong Census and Statistics Department, n.d.) and, hence, directly comparable with the occupancy rate for hotels investigated by STR. The results are similar to the other two variables, in that the correlation is significant and very strong with ρ =0.96. Again, this implies that STR data can be used as representative sample for the occupancy rate of Hong Kong and probably for the other destinations as well.

6.2.14 Long-Term Interest Rate

The long-term interest rate (in percentage points, p.a.) is "one of the determinants of business investment. Low long-term interest rates encourage investment in new equipment and high interest rates discourage it" (OECD, n.d.-a). As such, it is part of the shift factors in the standard tourism supply model. For London, Barcelona and New York City, the long-term interest rates for their respective country were taken from the OECD (n.d.-b). For Mexico City, Hong Kong, Delhi and Rio de Janeiro¹⁴, an average of monthly high and low prices for their respective country's 10-year government bond rates were used (Investing.com, n.d.). A comparison between monthly long-term interest rates for the UK according to the OECD (n.d.-b) and an average of monthly high and low values for 10-year government bond yields for the UK resulted in ρ =0.998, which is an almost perfect correlation.

¹³ Sufficient data for such a reliability check was not available for the other city destinations.

¹⁴ Data is missing for the first five months of 2010 and was substituted with average values.

6.2.15 Short-Term Interest Rate

The short-term interest rate (in percentage points, p.a.) is the rate "at which short-term borrowings are effected between financial institutions or the rate at which short-term government paper is issued or traded in the market" (OECD, n.d.-c). The data for these interest rates on credits is obtainable from the OECD (n.d.-b) for the UK, Spain, the USA and Mexico, from the International Monetary Fund (n.d.) for Hong Kong, from Investing.com (n.d.) for India as the average between monthly high and low prices for its 3-year government bond rates and from the Brazilian Central Bank (n.d.) as their actual Selic rate¹⁵.

6.2.16 Labor Costs

Labor costs (OECD, n.d.-b) were only available for the UK, Spain and partially Mexico, namely as yearly index (2010=100) of unit labor costs for wholesale, retail, trade, accommodation, food, services, transportation and storage. Unit labor costs are "often viewed as a broad measure of (international) price competitiveness. They are defined as the average cost of labour per unit of output produced" OECD (n.d.-d). These values have to be assumed to be applicable and unchanging for every month. No readily comparable data was found for the other destinations.

¹⁵ The Selic rate is not set monthly but for one and a half months. Wherever two different rates applied to the same month, their average was calculated for that month.

6.3 Modeling

In order to choose the final model type and specification, various adjustments and tests have to be performed, which will be outlined and described in this section. To be considered are seasonality, the transformation of variables, panel effects, the case of seemingly unrelated regressions (SUR), cross-sectional dependence, autocorrelation and heteroscedasticity. The software Stata (version 12) is used for tests, regressions and modeling.

6.3.1 Seasonality

As previously mentioned and as observed in Figure 8, seasonality is present in all seven crosssections. Since these seasonal components of the timeline are distracting and do not provide further insight into the topic in question, they need to be filtered out. For this analysis, a 12month moving average filter was employed (Wu et al., 2010) with a one-sided window before the current date. By taking the average of the preceding eleven and the current periods' values, it smooths the variables along the time dimension and eliminates seasonal components. For consistency, all variables besides the dummy variables were filtered using the same mechanic. Figure 10 shows the smoothed development over time of rooms sold for the seven cities. In comparison to Figure 8, seasonal effects are clearly absent after the unadjusted first few months. The issue of these kinks at the beginning of the series due to a lack of preceding data for the MA filter is acknowledged but considered marginal. For the rest of this thesis, when variables are mentioned and if not indicated otherwise, the MA filtered variables are referred to. Appendix 2: Moving-Average Filter Scenarios further shows other possible MA windows and the development of MA filtered variables are exhibited in Appendix 3: Development of MA Filtered Variables.

6.3.2 Variable Transformations

Transforming variables before using them in models can help simplify the data or make the pattern more consistent and hence can lead to more accurate forecasts (Hyndman & Athanasopoulos, 2012). Taking natural logarithms (ln(x) for x>0), for instance, allows coefficients to be interpreted as elasticities, linearizes non-linear trends and can reduce other problems in the data (e.g. heteroscedastic error terms or skewness). For the variables with entries equal to or smaller than zero, a constant (1) was added before the calculation of logarithms, in order to allow the mathematical transformations.

For this dataset, logarithmic, power and no transformations were considered. Thus, three types of variables emerged: untransformed variables (level or lin variables), natural logarithms (log) and square roots (root). Combinations thereof, for instance log-level models where the dependent variables are in natural logarithms and the exlanatory variables are untransformed, were

modeled to find the model with the best economic and statistical fit (see 6.3.8.2 Variable specification).

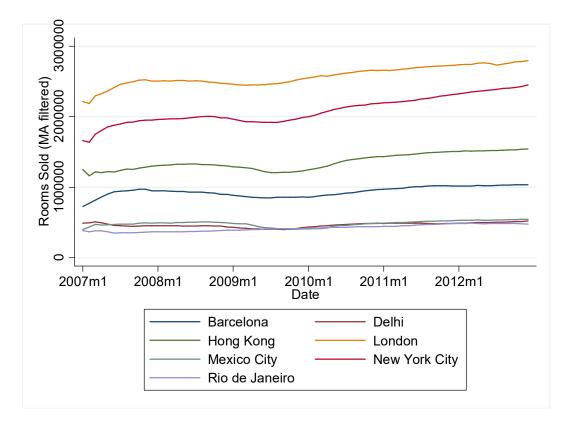


FIGURE 10: DEVELOPMENT OF ROOMS SOLD (MA FILTERED) BY DESTINATION, OWN ILLUSTRATION. SOURCE: STR (2017A-G), OWN CALCULATIONS

6.3.3 Panel Effects

As previously mentioned, the structure of the dataset with both a time and a cross dimension, i.e. panel data, presumably entails panel estimation methods. As a reference for tests and modeling in regards to panel data, Baltagi's (2013) book "Econometric analysis of panel data" was used.

Such panel regressions are positively preferred over distinct time-series analyses for multiple reasons. Besides fitting the data, panel estimation reduces the problem of multicollinearity, it synergizes information from both cross-sectional and time-series data, it provides more degrees of freedom in the model estimation (Song & Li, 2008) and it allows the identification and estimation of effects and behavior that is normally undetected using only cross-sectional or time-series data (Ledesma-Rodríguez et al., 2001). Further benefits of panel data over other methods are described by Baltagi (2013, pp. 6-8). Panel data allows the researcher to control for individual heterogeneity, it gives more variability, more efficiency and more informative data, it provides the researcher the ability to better study the dynamics of adjustment to, for instance, economic policy changes and macro panels encounter fewer problems with unit roots than time-series. Since secondary data is used for the present research, many of the weaknesses of panel data

mentioned by Baltagi (2013, pp. 8-10) are related to the gathering and preparation of data, for instance measurement errors or problems of data collection and reporting. One possible limitation regarding macro panels, if not treated correctly, is cross-section dependence between locations.

Scatter plots for both equations in the model with their respective dependent variables and, as an example, one explanatory variable each show that the intercepts are, indeed, different for diverse location (see Figure 11 and Figure 12 and compare with Appendix 4: Scatter Plots).

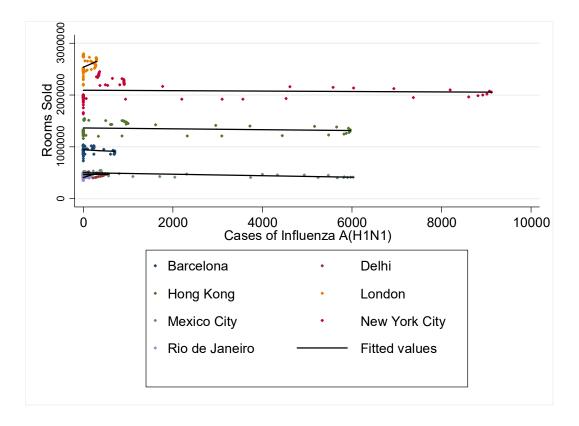


FIGURE 11: SCATTER PLOT: ROOMS SOLD – CASES OF INFLUENZA WITH FITTED VALUES BY DESTINATION, OWN ILLUSTRATION. SOURCE: STR (2017A-G), WHO (N.D.-C), OWN CALCULATIONS

In addition to visual inspection, Stata offers the possibility to statistically test whether panel estimation is appropriate or not. In fact, the Breusch-Pagan Lagrange multiplier (LM) test (cf. Baltagi, 2013, p. 68) tests the null hypothesis that the variances across cities is zero¹⁶ and, therefore, whether a random effects model or an OLS model is suitable. For various transformations of the supply function's (Equation 4) variables, the $\bar{\chi}^2$ statistic is high and the null is rejected at a 1% significance level. Hence, the variance across cities is not zero and a random effects panel regression is appropriate.

¹⁶
$$H_0: \sigma_{\mu}^2 = \sigma_{\lambda}^2 = 0$$

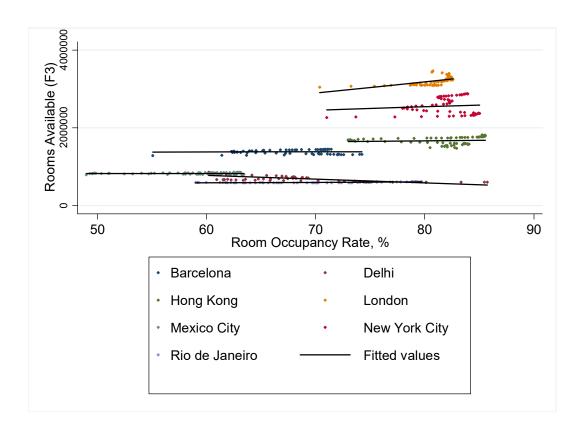


FIGURE 12: SCATTER PLOT: ROOMS AVAILABLE (3 MONTH FORWARD) – ROOM OCCUPANCY RATE WITH FITTED VALUES BY DESTINATION, OWN ILLUSTRATION. SOURCE: STR (2017A-G), OWN CALCULATIONS

To check whether random (RE) or fixed effects (FE) are present in the model, Hausman's specification test (Baltagi, 2013, p. 76) can be used. For this test, the null hypothesis is that individual effects are not correlated with the regressors¹⁷, i.e. that they are random. FE estimators derived via a within transformation give consistent results in either case – with the individual effects and the regressors being correlated or not. However, a RE estimator is the "best linear unbiased, consistent and asymptotically efficient" (Baltagi, 2013, p. 76) estimator when H₀ holds. This renders the FE estimator inefficient – yet still consistent – under the null. On the other hand, when the null hypothesis of the Hausman test is rejected, i.e. when the individual effects and the regressors are correlated, the RE estimation results are inconsistent.

Whether the covariance matrices of the test are based on the estimated disturbance variance from the efficient estimator (random effects regression) or the consistent estimator (fixed effects regression) and regardless of the variables' transformations in the functions, the test statistics suggest the presence of fixed effects in the demand function (Equation 3) and of random effects in the supply function (Equation 4). Indeed, for the demand function the null hypothesis

 $^{17}H_0: E(u_{it}/X_{it}) = 0$

is rejected at a 1% significance level, although it is not rejected for the supply function. Moreover, according to a post on the official Stata forum email list (Statalist Archive, 2014), in the case of balanced panels, the standard Hausman test based on the consistent estimator gives the same results as the heteroskedasticity robust Hausman-type test as proposed by Wooldridge (2002).

6.3.4 Autocorrelation

Wooldridge (2002) also proposed a test for serial correlation in panel data. The null hypotheses is that there is no first-order autocorrelation in the series. For both equations in their different variations, the null is rejected at a 1% significance level. Hence, the test indicates that first-order autocorrelation is present.

6.3.5 Heteroskedasticity

For heteroskedasticity, the test performed in Stata depends on whether the regression is a fixedeffects or random-effects model. Thus, heteroskedasticity in the demand function can be tested with a modified Wald test for groupwise heteroskedasticity¹⁸. Heteroskedasticity in the supply function, on the other hand, can be tested with a likelihood-ratio (LR) test between maximumlikelihood parameter estimates from an iterated generalized least squares (GLS) panel regression with assumed heteroskedasticity and from an ordinary GLS estimation without heteroskedasticity (Stata, n.d.). For both tests, the null hypothesis is homoskedasticity.

In the case of the FE demand function, the test statistic of the modified Wald test, χ^2 is significant at a 1% level of significance, hence the null of homoskedasticity is rejected and heteroskedasticity has to be assumed. The χ^2 test statistic of the LR test for the RE supply function is high and significant at a 1% significance level, too, thus the null of homoskedasticity is rejected and the alternative hypothesis of heteroskedasticity can be accepted.

6.3.6 Cross-Sectional Dependence

Stata offers two tests for contemporaneous correlation: a Breusch-Pagan LM test of independence for FE models and Pesaran's test for cross-sectional dependence (CD) for fixed or random effects. Both tests examine whether residuals are correlated across the cities, and for both tests the null hypothesis states that these residuals are independent or not correlated.

 $^{^{\}mbox{\tiny 18}} H_0 {:}\, \sigma_i^2 = \sigma^2$; $\forall \, i$

For the demand function (FE), the χ^2 test statistic of the Breusch-Pagan LM test of independence is significant at a 1% significance level and Pesaran's CD test is significant at a 10% level of significance. Both indicate the presence of contemporaneous correlation. Pesaran's CD test for the supply function (RE) is significant at a 1% significance level and, hence, also rejects the null of cross-sectional independence.

6.3.7 Seemingly Unrelated Regressions

Zellner's (1962) seemingly unrelated regressions (SUR) approach is able to capture efficiency due to the correlation of the disturbances across various equations in cases where a set of equations has to be estimated (Baltagi, 2013). Indeed, some of the variables in the model are equal for both equations, (3) and (4): ADR_{it} is an explanatory variable in both cases and N_{jit} is the dependent variable in (3) and, indirectly, an explanatory variable in (4) via OCC_{it}.

In Stata, testing for SUR can be done with non-panel data using a Breusch-Pagan LM test of independence. Indeed, the test reveals that it is appropriate to estimate the model using the SUR approach (the null hypothesis of independence is rejected at a 1% significance level).

The model was not enriched with a third equation, which would model OCC_{it} on ADR_{it} to account for the issue of collinearity between ADR_{it} and rooms available (cf. Smeral, 2014), due to the fact that such a model does not computationally converge with the appropriate, also SUR, approach.

6.3.8 Model Specification

According to the pretests presented in the previous sections and summarized in Table 4, two models were chosen. On the one hand, due to the panel structure of the data and the results of the Breusch-Pagan LM test regarding the SUR approach, one SUR model using Stata's *–xtsur–* command (Biorn, 2004; Nguyen & Nguyen, 2010) was selected and, on the other hand, because this SUR model does not correct for autocorrelation, heteroskedasticity or, arguably, cross-sectional dependence, two panel regressions – one per equation – using Stata's *–xtscc*– command (Hoechle, 2007) were chosen. Indeed, *–xtscc*– produces Driscoll-Kraay standard error estimates that are robust to these disturbances (Hoechle, 2007, Table 1).

6.3.8.1 Stationarity

In addition to the previous tests, stationarity was tested. The Breitung test (Breitung, 2000; Breitung & Das, 2005) and the Fisher-type test (Choi, 2001), both accounting for a deterministic time trend, the former controlling for cross-sectional dependence and the latter being conducted for short-term lag specifications, do not reject the null hypothesis of a series containing unit roots for every variable. However, given that many observations are zero and since, in general, unitroot tests have low power (e.g. Baltagi, 2013), taking the first difference of all variables in the dataset was determined to be pointless and the data's stationarity, therefore, disregarded. Moreover, this decision is supported by the fact that taking the first difference of a series leads to a loss of long-term information (Buck, 1999).

6.3.8.2 Variable Specification

The comparison between different variations in the previously specified models led to the selection of a root-level primary specification for the regressions (as presented in the next chapter, Results). Other supporting models and variants are reported in Appendix 5: Regression Sensitivity Checks and Variants. The root-level variable specification makes the most sense both statistically and economically and is mathematically computable. While other variations, like levellevel regressions, are also viable, but are, in some cases, prone to the disadvantages of nontransformed regressions (cf. 6.3.2 Variable Transformations), regressions that contain logarithmic variables are either mathematically not computable or only computable in very specific and economically poor variations.

In any case, whether untransformed, square root transformed or logarithmic, scatter plots between residuals and predicted values of the not-joined models do not deviate significantly from each other. The same can be seen for kernel density estimations and the overall distribution of the dependent variable using histograms and distributional diagnostic plots.¹⁹ Hence, the abovementioned argument is used to justify the chosen transformation of the dependent variable in the models.

In order to account for planning, construction, adjustment, reaction or comprehension times as well as decision-making and learning processes (cf. Smeral, 2014), lags and forwards were included (marked with Lx and Fx, respectively, with x being the number of divergent periods). In other words, the progression of time between a decision – and the information available at that time – and an action is incorporated by means of these time shifts. Regarding the demand side of the chosen models, time lags between rooms sold and the general economy were also expected to be present due to the research by Gouveia and Rodrigues (2005), who provide evidence of lags between economic cycles (represented by GDP and the GFC in the regressions) and tourism demand cycles (represented by rooms sold).

Moreover, the Olympic Games dummy variables were varied (to either reflect changes in only the respective destination (d_OGLs and d_OGHKs) or all cities (d_OGL and d_OGHK)) in order to find the models with the best fit.

¹⁹ Available on request.

	Seasonality	Breusch- Pagan LM test	Hausman's specification test	Auto- correlation	Hetero- skedasticity	Cross-sectional dependence	SUR	Unit roots
Command (Stata)	xtline y, overlay (visual)	xttest0	hausman fixed random, sigmaless	xtserial y x	xttest3 - Irtest	xttest2 - xtcsd, pesaran abs	sureg (y x) (y x), corr	xtunitroot breitung y, trend robust - xtunitroot fisher y, dfuller trend lags(1-6)
Demand function	Yes	N/A	H	Yes	Yes	Yes		Yes
Supply function	Yes	RE	RE	Yes	Yes	Yes	202	Yes

TABLE 4: PRETEST STATA COMMANDS AND RESULTS BY FUNCTION

7 RESULTS

The model with the best economic fit in combination with the best statistical fit is summarized in Table 5 and shows promising results. Table 5 depicts the relationships between the dependent variables rooms sold and rooms available and their respective explanatory variables. For the demand side, the square root of rooms sold is modeled with the GDP of the source market aggregation three months prior, the average daily rates of the destination and competitors, the consumer price indices of the source market aggregation in relation to the destination and its competitors, the cases of the swine flu, the dummy variable regarding the GFC three months prior and the two binary variables for the Olympic Games. For the supply side, the square root of rooms available three months in the future is modeled with the average daily rate of the destination, the occupancy rate and the long-term and short-term interest rates.

Model (1) in Table 5 summarizes the seemingly unrelated regression that incorporates both, the demand and the supply side, into one model. It includes 462 out of 504 observations. In fact, 42 observations are missing due to the lags and forwards of some variables. Besides where noted, the coefficients of the explanatory variables are significant at the 1% level of significance.

The demand side of the model postulates that, always keeping all other variables equal, when the GDP of the source market aggregation 3 months prior increases, current rooms sold at the destination grow as well. The average daily rates of destination and competing destinations inversely affect rooms sold. More specifically, when the average daily rates of the destination grow, the rooms sold at the destination decrease, while when the average daily rates of competing destinations grow, the rooms sold increase. It appears that of the two, the negative effect of the ADR at the destination is more impactful than the positive effect of the competing destinations in the dataset. The impacts of the consumer price indices are similar: when the prices of the destination relative to the prices of the source market aggregation increase, the rooms sold at the destination diminish. Contrarily, the growth of the consumer prices of competitors relative to the source market aggregation increases the number of rooms sold, albeit not as strongly as CPl_{jit} decreases it. However, in model (1) this variable (CPl_{jct}) is statistically not significant.

The variable accounting for the effects of the swine flu negatively affects the number of rooms sold, i.e. when there were more cases of influenza, fewer rooms were sold. Equivalently, the GFC three months before the current date led to a decrease in rooms sold. The Olympic Games in Beijing, including the equestrian competitions in Hong Kong, increased the number of rooms sold in Hong Kong (or decreased the number of rooms sold for all seven destinations, see Appendix 5: Regression Sensitivity Checks and Variants). However this variable is statistically not significant. The Olympic Games in London, on the other hand, led to a decrease in rooms sold in London. In this case, the variable is significant at the 10% level of significance.

The variables of model (1)'s supply side are all statistically significant at the 1% level of significance. The average daily rate, the occupancy rate and the long-term interest rate at the destination negatively affect the number of rooms available in three months hence. Only an increase in the short-term interest rate leads to a future growth in rooms available.

The second model (2)(3) summarizes the regression which corrects for some of the problems in the data. It is modeled with 483 observations. The 21 missing observations are due to the lagged variables. Regarding the first part of the model, the demand side (2), overall the F-statistic – and hence this demand model – is significant at the 1% level of significant. The within R² is equal to 0.787, hence the model accounts for almost 80% of the variance within the panels. Furthermore, all variables besides CPl_{jit} are significant at the 1% level of significance, while CPl_{jit} is significant at the 5% significance level. The results are similar to the ones of the SUR model (1). The signs of the coefficients of only the GDP and the ADR at the destination are inverted: according to this model (2), growth in GDP of the source market aggregation reduces rooms sold at the destination, while an increase in the ADR increases the number of rooms sold at the destination. Moreover, the effects of the variables concerning the relative price levels regarding the competitors are more impactful than the effects of the same variables regarding the destination itself.

The second part (3) of the second model, the supply regression, is also calculated with 483 observations for the same reasons as for the demand side. The F-statistic is significant at the 1% level of significance, too. The R² is equal to 0.72, hence the model accounts for more than 70% of the variance in the data (between and within panels). As for the variables themselves, they are also all significant at the 1% level of significance. The coefficient of only the occupancy rate is in contrast to the same variable in model (1). In this model, an increase in the occupancy rate results in a rise of rooms available three months following. Standardized beta coefficients to estimate the magnitude of each variable in the disjointed model are reported in Appendix 6: Regression Summary Table – standardized beta coefficients.

	(1)	(2)	(3)
	SUR	Demand (FE)	Supply (RE)
sqN _{jit}			
Y _{jt} <i>L3</i>	0.0000367***	-0.0000805***	
	(0.00000400)	(0.0000116)	
	***	• • • • • * *	
ADR _{it}	-0.282***	0.167***	
	(0.0472)	(0.0573)	
ADR _{ct}	0.179***	0.675***	
	(0.0233)	(0.150)	
	(0.0233)	(0.130)	
CPI _{jit}	-57.95***	-73.27**	
	(9.286)	(30.14)	
CPI _{jct}	24.75	2483.7***	
	(25.18)	(155.1)	
H1N1 _{it}	-0.000993***	-0.00317***	
IIIINII((0.000173)	(0.000941)	
	(0.000173)	(0.000941)	
d_GFC <i>L3</i>	-4.116***	-11.57***	
_	(0.725)	(3.609)	
	, , , , , , , , , , , , , , , , , , ,	, , , , , , , , , , , , , , , , , , ,	
d_OGHKs	0.861	22.22***	
	(4.570)	(6.960)	
d_OGLs	-6.168*	-5.963***	
	(3.276)	(2.105)	
sqB _{it} F3	· · · · ***		***
ADR _{it}	-0.255***		-0.973***
	(0.0513)		(0.210)
OCC _{it}	-6.183***		18.14***
	(0.0849)		(1.615)
	(0.00 13)		(11010)
LT_r _{it}	-1.865***		-89.14***
	(0.507)		(6.110)
CT .	~ ~~~***		~ ~ ~ ~ * * *
ST_r _{it}	2.338***		24.37***
	(0.360)	1004 0***	(7.672)
_cons		-1364.9 ^{***} (163.4)	499.4 ^{***} (110.3)
Observations	462	483	483
F-statistic	402	485 538.6***	485 1508.9***
Within R ²		0.787	
R ²			0.720
Standard errors ii * <i>p</i> < 0.10, ** <i>p</i> < 0			
p < 0.10, p < 0	$\mu < 0.01$		

TABLE 5: REGRESSION SUMMARY TABLE, OWN CALCULATIONS

8 INTERPRETATION AND LIMITATIONS

This chapter first delivers an interpretation of the variables according to the models and compares the outcomes to those of existing studies. At the end, limitations are reported.

8.1 Interpretation

The results show that the model includes, indeed, a panel effect and, thus, that the explanatory variables determine the level of the dependent variable no matter the destination. For just one explanatory variable for each equation (the focal variables regarding the influenza and the demand, respectively), these effects can also be seen in Figure 11, Figure 12 and Appendix 4: Scatter Plots. The following sections present possible interpretations of the variables' impacts and then report some limitations.

8.1.1 Gross Domestic Product

In the joint model, GDP influences demand as expected (cf. e.g. Andraz & Rodrigues, 2016; Eugenio-Martin & Campos-Soria, 2014; Gunter & Smeral, 2017; Song et al., 2011) and suggests tourism to be a normal good. In fact, the increase in demand after a rise in income (income elasticity of demand²⁰ greater than 0) rejects the possibility of tourism being considered an inferior good where demand would fall given a rise in income. Indeed, tourism is generally assumed to be a luxury good with income elasticity greater than 1 (a change in income produces a more than proportional change in demand) or at least a normal good (Gunter & Smeral, 2016) – especially during times of economic distress or uncertainty (Gunter & Smeral, 2017; Smeral, in press) – which fits the results of model (1). For the period of the study, a small income elasticity of demand could also be an indicator of a fast-growth period and of consumers behaving as lossaverters, i.e. they tried, whenever possible, to avoid losses in their satisfaction caused by a reduction of their leisure and tourism budget (Gunter & Smeral, 2017). In other words, consumers, when seeing tourism as a necessity or basic need in their lives, might have evaded situations where they had to reduce their tourism-induced satisfaction by not overproportionally increasing it in the first place. However, in model (2), where supply is not taken into account, the GDP negatively affects demand and, hence, acts like an inferior good.

Besides faults in the data or the model, this might be explained with the omission of variables that are not part of (2) but of (1), those variables that are included in both equations in the SUR

model and the difference in disturbances corrected for by each model. Otherwise, this may indicate the presence of uncertainty: instead of spending their income on travel to any of the seven destinations, tourists chose to travel to other substitute destinations not included in the model, decided to spend their money on different products altogether or elected to save their wages for future spending. Another possibility emerges when considering a decrease in GPD, which leads to an increase in rooms sold. This sounds similar to cases like the Veblen effect (more thoroughly looked at in light of the prices at the destination in the next section): tourists might elect to continue spending their decreasing income on more holidays when they are seen as a symbol of status and when a higher status outweighs the other negative ramifications of a smaller income. In other words, tourism could give consumers proportionally more utility (including status) than other bundles of goods and services.

These observations are for impacts on rooms sold at the current date due to the GDP at the source market aggregation three months before. Models with different lag-specifications (from no lag up to 6 months), however, do not significantly alter the outcomes; all that changes is the magnitude of the effect of some variables. For instance, by taking no lag in model (1), GDP has a higher impact on rooms sold compared to the 3-month-lag value – the non-standardized coefficients of the other variables decrease at the same time. This may be an indicator that the effects of the GDP are not constricted to only one respective future period.

8.1.2 Average Daily Rate – Destination (Demand)

In model (1), this explanatory variable behaves in line with the law of demand and thus, as expected, when the room prices rise, demand falls (negative price elasticity of demand). In model (2), however, the ADR behaves like a Giffen or Veblen good: an increase in prices results in an increase in demand (positive price elasticity of demand) or, in other words, tourists choose to purchase the more expensive product.

The Giffen case is rather unlikely, hence the Veblen effect of conspicuous consumption might provide an explanation. The Veblen effect states that consumers, when faced with two functionally equivalent products, choose the product which provides a higher status or, in similar words, that they are willing to pay a higher price for one product over the other simply because of the prestige, image or status associated with it (Papatheodorou, 2001). In the case of the present analysis, this might apply as such: due to a crisis, probably the GFC, the cost for taking vacations is higher than in previous periods. Yet, since going on international holidays is seen as a symbol of status – especially to destinations that are known to be expensive (Dwyer & Forsyth, 2008) – consumers feel the need to thusly demonstrate their superiority.

A similar trail of thought can be applied to the snob effect, where consumers choose products based on exclusivity and not directly due to the status associated with higher prices. It might also be the case that the prices of hotels are perceived as signals of the current state of the destination. Lower prices are seen as admitting to a lower level of quality; higher prices signal that there is no need for price competitition due to a lack of qualitatively high products.

A further corroborating element is the fact that the destinations analyzed are cities and therefore places of city and business tourism. This signifies that business travelers are included in the regression as part of the demand. This is of importance because the price elasticity of demand for business tourists is, generally, more inelastic than for holiday tourists, which means that this group is less sensitive to price changes. Indeed, the price elasticity of business tourists may even be positive (as is the case in (2)). This can be explained with their lower flexibility in regards to postponements or cancellations of trips and the possibility that the profit generated with support of the business travel eclipses the expenses of the trip (Konovalova & Vidishcheva, 2013).

8.1.3 Average Daily Rate – Competitors

In both models, a rise in prices in competing destinations acts as incentive for tourists to travel to the destination. This is generally as expected, since the destination acts as a substitute for the competitors (positive cross-price elasticity of demand) (Konovalova & Vidishcheva, 2013).

8.1.4 Consumer Price Index – Destination

The CPI is a variable that accounts for relative prices between locations, just as is the original purpose of the ADR. Hence, the interpretation is similar: since the coefficients are negative, the price elasticity of demand is negative and demand falls as prices rise. In this case, it is the relative price level of consumer goods between the destination and its source markets. This means that when the prices of the destination are higher than those of the source markets and when this difference increases, demand for rooms at the destination decreases.

8.1.5 Consumer Price Index – Competitors

As with the previous section (CPI_{jit}), this variable is analogous to the ADR of competitors as are the coefficients calculated in the regressions: the cross-price elasticity of demand is positive and, thus, when the consumer prices of competitors relative to those of the destination's source market increase, so does the demand for rooms at the destination.

8.1.6 Cases of Influenza H1N1

In both models, the focal variable in this analysis negatively affects tourism demand (rooms sold and, consequently, the occupancy rate (Wu et al., 2010)). This is as expected and suggests that the crisis did indeed have consequences for the tourism industry at the destinations. In point of fact, since the analysis is a panel regression, the coefficient is interpreted as a panel effect across all destinations. In other words, the negative impact of the swine flu is a ubiquitous phenomenon. That the models agree on this outcome further validates these results and the conclusions of existing studies (e.g. Page et al., 2011; Wu et al., 2010).

This does, however, not preclude varying effects in single cases. Figure 11 shows that, for high numbers of cases of the swine influenza, rooms sold decrease. On the other hand, for destinations with fewer cases of the pandemic, these results do not always hold true. In these cases, the linear predicted values can manifest positive trends. Hence, while the overall panel regression evidences a downward effect of the pandemic on tourism demand, which is true in general, a specific destination may exhibit a dissimilar behavior. This assertion has to be viewed with caution, seeing that Figure 11 does not account for other explanatory factors besides the cases of the H1N1 pandemic and may, thus, suffer from omitted variables.

The standardized beta coefficients of the FE demand-only regression (see Appendix 6: Regression Summary Table – standardized beta coefficients) are able to help deduce the magnitude of impact on the explained variable – rooms sold to the power of one half – of a one-unit change in an explanatory variable. For example, according to those values, the negative effects of the pandemic on the square root of rooms sold were, in comparison, more pronounced than all other negative effects except those of the GDP. The smaller impacts of the GFC concur with the findings by Page et al. (2011), which show that in the second quarter of 2009 (the time period analyzed by that paper), the effects of the swine flu were stronger than those of the GFC²¹.

The effects of the H1N1_{it} variable translate to tourism demand in the same period and to tourism supply, via the occupancy rate, three months in the future (compare with the respective sections of this chapter). This shows the progression of time in the field of a crisis. Indeed, some effects are felt immediately and others deferred to the future. Alongside the immediate effects shown in this regression (the reduction in rooms sold), the pandemic had other undelayed influences on the world. One obvious example is that people took ill and as a results the numerous – also future – ramifications thereof (recovery costs, reduced income, contagion risks and so on). Another example is that of impacts the pandemic had on other industries and areas. Future effects may include, in addition to the indirect effects on tourism supply, any longer-lasting consequences of the immediate effects, as well as knowledge or learning, in other words, the effects on the future behavior of parties affected or not affected by the crisis.

Connected to this are also impacts of past events or situations, in the case of these regressions the economic situations as approximated via the GDP of the source market aggregation and the

²¹ Overall, the effects due to the GFC were, of course, far more impactful on tourism demand (Page et al., 2011), because of the different natures of the two crises.

presence of the GFC three months before the swine flu. Since these factors also affected tourism demand, together with the pandemic, the current and future consequences are in part due to these past occurrences. Naturally, depending on the type of crisis, the prior planning and the crisis management during that time, the repercussions and prerequisites would differ.

In conjunction with extrapolations from previous literature on crises, the results related to this variable may possibly be understood as an indicator of deficient or partially wanting crisis management, at least with respect to this type of crisis. Indeed, the negative effects of the swine flu pandemic on rooms sold could be taken as evidence of poor preparation and contingency planning regarding influenza pandemics (or crises in general) in tourism. On the other hand, it is also conceivable that crisis management was properly performed and that, thus, the effects of the swine flu would have been stronger without it. In either case, it is probably necessary for destinations, tourism suppliers and related organizations to rethink or redo their crisis management approach and strategy by, for example, incorporating recommendations from experts or by learning from past situations.

8.1.7 Dummy: Global Financial Crisis

As expected due to the overall bad mood and the decrease in economic performance, the shock of the GFC had significant negative impacts on tourism. On one hand, this confirms and is in line with papers on and simple observations of the economy during and after these months. On the other hand, this serves to prove that the inclusion of this dummy variable was indeed appropriate, since the changes in tourism demand were also due to this crisis and not solely a result of, besides standard factors, the influenza pandemic.

These observations are for impacts on rooms sold at the current date due to the GFC three months before. However, models with different lag-specifications (from no lag up to 6 months) do not significantly alter the outcomes. This could be an indication that the effects of the GFC were present for longer than its respective duration.

8.1.8 Dummies: Olympic Games

The Olympic Games in London, according to this model, apparently led to a decrease in rooms sold for the sampled hotels in London and in all destinations during the event. Regarding the Beijing Olympic Games, their effects were different. Indeed, more rooms were sold during the Olympic Games in Hong Kong, but overall fewer rooms were sold when simultaneously looking at all the destinations. However, both variables sometimes exhibit problems of statistical significance and, while having had impacts on the situation, these effects were rather small in the model (cf.Appendix 6: Regression Summary Table – standardized beta coefficients).

8.1.9 Average Daily Rate – Destination (Supply)

The negative effect of the ADR at the destination on future rooms available is acknowledged. However, only isolated models with, according to pretests, wrong specifications were, in some cases, able to result in the economically expected outcome of a positive relationship. Thus, the models that suggest this relationship prevailed. An explanation is an indirect influence via rooms sold. In fact, as mentioned earlier, ADR_{it} negatively affects rooms sold. Since rooms available strive to, according to the theoretical equilibrium condition, approximate the number of rooms sold, the decrease in prices should indirectly cause rooms available to fall, as to reduce the producer surplus in form of the occupancy rate. It is also potentially possible that tourism is, in the sample, a decreasing costs economy that, innately, possesses a negatively sloped supply curve or that the negativity is due to the inclusion of the occupancy rate in the same equation (cf. 6.3.7 Seemingly Unrelated Regressions).

8.1.10 Occupancy Rate

The occupancy rate is the number of rooms available divided by the number of rooms sold. As such, this variable partially models the dependent variable, rooms available, with itself in a partial and periodically shifted autoregressive process: rooms sold divided by rooms available today causes alterations in rooms available three months hence. Therefore, the occupancy rate increases when either rooms sold increase or rooms available decrease to a stronger degree than the other variable moves in the same direction, i.e. when there is a net growth of the quotient. Consequently, it depends on which variable has a stronger impact on the occupancy rate for OCC_{it} to positively or negatively influence rooms available.

Indeed, model (1) suggests that the reduction of rooms available in the future is caused by a growth of the occupancy rate due to a larger decrease of rooms available today than the effect of rooms sold. Conversely, model (3) suggests that rooms sold increase proportionally more than rooms available today, hence the reason the occupancy rate grows, which in turn increases rooms available three months from now.

8.1.11 Interest Rates

As already mentioned, the OECD (n.d.-a) asserts that "[I]ow long-term interest rates encourage investment in new equipment and high interest rates discourage it." The regressions support this statement. As a matter of fact, when the interest rate grows, the future number of rooms available, in other words investments by hotels, decreases.

A rising short-term money market rate, on the other hand, leads to an increase in future rooms available. Only if a lag of one year is considered, does the short-term interest rate reduce investment in new rooms. However, by then the variable is statistically highly unsignificant. This could suggest that rates of short-term credits are not very important in the decision-making process

regarding the expansion of capacity or that other irrational behavior is occurring. Alternatively, another possible explanation is the saving behavior of hoteliers. An increase in the short-term interest rates might convince them to put their money into their bank accounts instead of immediately spending it. In the future, according to this explanation, this money is then implied to be used for investments in order to increase the number of rooms available.

8.2 Limitations

Some limitations to this research, besides assumptions and weaknesses regarding panel data regression and the methodology, are "problems of significance" (Ledesma-Rodríguez et al., 2001, p. 77). In other words, some variables might not be statistically significant in the regression, conditional on specifications, and, hence, not be able to explain variations in tourism demand or tourism supply. Similarly, since not all factors and parameters can be accounted for, missing variables and factors unaccounted for – such as, for instance, word of mouth (Song et al., 2011) – may influence the dependent variables as might the use of dummy variables instead of methods which deliver more significant or more efficient results when including other factors (Song et al., 2011).

In addition, only one proxy for tourism demand is used: rooms sold. Other possible tourism demand proxies, such as tourist expenditures, hotel revenues or arrivals, might give a better insight into the situation. For both sides of the market, only hotels were taken into account. However, tourism is comprised of more businesses than just lodging, which could be included in a holistic approach for a complete analysis of the industry.

Another limitation is the representativeness of the source market aggregation. As shown in Table 3, the source markets incorporated into the regression do not represent the entirety of tourists. In fact, the average representability of the source market aggregation is slightly above 51%. Thus, while these countries are the source of more than half of the foreign tourism inflows, a large share is not accounted for. By collecting data for a higher percentage of source countries, the error due to this issue could be remedied. Instead of choosing the top five source markets, it is conceivable to aim for a set threshold for each destination, for instance the top source markets, which together account for, say, 75% of a country's foreign tourism inflows.

A constricting weakness is the selection of competitors. With more data and a thorough market analysis, proper destinations could be chosen and included as substitutes for each city. These competitors would offer similar tourism products and appeal to the same target segment as the respective destination.

A last limitation is procedural. The program used for the analysis, Stata, was not able to fully include all disturbances, issues and characteristics present in the data. A possibility is the creation of a single command, which takes all those factors into account or the utilization of different softwares. Moreover, certain configurations and specifications would not converge and compute with existing commands. These restrictions further inhibited the use of possibly more efficient models.

9 SUMMARY AND CONCLUSION

Crises, disasters and catastrophes, by their very nature and definition, significantly alter the current situation and shift it away from the status quo. While systems would, without conscious external input, rearrange themselves into new functioning structures, careful planning, strategizing and management is necessary in order to ensure that the new conditions are an improvement compared to the pre-crisis situation. The literature has produced plenty of frameworks and recommendations intended to support such endeavors. In general, these suggestions tend to be similar. They emphasize proper communication and knowledge, joint and collaborative actions, training and appropriate marketing activities. Yet, differences depending on the specific situation²² result in the need for different approaches. Indeed, while one strategy might be feasible for situation A, it will not necessarily be the best option for situation B. Therefore, the recommended plans need to be adapted as to function with the present circumstances.

The literature analyzed as part of this thesis shows that in reality this is not at all, not completely or differently done. In fact, although the focus of the various studies was on only one part and did not look at other elements of crisis management, a clear trend can be seen that organizations are underprepared for certain shocks. On one hand, plans were exposed as inadequate and, on the other hand, plans for the specific crisis had not been created. Still, decision needed to be made. Yet, the decision-makers were not prepared to make choices based on thorough research, satisfactory communication and well-thought-out options, hence deficient resolutions were sometimes enacted.

The crisis studied in the latter half of this thesis created one such situation where some managers were unable to cope with the rapidly deteriorating status. Although numerous people are affected by the seasonal flu every year and notwithstanding the impactful effects diseases have always had on humankind (for instance the multitudinous deaths due to the Spanish flu in 1918), organizations still lacked preparatory measures for the case of an influenza pandemic, as seen in the incidence of the swine flu in 2009 and 2010.

The outcomes of the regression analyses evidence the negative effects of this H1N1 pandemic on room-nights sold by hotels in several important city destinations around the globe. Based on the literature, the recovery after the crisis²³, notwithstanding the GFC, would be due to two factors. First, the reordering and regeneration according to the chaos theory and, second, the role of local management as well as organizations as stabilizers and as pillars of growth. While

²² For instance the type of crisis or disaster, the location, the industry, the market, the environmental and social constraints, outside help and so on.

²³ As apparent in the graphs in Appendix 2: Moving-Average Filter Scenarios and in Figure A.14.

the econometric results do not include a greater number of qualitative factors, like management's behavior or the number of hotels that went out of business, existing patterns help in constructing possible arguments regarding the evolution of rooms sold and rooms available.

It can be conjectured that, although they might have existed, no plans or measures were able to fully counteract the negative impacts of the pandemic. Alternatively, it is possible that the effects of the crisis were not more noticeable due to the efforts of the organizations – a full equalization is improbable due to the results of the regression and because "a significant reduction in travel volume, which will have an impact on tourism supply" is expected (Page et al., 2011, p. 143). Moreover, the literature shows that it is unlikely that tourism providers take advantage of all possible ways that could fully mitigate the damages caused by shocks. This might, in part, be due to a lack of proper and sound communication within a destination or a local industry.

Although not analyzed as part of this thesis, it may be speculated that the swine flu had effects that transcended the direct impacts on rooms sold. Indirectly, the reduction in tourists and hotel revenue would have probably been relayed to other parties, for instance up the supply chain or down to employees. As such, the ramifications that started with the advent of the pandemic would have affected, apart from the tourism business, other organizations with unilateral or mutual relationships to it. While history shows that no momentous consequences followed and that, instead, the economy recovered, a more severe crisis could lead to more intense, difficult and punishings aftereffects. These consequences are understood to be for neighboring industries and markets. Hence, tougher situations could induce more pervasive and extensive predicaments, where difficulties spiral outwards and permeate a larger area.

A factor that cannot be neglected when considering the impacts of the swine flu is the GFC. Since it happened before the pandemic, it was still having negative effects on the world – and the tourism industry – during the months of the swine flu crisis, as also seen from the regressions. The possibility of a compounded reaction cannot be rejected without further study. Yet, the recovery and growth of the hospitality industry in the sample locations – and also elsewhere – shows that the sector as a whole was able to recuperate regardless.

Irrespective of the industry's recovery after the crisis, during those months demand unquestionably decreased due to several factors, including the swine flu and the GFC. This, in turn, had effects on the supply offered by the hotels. The models show conflicting results, however, they agree that the occupancy rate, which is evenly based on rooms sold and rooms available, influenced the availability of rooms. Because of the theoretical equilibrium market condition that supply would converge with demand, the changes in rooms sold due to, partially, the pandemic are reflected in the supply of rooms. Indeed, supply adapts to demand via the occupancy rate and, in theoretical models, approximates an occupancy of 100% (Smeral, 2014), yet excluding various constraints. This thesis has hence given evidence that the influenza pandemic in 2009 and 2010 had an impact on tourism demand, as seen by the changes in room-nights sold, and, consecutively, on tourism supply in terms of rooms available. While a deeper analysis of every destination with further methods is beyond the scope of this thesis and also constricted by resources and data available, the present paper corroborates existing studies in their assessment that diseases – and crises in general – are dangerous and risky. Further, this thesis highlights that organizations and managers should scrutinize and adapt the plans and strategies they have in place for crisis management or, if they do not have any such plans, develop them.

Due to limitations regarding the underlying resources and the method, this thesis could be improved by increasing the amount of data, sample locations and variables employed, for a more holistic analysis, and by creating appropriate algorithms to properly compute and process the input data. Consequent studies could expand upon such an analysis by incorporating more data. Whether the same impacts can be observed for other crises with different situational circumstances could also be contemplated. Alternatively, a qualitative approach to these concepts could be considered. In other words, the reactions of management and the strategies enacted by firms and organizations at the sample locations.

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APPENDICES

Appendix 1: Summary Tables and Statistics Variable Description

Variable	Description	Source
Njit	Room-nights sold by a destination to a source market	STR
Y _{jt}	Total GDP of the source market aggregation for each des- tination in million US dollars at constant (2010) prices	OECD, adapted
ADR _{it}	Average Daily Rate of each destination in US dollars at con- stant (2010) prices	STR, adapted
ADR _{ct}	Average Daily Rate in US dollars at constant (2010) prices of a destination's competing destinations as weighted av- erage. Weights are the respective proportion of tourists from the destination's source market aggregation traveling to its competitors	STR, adapted
CPI _{jit}	Consumer Price Index for price levels of the destination in relation to the source markets. Calculated as $\frac{CPI_{it}}{CPI_{jt}}$	Own calculation
CPI _{jct}	Consumer Price Index for price levels of competing destinations in relation to the source markets. Calculated as $\frac{CPI_{ct}}{CPI_{jt}}$	Own calculation
CPI _{jt}	Consumer Price Index (2010=100) of the source markets as weighted average. Weights are the proportion of a source market's GDP over the sum of the GDPs for the source mar- ket aggregation	OECD, adapted
CPI _{it}	Consumer Price Index (2010=100) of the destination	OECD, The World Bank
CPI _{ct}	Consumer Price Index (2010=100) of competing destina- tions as weighted average. Weights are the respective pro- portion of tourists from the destination's source market aggregation traveling to its competitors	OECD, adapted

H1N1 _{it}	Number of reported cases per destination (country)	WHO, adapted
Q _{it}	Qualitative factors:	
d_GFC	Dummy variable with 1 during the GFC (2008M09 – 2009M04), 0 otherwise	
d_OGHK	Dummy variable with 1 during the 2008 Summer Olympics in Beijing/Hong Kong (2008M08), 0 otherwise	
d_OGL	Dummy variable with 1 during the 2012 Summer Olympics in London (2012M07, 2012M08), 0 otherwise	
B _{it}	Rooms available at a destination	STR
ADR _{it}	Average Daily Rate of each destination in US dollars at con- stant (2010) prices	STR, adapted
OCC _{it}	Room Occupancy Rate of the destination in percent. Calculated as $\frac{N_{it}}{B_{it}}$	STR, own calcula- tion
Fit	Shift factors:	
LT_r _{it}	Long-term interest rates in percent p.a.	OECD, invest- ing.com, adapted
ST_r _{it}	Short-term interest rates in percent p.a.	OECD, IMF, Invest- ing.com, Brazilian Central Bank, adapted
LC _{it}	Yearly index (2010=100) of unit labor costs for wholesale, retail, trade, accommodation, food, services, transporta- tion and storage. Assumed to be the same for each month.	OECD

TABLE A.1: VARIABLE DESCRIPTION:

DEPENDENT VARIABLES ARE BOLDED

SUBSCRIPT I: DESTINATION/HOST COUNTRY; 1-7

SUBSCRIPT J: SOURCE MARKET/HOME COUNTRY AGGREGATION AS REPRESENTED BY TOP 5 FOREIGN SOURCE MARKETS SUBSCRIPT C: AVERAGE OF 6 COMPETING DESTINATIONS

Subscript t: time factor; 1-72. Monthly periods from 01/2007 until 12/2012

Variable	Obs	Mean	Std. Dev.	Min	Мах
N _{jit}	72	952712	187019	600778	1278966
\mathbf{Y}_{jt}	72	2189798	75547	2078447	2338649
ADR _{it}	72	164.93	33.22	113.02	241.08
ADR _{ct}	72	214.69	28.13	167.59	288.47
CPI _{jit}	72	1.00	0.01	0.99	1.02
CPI _{jct}	72	0.99	0.02	0.96	1.03
H1N1 _{it}	72	156	633	0	4406
B _{it}	72	1389992	68396	1201144	1490511
OCC _{it}	72	68.51%	12.58%	42.08%	86.18%
LT_r _{it}	72	4.70%	0.77%	3.77%	6.80%
ST_r _{it}	72	2.15%	1.71%	0.19%	5.11%
LC _{it}	72	98.76	3.88	90.41	102.25

TABLE A.2: SUMMARY STATISTICS – BARCELONA, OWN CALCULATIONS

Variable	Obs	Mean	Std. Dev.	Min	Max
Njit	72	467107	64383	316389	598304
\mathbf{Y}_{jt}	72	2332121	73082	2191218	2427128
ADR _{it}	72	224.28	101.30	90.29	488.81
ADR _{ct}	72	205.49	24.70	165.07	266.12
CPI_{jit}	72	0.95	0.13	0.76	1.19
CPI _{jct}	72	1.00	0.02	0.97	1.04
H1N1 _{it}	72	151	317	0	1730
B _{it}	72	708960	94507	552356	896954
OCC _{it}	72	66.57%	10.04%	48.32%	90.98%
LT_r _{it}	72	7.87%	0.64%	5.63%	9.14%
ST_r _{it}	72	6.72%	1.82%	3.15%	9.13%
LC _{it}	0				

TABLE A.3: SUMMARY STATISTICS – DELHI, OWN CALCULATIONS

Variable	Obs	Mean	Std. Dev.	Min	Max
N _{jit}	72	1385888	160968	999387	1712282
\mathbf{Y}_{jt}	72	2304488	184017	2056163	2605732
ADR _{it}	72	195.82	25.43	145.40	252.25
ADR _{ct}	72	197.75	28.96	155.51	268.29
CPI _{jit}	72	1.00	0.03	0.96	1.06
CPI _{jct}	72	0.99	0.03	0.94	1.04
H1N1 _{it}	72	1.164	3.404	0	17.491
B _{it}	72	1690781	111640	1373708	1906004
OCC _{it}	72	81.83%	6.21%	60.73%	91.69%
LT_r _{it}	72	2.54%	1.05%	0.63%	4.77%
ST_r _{it}	72	0.93%	1.46%	0.06%	4.75%
LC _{it}	0				

TABLE A.4: SUMMARY STATISTICS – HONG KONG, OWN CALCULATIONS

Variable	Obs	Mean	Std. Dev.	Min	Max
Njit	72	2616327	250822	2104111	3157143
\mathbf{Y}_{jt}	72	2087447	56231	2007920	2212566
ADR _{it}	72	211.44	32.25	158.99	283.12
ADR _{ct}	72	197.70	27.18	154.89	263.97
CPI _{jit}	72	0.99	0.03	0.95	1.04
CPI_{jct}	72	0.99	0.02	0.96	1.03
H1N1 _{it}	72	97	321	0	1784
B _{it}	72	3227503	169198	2846704	3632487
OCC _{it}	72	81.02%	5.92%	66.39%	92.07%
LT_r _{it}	72	3.65%	1.07%	1.65%	5.43%
ST_r_{it}	72	2.51%	2.34%	0.50%	6.58%
LC _{it}	72	96.69	5.06	87.39	101.41

TABLE A. 5: SUMMARY STATISTICS – LONDON, OWN CALCULATIONS

Variable	Obs	Mean	Std. Dev.	Min	Max
N _{jit}	72	490337	72487	191850	630286
\mathbf{Y}_{jt}	72	1759001	51475	1667091	1861423
ADR _{it}	72	124.35	14.61	101.77	159.02
ADR _{ct}	72	215.54	28.39	170.71	289.14
CPI _{jit}	72	0.97	0.04	0.91	1.04
CPI _{jct}	72	1.00	0.02	0.97	1.03
H1N1 _{it}	72	1.076	3.422	0	20.342
B _{it}	72	827979	33625	733320	884089
OCC _{it}	72	59.24%	8.46%	23.12%	71.96%
LT_r _{it}	72	7.29%	0.96%	5.33%	9.29%
ST_r _{it}	72	6.12%	1.54%	4.76%	8.83%
LC _{it}	36	99.25	0.89	98.01	100.00

TABLE A.6: SUMMARY STATISTICS – MEXICO CITY, OWN CALCULATIONS

Variable	Obs	Mean	Std. Dev.	Min	Max
Njit	72	2146345	288367	1481776	2661807
\mathbf{Y}_{jt}	72	1071660	76440	952236	1237270
ADR _{it}	72	253.59	44.76	184.73	358.70
ADR _{ct}	72	193.93	27.14	150.53	253.65
CPI_{jit}	72	1.00	0.01	0.99	1.03
CPI _{jct}	72	1.00	0.02	0.97	1.04
H1N1 _{it}	72	1738	5098	0	34145
B _{it}	72	2594324	230575.4	2116912	2980805
OCC _{it}	72	82.62%	7.08%	60.41%	90.82%
LT_r _{it}	72	3.23%	0.95%	1.53%	5.10%
ST_r _{it}	72	1.61%	1.93%	0.19%	5.49%
LC _{it}	0				

TABLE A.7: SUMMARY STATISTICS – NEW YORK CITY, OWN CALCULATIONS

Variable	Obs	Mean	Std. Dev.	Min	Max
N _{jit}	72	427673	56712	274731	537505
Y _{jt}	72	2189798	75547	2078447	2338649
ADR _{it}	72	191.60	31.18	134.60	293.47
ADR _{ct}	72	205.74	28.27	162.70	275.98
CPI_{jit}	72	0.98	0.06	0.90	1.09
CPI _{jct}	72	0.99	0.02	0.97	1.03
H1N1 _{it}	72	44	86	0	424
B _{it}	72	597366	22125	539448	641731
OCC _{it}	72	71.52%	8.50%	46.37%	88.83%
LT_r _{it}	72	12.20%	1.49%	9.20%	17.59%
ST_r _{it}	72	2.15%	1.71%	0.19%	5.11%
LC _{it}	0				

TABLE A.8: SUMMARY STATISTICS – RIO DE JANEIRO, OWN CALCULATIONS

Appendix 2: Moving-Average Filter Scenarios

These figures show five possible variants of temporal development of rooms sold (N_{jit}). The blue line is the original data as received from STR (2017a-g). The other four graphs are different depending on the moving-average filter employed. The three numbers in parentheses are the number of periods a specific line includes in the calculation of a moving-average. For instance, the red line shows the moving-average of rooms sold for five months in the past and the current period without any future periods. Seasonal effects are visible in all lines except in the yellow graph (one-sided moving-average filter for the trailing eleven months plus the current month), which was chosen for the models.

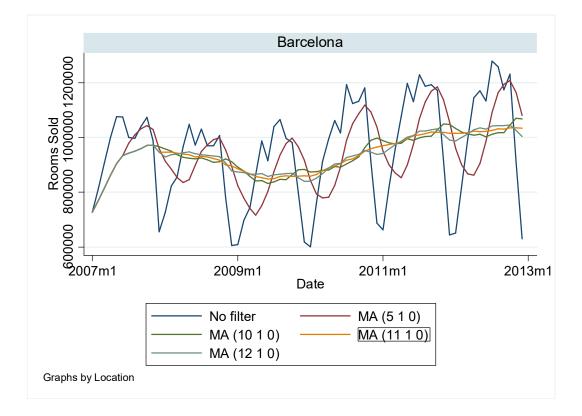


FIGURE A.1: MOVING-AVERAGE FILTER COMPARISON FOR BARCELONA, OWN ILLUSTRATION. SOURCE: STR (2017A-G), OWN CALCULATIONS

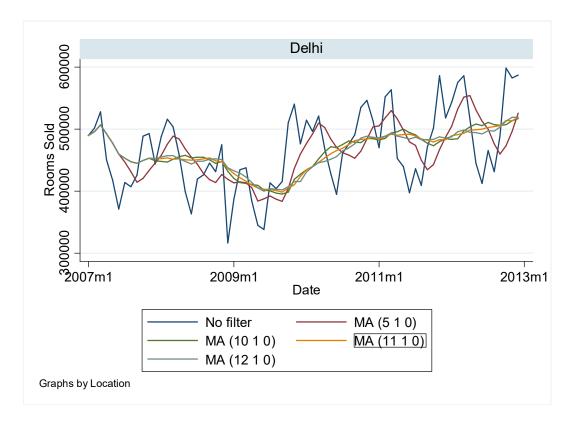


FIGURE A.2: MOVING-AVERAGE FILTER COMPARISON FOR DELHI, OWN ILLUSTRATION. SOURCE: STR (2017A-G), OWN CALCULATIONS

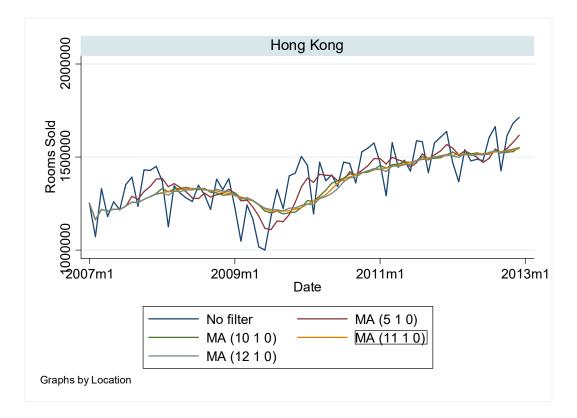


FIGURE A.3: MOVING-AVERAGE FILTER COMPARISON FOR HONG KONG, OWN ILLUSTRATION. SOURCE: STR (2017A-G), OWN CALCULATIONS

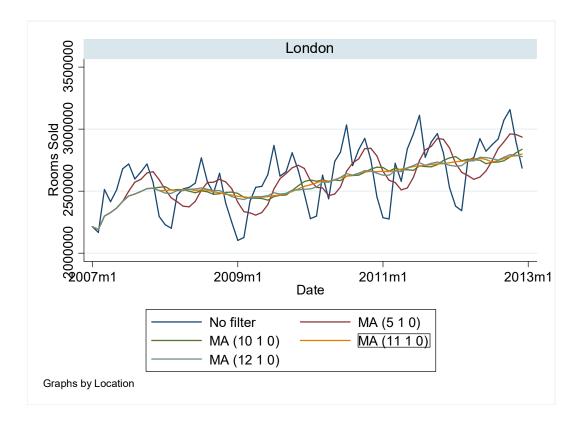


FIGURE A.4: MOVING-AVERAGE FILTER COMPARISON FOR LONDON, OWN ILLUSTRATION. SOURCE: STR (2017A-G), OWN CAL-CULATIONS

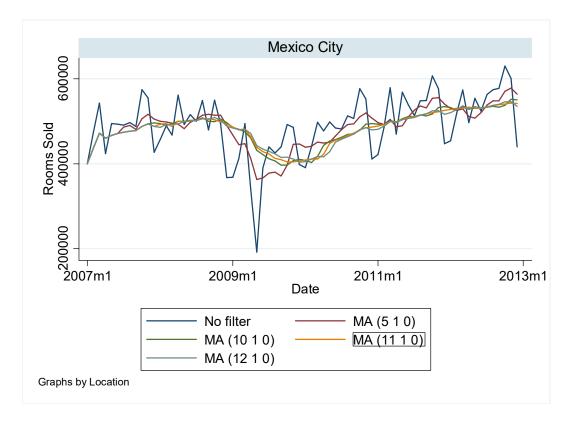


FIGURE A.5: MOVING-AVERAGE FILTER COMPARISON FOR MEXICO CITY, OWN ILLUSTRATION. SOURCE: STR (2017A-G), OWN CALCULATIONS

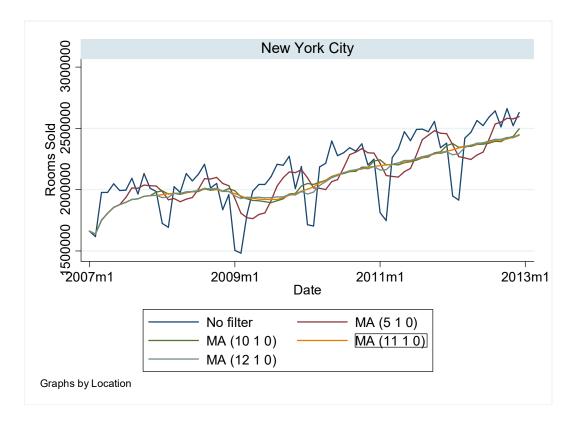


FIGURE A.6: MOVING-AVERAGE FILTER COMPARISON FOR NEW YORK CITY, OWN ILLUSTRATION. SOURCE: STR (2017A-G), OWN CALCULATIONS

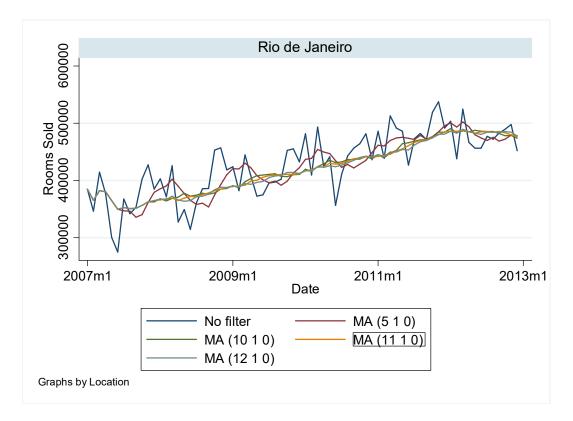


FIGURE A.7: MOVING-AVERAGE FILTER COMPARISON FOR RIO DE JANEIRO, OWN ILLUSTRATION. SOURCE: STR (2017A-G), OWN CALCULATIONS

Appendix 3: Development of MA Filtered Variables

These graphs depict the various variables over time for the seven cities. The variables used to draw the graphs were filtered with a trailing one-sided twelve-month moving-average filter. Note the impacts of the GFC or the swine flu pandemic around and after the marker denominated "2009m1" (January 2009).

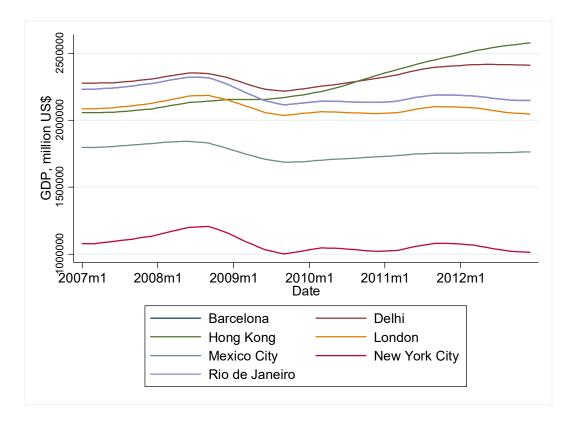


FIGURE A.8: DEVELOPMENT OF THE GROSS DOMESTIC PRODUCT OF THE SOURCE MARKET AGGREGATION BY DESTINATION, OWN ILLUSTRATION. SOURCE: SEE TABLE A.1

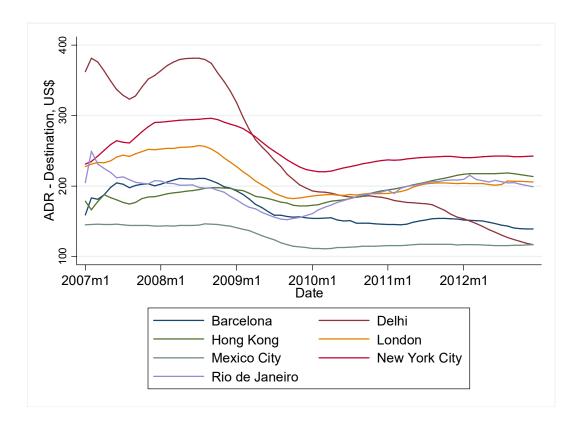


FIGURE A.9: DEVELOPMENT OF THE AVERAGE DAILY RATE AT DESTINATION BY DESTINATION, OWN ILLUSTRATION. SOURCE: SEE TABLE A.1

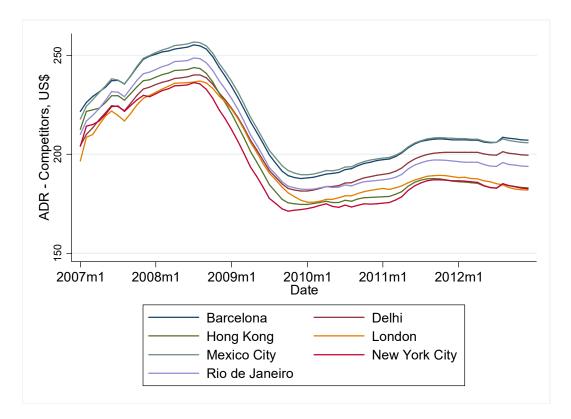


FIGURE A.10: DEVELOPMENT OF THE AVERAGE DAILY RATE AT COMPETING DESTINATIONS BY DESTINATION, OWN ILLUSTRA-TION. SOURCE: SEE TABLE A.1

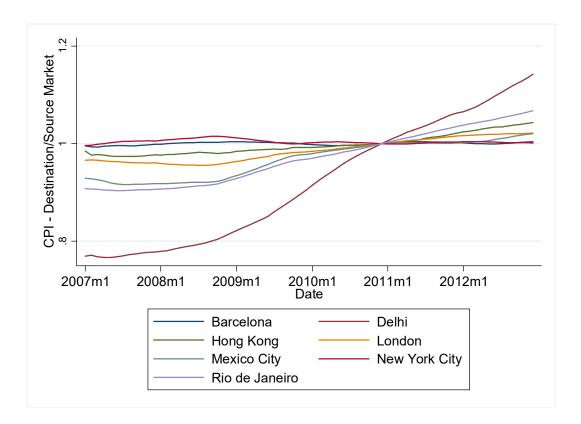
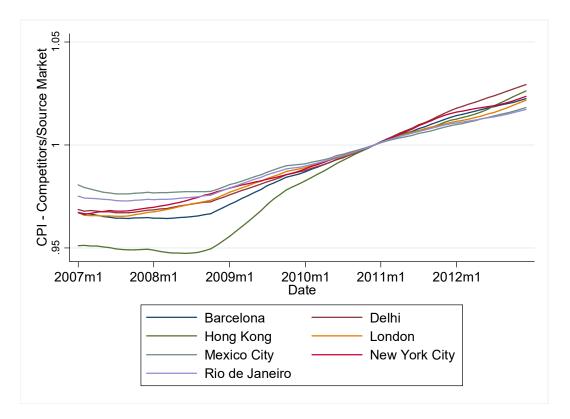
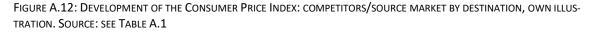


FIGURE A.11: DEVELOPMENT OF THE CONSUMER PRICE INDEX: DESTINATION/SOURCE MARKET BY DESTINATION, OWN ILLUS-TRATION. SOURCE: SEE TABLE A.1





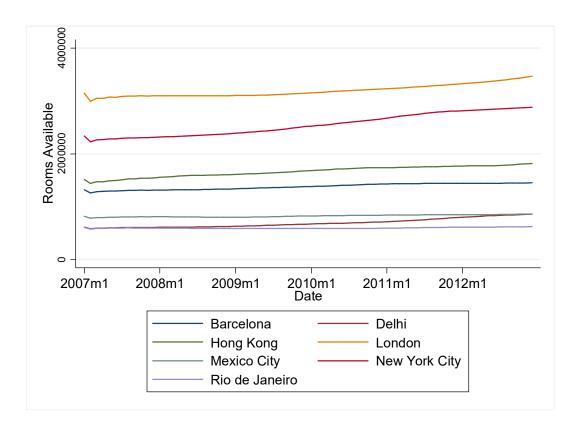
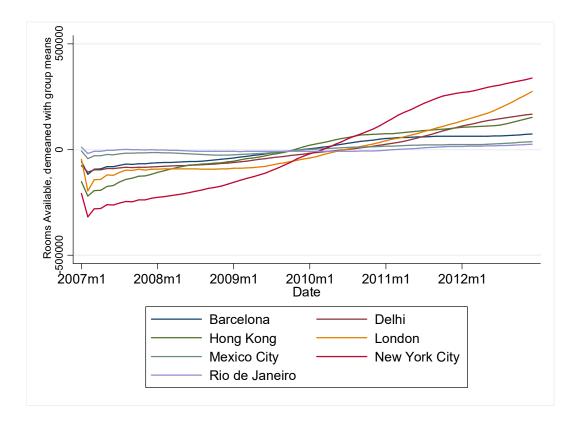
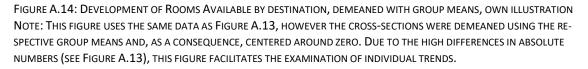


FIGURE A.13: DEVELOPMENT OF ROOMS AVAILABLE BY DESTINATION, OWN ILLUSTRATION. SOURCE: SEE TABLE A.1





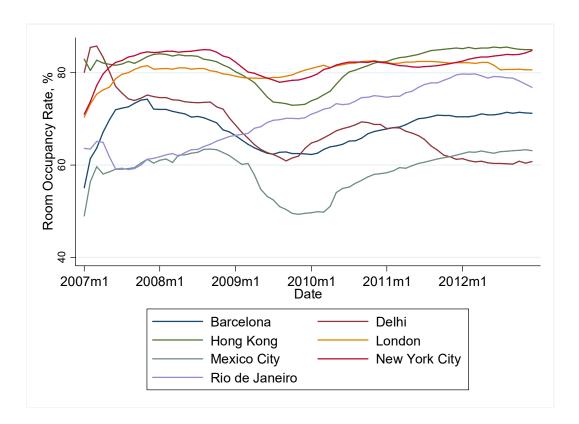


FIGURE A.15: DEVELOPMENT OF THE ROOM OCCUPANCY RATE BY DESTINATION, OWN ILLUSTRATION. SOURCE: SEE TABLE A.1

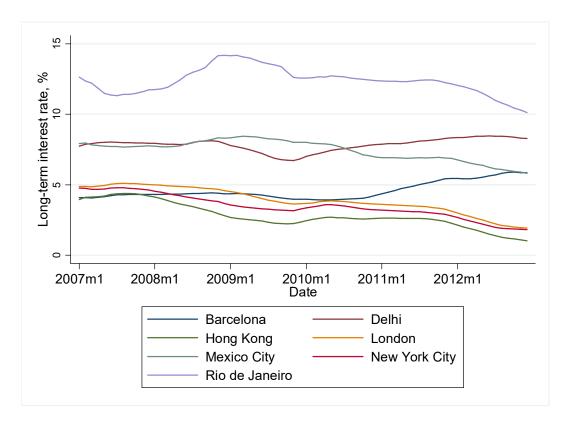


FIGURE A.16: DEVELOPMENT OF THE LONG-TERM INTEREST RATE BY DESTINATION, OWN ILLUSTRATION. SOURCE: SEE TABLE A.1

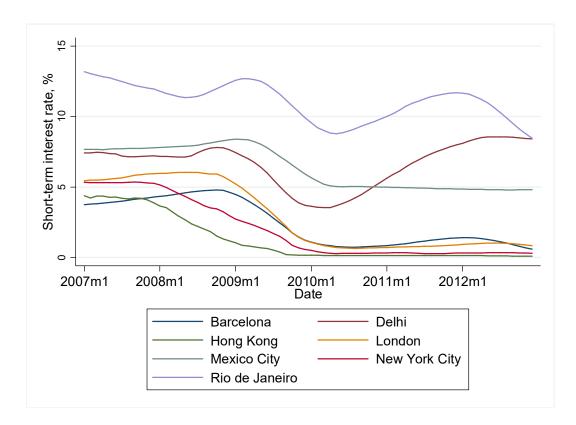
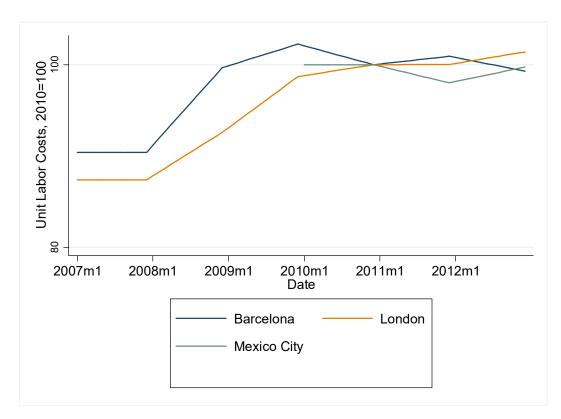
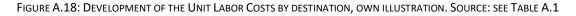


FIGURE A.17: DEVELOPMENT OF THE SHORT-TERM INTEREST RATE BY DESTINATION, OWN ILLUSTRATION. SOURCE: SEE TABLE A.1





Appendix 4: Scatter Plots

These figures graph the dependent variables and one respective explanatory variable each. The black lines are linear fitted values for each destination.

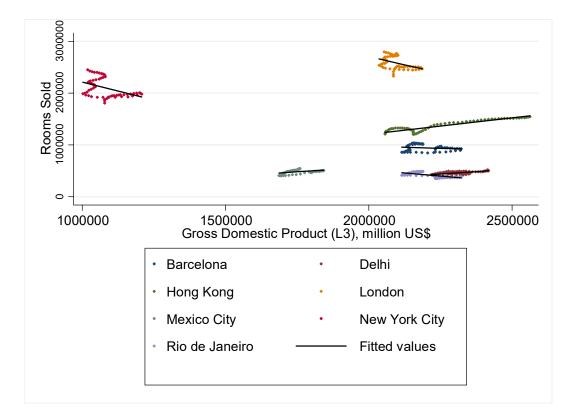


FIGURE A.19: SCATTER PLOT: ROOMS SOLD – GDP (3 MONTH LAG) WITH FITTED VALUES BY DESTINATION, OWN ILLUSTRATION. SOURCE: SEE TABLE A.1

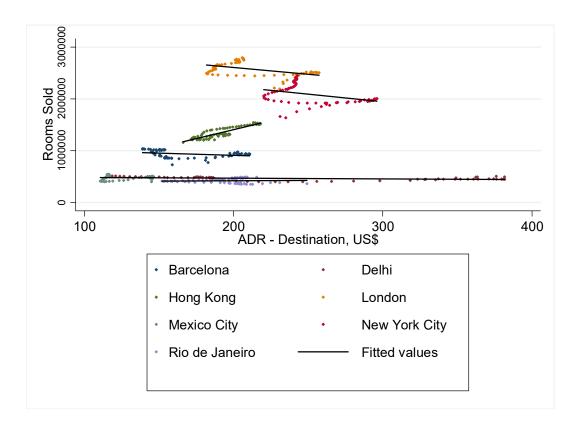
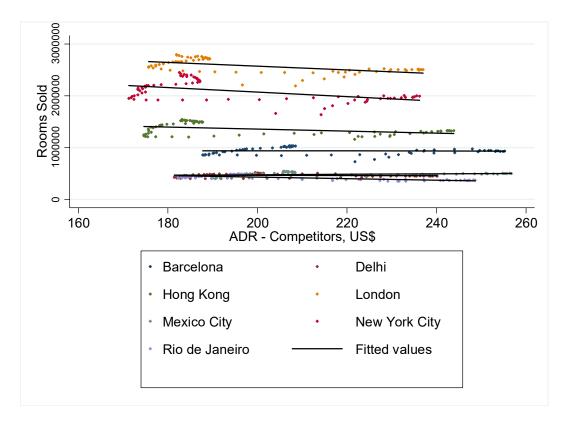


FIGURE A.20: SCATTER PLOT: ROOMS SOLD – AVERAGE DAILY RATE AT DESTINATION WITH FITTED VALUES BY DESTINATION, OWN ILLUSTRATION. SOURCE: SEE TABLE A.1





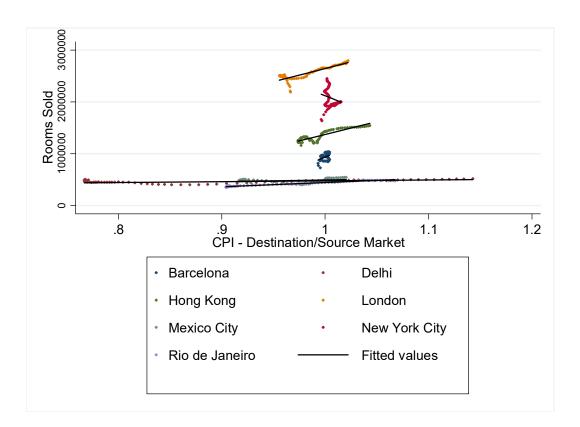


FIGURE A.22: SCATTER PLOT: ROOMS SOLD – CONSUMER PRICE INDEX: DESTINATION/SOURCE MARKET WITH FITTED VALUES BY DESTINATION, OWN ILLUSTRATION. SOURCE: SEE TABLE A.1

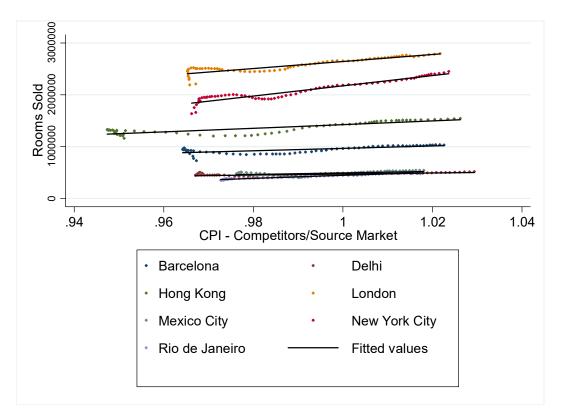


FIGURE A.23: SCATTER PLOT: ROOMS SOLD – CONSUMER PRICE INDEX: COMPETITORS/SOURCE MARKET WITH FITTED VALUES BY DESTINATION, OWN ILLUSTRATION. SOURCE: SEE TABLE A.1

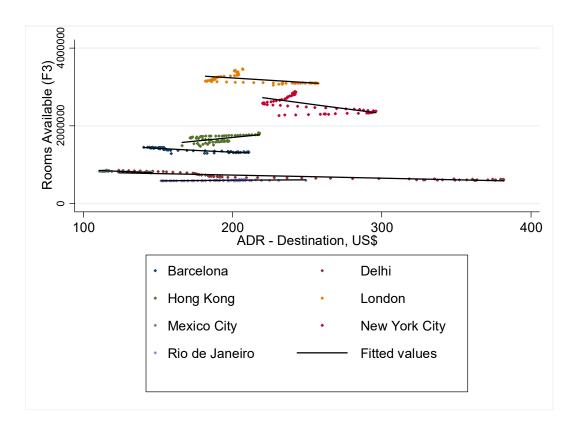


FIGURE A.24: SCATTER PLOT: ROOMS AVAILABLE (3 MONTH FORWARD) – AVERAGE DAILY RATE AT DESTINATION WITH FITTED VALUES BY DESTINATION, OWN ILLUSTRATION. SOURCE: SEE TABLE A.1

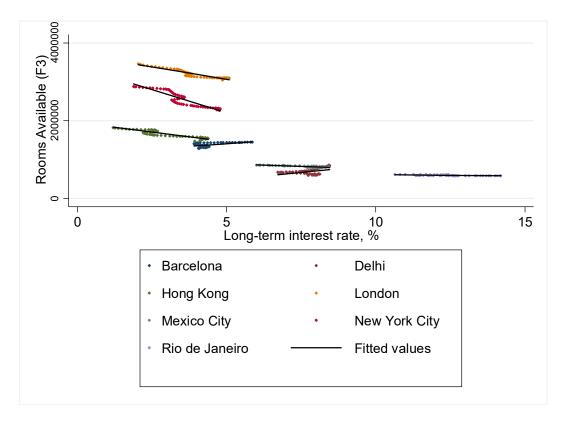


FIGURE A.25: SCATTER PLOT: ROOMS AVAILABLE (3 MONTH FORWARD) – LONG-TERM INTEREST RATE WITH FITTED VALUES BY DESTINATION, OWN ILLUSTRATION. SOURCE: SEE TABLE A.1

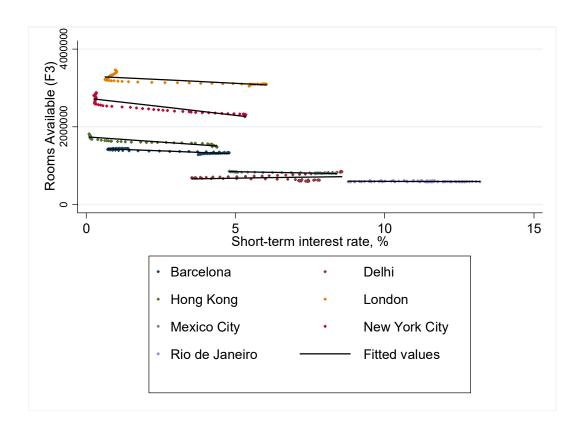


FIGURE A.26: SCATTER PLOT: ROOMS AVAILABLE (3 MONTH FORWARD) – SHORT-TERM INTEREST RATE WITH FITTED VALUES BY DESTINATION, OWN ILLUSTRATION. SOURCE: SEE TABLE A.1

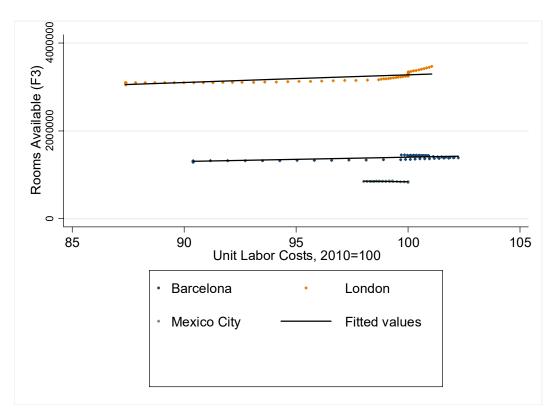


FIGURE A.27: SCATTER PLOT: ROOMS AVAILABLE (3 MONTH FORWARD) – UNIT LABOR COSTS WITH FITTED VALUES BY DESTINATION, OWN ILLUSTRATION. SOURCE: SEE TABLE A.1

Appendix 5: Regression Sensitivity Checks and Variants

This table reports pertinent variants of the regression around the two dummy variables for the Olympic Games in Beijing (with equestrian competitions in Hong Kong) and London. For d_OGLs, a value of 1 was only given for the time series of London, the other dummy variables have positive binary values across all panels for the relevant periods. While sometimes these dummies have significant effects in the regression, the other variables do not notably change due to changes in the dummies.

	(4) SUR	(5) SUR	(6) SUR
sqN _{jit}	0011	0011	561
Y _{jt} L3	0.0000372***	0.0000368***	0.0000374***
	(0.00000399)	(0.00000399)	(0.00000398)
ADR _{it}	-0.282***	-0.282***	-0.282***
	(0.0472)	(0.0472)	(0.0472)
ADR _{ct}	0.182***	0.183***	0.176***
	(0.0235)	(0.0234)	(0.0231)
CPI _{jit}	-57.40***	-57.09***	-57.68***
	(9.316)	(9.282)	(9.301)
CPI _{jct}	24.64	22.83	18.73
	(25.73)	(25.17)	(25.09)
H1N1 _{it}	-0.000991***	-0.000988***	-0.001004***
	(0.000173)	(0.000173)	(0.000174)
d_GFC <i>L3</i>	-4.154***	-4.134***	-4.164***
	(0.727)	(0.725)	(0.728)
d_OGHK	-1.559	-1.554	
	(1.764)	(1.759)	
d_OGL	-1.032		
	(1.303)		
d_OGL <i>s</i>		-6.155*	
		(3.273)	
sqBitF3 ADR _{it}	-0.256***	-0.256***	-0.256***
	(0.0514)	(0.0513)	(0.0513)
000	-6.190***	-6.178***	-6.186***
OCC _{it}	-6.190 (0.0853)	-6.178 (0.0848)	-6.186 (0.0852)
	-1.954***	-1.904***	-2.004***
LT_r _{it}			

ST_r _{it}	2.382***	2.388***	2.371***
	(0.364)	(0.361)	(0.359)
Observations	462	462	462
Standard errors in * <i>p</i> < 0.10, ** <i>p</i> < 0.0	•		

TABLE A.9: REGRESSION SENSITIVITY CHECK – DUMMIES: OLYMPIC GAMES, OWN CALCULATIONS

Table A.10 shows a variant of the model with different lags of some variabes. Generally, these models support the chosen model in Table 5.

	(7)	(8)	(9)
	SUR	Demand (FE)	Supply (RE)
sqN _{jit}			
Y _{jt} <i>L3</i>	0.0000382***	-0.0000817***	
	(0.00000507)	(0.0000130)	
ADR _{it} L1	-0.305***	0.155**	
	(0.0407)	(0.0625)	
ADR _{ct} L1	0.213***	0.715***	
	(0.0280)	(0.174)	
CPI _{jit} L1	-107.8***	-79.49**	
	(11.38)	(32.32)	
CPI _{jct} L1	216.6***	2546.6***	
	(32.13)	(180.8)	
H1N1 _{it} <i>L1</i>	-0.000767***	-0.00217*	
	(0.000201)	(0.00111)	
d_GFC <i>L3</i>	-5.673***	-14.18***	
	(0.848)	(3.686)	
d_OGHKs	3.015	21.98***	
u_001110	(5.361)	(6.936)	
d_OGLs	0 (omitted)	-6.580***	
4_0015	(N/A)	(2.318)	
sqB _{it} F6			
ADR _{it}	-0.269***		-1.040***
	(0.0460)		(0.196)
OCC _{it}	-6.424***		18.70***
	(0.104)		(1.537)
LT_r _{it}	-1.313 [*]		-90.13***
	(0.699)		(6.021)

ST_r _{it}	1.274***		25.76***
	(0.449)		(7.388)
_cons		-1423.2***	478.7***
		(191.2)	(111.1)
Observations 44	1	483	462
F-statistic		476.9***	1459.5***
Within R ²		0.779	
R ²			0.723
Standard errors in parentheses			
* p < 0.10, ** p < 0.05, *** p < 0.01			

TABLE A.10: REGRESSION VARIANT – DIFFERENT LAG/FORWARD LENGTHS, OWN CALCULATIONS

This table reports the results of a root-root model, i.e. a model where the explained and explanatory variables were all transformed with a power of -1, a square root transformation. In addition, the lags in this model are a variation of those chosen for the regressions in Table 5.

			0
	(10)	(11)	(12)
	SUR	Demand (FE)	Supply (RE)
sqN _{jit}			
sqY _{jt} L3	0.0988***	-0.287***	
	(0.0141)	(0.0383)	
sqADR _{it} L1	-8.299***	6.683***	
	(1.292)	(2.012)	
sqADR _{ct} L1	2.546***	19.89***	
	(0.838)	(4.807)	
sqCPI _{jit} L1	-143.5***	-84.33	
	(26.27)	(71.85)	
sqCPI _{jct} L1	139.5**	5082.2***	
. ,	(59.53)	(337.9)	
sqH1N1 _{it} L1	-0.0684***	-0.178	
	(0.0206)	(0.113)	
d_GFC <i>L3</i>	-4.754***	-14.08***	
_	(0.876)	(3.780)	
d_OGHKs	5.246	21.92***	
_	(5.512)	(7.251)	
d_OGLs	-7.991**	-8.452***	
_	(4.010)	(2.699)	
sqB _{it} F3			
sqADR _{it}	-7.748***		-22.56***
	(1.345)		(5.997)

sqOCC _{it}	-97.50***		270.5***	
	(1.642)		(30.14)	
sqLT_r _{it}	-6.915**		-457.7***	
	(2.984)		(21.80)	

sqST_r _{it}	1.503		89.73***	
	(1.658)		(21.54)	
_cons		-3912.5***	127.0	
		(358.1)	(224.8)	
Observations	462	483	483	
F-statistic		514.7***	829.4***	
Within R ²		0.783		
R ²			0.709	
Standard errors in parentheses				
* p < 0.10, ** p < 0.05, *** p < 0.01				

 TABLE A.11: REGRESSION VARIANT – ROOT-ROOT SPECIFICATION WITH LAGS, OWN CALCULATIONS

Appendix 6: Regression Summary Table – standardized beta coefficients

This table reports the standardized beta coefficients for the demand and supply model via the *-xtscc-* command in Stata. The coefficients were generated together with the table by using the *-esttab-* command.

	(13)	(14)
	Demand (FE)	Supply (RE)
sqN _{jit} Y _{jt} L3	-0.092***	
ADR _{it}	0.025***	
ADR _{ct}	0.044***	
CPI _{jit}	-0.012**	
CPI _{jct}	0.135***	
H1N1 _{it}	-0.014***	
d_GFC <i>L3</i>	-0.010***	
d_OGHKs	0.003***	
d_OGLs	-0.001***	
sqB _{it} F3 ADR _{it}		-0.151***
OCC _{it}		0.465***
LT_r _{it}		-0.792***
ST_r _{it}		0.247***
Observations	483	483
F-statistic	538.6***	1508.9***
Within R ²	0.787	0 700
R ² * <i>p</i> < 0.10, ** <i>p</i> < 0	05 *** 0.04	0.720

 TABLE A.12: REGRESSION SUMMARY TABLE – STANDARDIZED BETA

 COEFFICIENTS OF THE DISJOINTED MODEL, OWN CALCULATIONS