BEHAVIORAL ASPECTS IN OPERATIONAL DECISIONS. APPLIED FACTOR INVESTIGATIONS ON THE MICRO (INDIVIDUAL) AND MESO (CLUSTER) LEVELS

by

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Abstract

Normative theoretical models in operations management have been widely utilized by businesses and scientists to explain multiple phenomena. They assume that operating systems are managed by fully rational decision-makers who always choose the most profitable solution. However, decision-makers are human beings with behavioral and cognitive biases which influence their choices. In this thesis we argue that a change in the social and operating environments explains the choice deviation from the normative theoretical predictions. We present three independent studies of behavioral patterns on the individual and cluster levels. In the first study we observe the effect of human faces on the behavioral judgments in supply chain contracting. We find that the decisions made in “face” and “blind” settings are not equivalent. Judgments about facial attractiveness, trustworthiness and dominance influence the decision-maker in addition to the cognitive bias. We continue to explore the economic value of facial information in the second study. In experimental settings human faces are used as a facilitator of trust and honesty in a supply chain with multiple retailers competing for the cooperation of a single supplier. The analytical results reveal that retailer’s information sharing behavior and supplier’s reliance and reciprocity are influenced by the shown faces. Moreover, we observe that the channel efficiency improves when faces of all retailers are revealed to the supplier. However, the change in profitability is linked to the difference in facial trustworthiness. In the third study we use the data of terrorist attacks to investigate the behavioral patterns of organizations through their operational choices. We find that almost half of ideological terrorist movements connect through clusters. While some links have been stable over decades, the structure of the network has transformed from a centralized hierarchy to a decentralized structure and eventually evolved into

the combination of two – a hybrid organization. Our findings suggest that the global terrorist network responses to the changes in operational environment by adopting the new structure.

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Chapter 1

Introduction

The field of Behavioral Operations Management examines operational issues with an integration of psychological and emotional contents. Through the combination of modeling and empirical approaches, the researchers aim to develop more accurate operations theory incorporating complex decision-making and behavioral patterns. The stream of studies has demonstrated various behavioral biases and social preferences in operational decision-making. The current thesis contributes to this research field through empirical tests of environmental arrangements of operational decisions.

The central theme of this thesis is to investigate the behavioral aspects in operational decisions. In particular, we study the nudges affecting human judgments and triggering to deviate from standard process or established strategy. It is hard to quantify the cumulative effect of managerial decisions shaped by behavioral factors. But given that human actions are responses to the current environment, it is important to understand why they do what they do. In this thesis we explore social, psychological and physical nudges of operational decisions which are exposed through the environment.

The thesis is structured of the three independent essays in the following manner. Chapters 2 and 3 present the studies of behavioral issues on the individual (micro) level and Chapter 4 provides the behavioral observations on the cluster (meso) level. In Chapters 2 we explore the “face effect” in supply chain contracting. It is the first in the literature attempt to incorporate the social context component such as human faces in the supply chain scenario. The core idea is that individuals form a judgment about behavioral traits of others when they see their faces, and this judgment changes decision-making behavior. With the goal to determine the effect of faces on decisions, we designed laboratory experiments with two differing treatments: (1) "blind"—when no facial information about a retailer is available to a supplier, and (2) "face"—where a face image of a retailer is shown to a supplier. We show original computer generated images of faces varying on dimensions of three facial traits: attractiveness, trustworthiness and dominance. We find that facial information has an economic value for a decision-maker. The decisions in "face" and "blind" settings are not equivalent and differ with the pricing strategy. From observed variations in a wholesale price we develop a strategic model of a supplier's pricing behavior. In doing so, we show that a decision mechanism is influenced by inner judgment about faces in addition to a cognitive solution. Thus, management of "face effects" could serve for strategic purposes in supply chain contracting.

In Chapter 3 we continue to explore the "face effect" as a valuable facilitator of trust and honesty in a supply chain. We present the results from a set of controlled experiments designed to reveal the behavioral responses in the forecast communication settings. Using a supply chain scenario with multiple retailers competing for the cooperation of a single supplier, we investigate the effect of human faces on the retailer's information-sharing behavior and supplier's inventory responses. The analytical results reveal that the deviations in the retailer's truth-telling and the supplier's trust and reciprocity are systematically influenced by revealed facial identities. Seeing faces of all retailers drives up supply chain performance and overall efficiency. However, the change in profitability is linked to the difference in facial trustworthiness. This suggests that the facial identity has an intrinsic economic value which can either serve or harm the cooperation in a supply chain.

In Chapter 4 we investigate the behavioral patterns of organizations through their operational choices. We use the data of terrorist attacks. Specifically, we perform a social network analysis combined with statistical techniques to explore the structure of the global ideological terrorist network and its evolution over time. We find that almost half of ideological movements connect through clusters with several links stable over decades. In response to the changes in operational environment, these networks transformed from a centralized hierarchy to a decentralized structure and eventually evolved into the combination of two – a hybrid organization.

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Chapter 2

Do Looks Matter in Supply Chain Contracting? An Experimental Study

Abstract

Although it is well known that people form impressions of others based on appearance, little is known about the role of faces in contracting. We present results of an experiment designed to reveal the "face effect" on pricing behavior in a supply chain game. In particular, we study the variation in wholesale prices driven by subjective judgments of three facial traits—attractiveness, trustworthiness, and dominance—of a retailer's face and own appearance. Our experimental data suggests that the distributions of decisions in settings whether individuals see, or not see, retailers' faces are not equivalent. We find that judgment of both faces—own and counterpart's—have a significant impact on a supplier's price choice. To measure the complex dependencies between decision behaviors and facial traits, we developed a hierarchical behavioral model nested on three pricing intervals labelled as cooperation, competition, and aggressive overcharge strategies. The model explains differences in the facial traits effects across the three pricing strategies. At an aggregate level, a supplier has a greater expected profit when he or she sees an attractive or trustworthy-looking retailer; whereas, a stronger self-reported dominance is associated with a lower expected efficiency of individual performance.

1. Introduction

In a survey conducted by Forbes Insight (2009), 84% of 760 business executives prefer face-to-face meetings to technology enabled, remote ones. They believe that face-to-face interactions help build stronger business relationships (85%), better social interactions (75%), and gives the ability to "read" another person (77%). Many other studies report the same. Wakefield Research Fourth Annual Business Travel Survey (2012) reports that 96% of business travelers value face-to-face meetings as the fundamentals for long-lasting business relationships. A Small Business Survey (2016) conducted by the Meetings Mean Business coalition and the Association of Public-Safety Communications Officials (APCO) finds that "96% of small business owners say in-person meetings yield a return on investments" (Berger, 2016). Requests made face-to-face are 34 times more effective than those made "blind" (Roghanizad and Bohns, 2017).

Behavioral economics literature, indeed, finds that seeing a face improves trust and cooperation (Lewis, 2004, Eckel and Petrie, 2011). In the Eckel and Petrie 2011 study, responders, in a trust game, were more trustworthy if they saw a photo of the sender. In addition, they were willing to pay to see the photo, as well as, to show their own photos to their counterparts (Heyes and List, 2016). These results establish, in general, that just the availability of images of faces, even without any verbal or social interactions, can change economic decisions. Surprisingly, there is little research of this issue in operations management contexts, given the importance of contexts in business decision making (Kremer et al., 2010). In particular, intuitively, one would expect this issue may be especially important to supply chain contracting.

In this study, by the use of laboratory experiments, we explore the "face effect" in a supply chain contracting scenario. The core idea is that individuals form judgments about behavioral traits of others when they see their faces, and these judgments change their decision-making behavior. Our goal is to determine how such judgments can nudge decisions. Note that it is out of the scope of this research of whether faces actually reflect behavioral traits, and whether these judgements are accurate. As we focus on the judgments of faces, we intentionally choose the simplest supply chain contracting scenario where a supplier sets a simple linear wholesale price for a newsvendor retailer. In this scenario, both a supplier and a retailer can react to the judgments of faces. We focus on the supplier's wholesale price decision as to help isolate the impact of face judgements. The retailer's order decision can be affected by both face judgments, if available, but also the wholesale price and the resulting social preference (e.g. fairness). Hence, we believe that focusing on the supplier's wholesale price decision behavior will be most appropriate for this research. As such, we conducted experiments where human subjects played the role of the supplier, and the retailers were controlled by software. Using "robot" players is not uncommon in behavioral operations management literature (e.g. Kalkanci et al., 2011, 2014).

If retailers are robots, whose face are we going to show the suppliers? We choose to use original computer generated images of faces, with an algorithm developed in the Social Perception Lab at the Princeton University (Oosterhof and Todorov, 2008, Todorov and Oosterhof, 2011, Todorov et al., 2011). Obviously, the subjects would know that these were not the real faces of their supply chain partners; in fact, in the instructions, we include the statement "Imagine that the person on the picture is your buyer" as to employ no deception in the experiment. Literature has shown that individuals do react to robot players with social preferences, abate weaker than when facing real humans, and other human-like considerations (Kalkanci et al., 2014). We believe the same principle allows here. This research strategy provides two significant advantages. First, the computer algorithm we employed allows us to manipulate several facial traits, discussed below, independently. Second, we can exact control for emotional neutrality, age and race.

Wilson and Eckel (2006) show that individuals can judge the level of trust by looking at a face appearance. Attractive trustees are perceived as more trustworthy and, consequently, are trusted more. Hence, behavioral traits may be reflected in the face image of a person. To facilitate exposition, we refer to such a trait (e.g., trustworthiness) as a “facial trait”, interpreted as a behavioral trait that can be informed by the image of a face. In this study, we focus on three facial traits, chosen for their importance to operations management decision-making, and the fact that the algorithm used to generate faces, discussed above, allows for the manipulation of these traits in the images that it creates. We pick the faces varying on dimensions of attractiveness, trustworthiness and dominance. Existing literature suggests these three traits may have impacts on how people are treated under business settings (Krumhuber et al., 2007, Fruhen et al., 2015, Linke et al., 2016, Todorov et al., 2015).

Evolutionary, humans are attentive to physical attractiveness (Thornhill and Gangestad, 1999, Rhodes, 2006, Little et al., 2011). Attractive people are seen as more intelligent, competent and trustworthy (Zebrowitz et al., 2002,Todorov et al., 2005, Wilson and Eckel, 2006) . These stereotypes influence people’s judgments and expectations. Thus, political scientists note the candidate attractiveness can drive election results (Laustsen, 2014, Berggren et al., 2010, Hart et al., 2011, King and Leigh, 2009, Rosar et al., 2008). Economists, too, find that attractive borrowers and trustees are granted with a better attitude (Jin et al., 2017) and earn more (Wilson & Eckel, 2006). Trustworthy-looking individuals are benefited with higher chances to obtain loans (Duarte et al., 2012) and earn more (Tingley, 2014, Wu et al., 2018). Dominance, on the other hand, evokes negative judgments as being associated with the individual's power and aggressiveness (Oosterhof and Todorov, 2008, Dietl et al., 2018).

Our experimental design employs a within subject design with a "blind" treatment where no face image is shown to the supplier, and a "face" treatment where a face image is shown. In the "face" treatment, we use 54 images which span three facial traits. First, we observe a significant treatment effect; the distributions of wholesale prices offered in "blind" and "face" settings are not equivalent. Second, via the use of a hierarchical behavioral model, we find that suppliers follow one of the three pricing strategies— cooperation, competition and aggressive (biased) overcharge—and the responses to facial traits depend on the employed strategy. For example, when a supplier uses the "cooperation" strategy, s/he offers a higher price to a more attractive retailer (i.e., a "beauty penalty" effect). However, if a supplier employs the "aggressive overcharge" strategy, s/he offers a lower price to a more attractive retailer (i.e., a "beauty premium" effect). At an aggregate level, the supplier is likely to have a greater expected profit when faces an attractive retailer. Similar results are found in other facial traits.

This paper makes two contributions. As far as we know, we are the first to, experimentally, study the impact of facial information (i.e., a face image) in supply chain contracting. Second, we adapted the quantal response framework to develop a hierarchical behavioral model that allows us to capture the responses to facial traits, and elaborate insights that may help facilitate supply chain contracting.

The reminder of this study is organized as follows. In section 2, we summarize the theoretical guidance of behavioral operations management literature and relevant behavioral economics studies. Section 3 describes the supply chain contracting environment we use to operationalize the faces and facial traits in our experiment. The experimental procedure is explained in section

4. We present experimental results in section 5 and discuss behavioral modelling in section 6. We offer strategic implications of face effect in section 7 and concluding remarks in section 8.

2. Theoretical Guidance (Literature Review)

Growing literature on behavioral operations management explains a choice deviation from its optimum by bounded rationality of a decision-maker. The stream of studies has demonstrated various behavioral patterns in contracting referring to fairness (Haitao Cui et al., 2007, Ho et al., 2014, Kalkanci et al, 2014, Wu and Niederhoff, 2014, Katok et al., 2014), loss-aversion (Zhang et al., 2016), friendly or long run relationships (Loch and Wu, 2008, Davis and Leider, 2018), trust and trustworthiness (Ozer et al., 2011, 2014, Beer et al., 2017). Despite the striking uniformity in pull-to-center and adaptive learning effects, the behavioral tendencies vary at the individual level. Both suppliers and retailers are highly heterogeneous what impacts the significance and the strength of decision biases (Becker-Peth et al., 2013, Bolton and Katok, 2008, Wu and Chen, 2014, Katok et al., 2014, Moritz et al., 2013).

Coordinating supply chain contracts, designed to align economic incentives of two parts (Cachon, 2003, Cachon and Lariviere, 2005), have been rigorously studied in behavioral experiments (e.g., Katok and Wu, 2009, Becker-Peth et al., 2013, Wu and Chen, 2014, Zhang et al., 2016, Davis, 2015). Theoretically, the contract should be optimally designed by rational authors; in practice, it often deviates from the optimum. One of the factors impacting the decision strategy is the context-sensitivity in supply chain contracting (Kremer et al., 2010); the context implies broad circumstances under which the contract is created, including social considerations (Loch and Wu, 2008). The social context refers to physical and social settings of human interactions, it influences human decision-makers, and is impossible to avoid. However, the intervention of behavioral patterns (e.g., fairness and trust) can be either restricted, or magnified, by the contracting settings. Kalkanci et al. (2014) have identified evidence of human interaction effects on bounds of rationality of a decision-maker. Researchers find that suppliers act less rationally in a human-to-human game than in a human-to-computer one, and are likely to provide better contracts with more favorable discount terms when interacting with humans. The idea of a change in behaviors in different settings triggered our interest to continue the research of the social context in supply chain contracting scenarios. We set two opposite settings: the first setup is the standard newsvendor problem with no revealed private information, which is widely used in the literature, and the second setting is the experiment which offers human features to the contracting content. Human features could be delivered via various venues including text, sound, photo, and video. In this study we are interested in the effect of faces.

Because the social context in contracting has received relatively little attention among experimental studies in operations management, we search for theoretical support from other research fields. We find more evidence of human-to-human interactions effects in the behavioral economics literature. Various economic studies conclude that human faces have indigenous values which can be measured economically. This statement may sound unnatural, but it has been proven by multiple laboratory experiments and surveys. Recent research shows that people are affected by the shown faces and shift their decisions in a direction unfavorable for themselves (Eckel and Petrie, 2011, Ma and Hu, 2015, Ma et al., 2015, 2017, Zhang et al. 2011). In a trust game experiment, Eckel and Petrie (2011) demonstrated the strong willingness of subjects to see a counterpart's photo; both senders and responders purchase the photo for a positive price. And those, who bought the photo, trusted more than those who did not. Moreover, Heyes and List (2016) experimentally revealed that subjects are willing to pay to show their own photo to counterparts. Following the examples from behavioral economics, we chose to use the face image to signal about human features in contracting scenario and set up the difference from utter human-to-computer settings. Although, human-to-human interactions are not realized in full, but manipulated by showing images of the counterparts, the decision-makers cannot ignore the difference between settings, and are expected to deviate in their performance.

We believe that our study is distinctive from previous behavioral research in operations management. By using the face images we apply the direct reference to human-to-human settings opposed to oblique assumptions typically provided through the experimental instructions read prior the trials. To the best of our knowledge, this study is the first in operations management to investigate the effect of faces on supply chain contact terms. We believe that our results make a valuable commitment into an understanding of the impact of social context on the contracting decisions.

3. Supply Chain Contracting Environment

To operationalize the contracting environment, we choose to apply standard settings of a supply channel with a single supplier (a seller) and a single retailer (a buyer) (Cachon, 2003). The supplier offers a supply chain contract to the retailer; within the contract terms the supplier identifies a linear wholesale price w for a product. The retailer decides on the amount of products to order and places the order quantity q with the supplier. Both the supplier and the retailer are facing the uncertain market demand D and exogenous retail price p. We use the simplest supply chain contract—a wholesale price contract—with the purpose to minimize a computational complexity and focus on the impact of social context on pricing decisions.

Under a wholesale price contract, the supplier is burdened with the right choice of w to persuade the retailer to order larger q and generate positive inflows after incurred the product cost c. The retailer is optimising $q(w)$ to avoid the excessive order leading to the obsolete stocks with zero value and the shortage resulting in the loss of customer demand with potential profit. The theoretical literature assumes that both players are rational and act with a purpose to maximize own profits:

$$\max \pi_R = p \min(D, q) - wq$$

$$\max\ \pi_S = (w - c)q$$

For simplicity we assume that D follows the uniform distribution between a and b, with $b > a \geq 0$. The deterministic (normative) solution of the system of equations results in the best response choices for the retailer $q^* = b - \frac{w}{p}(b - a)$ and for the supplier $w^* = \frac{c}{2} + \frac{pb}{2(b-a)}$ (please, for details see Chapter 2 Appendix 1).

3.1. Impact of Faces on Pricing Decision

We assume that human interactions are unavoidable in supply chain contracting, and they are carried either through face-to-face meetings (e.g., in person or virtual with visual representations) or technology-enabled blind communications (e.g., emails or texting). Social preferences are heterogenous on the individual level. However, business practice records and behavioral research literature provide multiple evidences of strong preferences for face-to-face meetings. Thus, 84% from 760 business executives surveyed for Forbs Insight study (2009) chose face-to-face meetings over virtual communications for their business goals. Wakefield Research Fourth Annual Business Travel Survey (2012) revealed that in-person meetings are fundamental for sustaining business relationships (96% of respondents). Moreover, a face-to-face communication “yields a return on investments” according to the Small Business Survey (2016) conducted by the Meetings Mean Business coalition and APCO (Berger, 2016). Judgments of CEOs faces corelate with the firms' financial performance (Re and Rule, 2016).

In controlled laboratory experiments, decision-makers also demonstrated a desire for a face-to-face communication (Eckel and Petrie, 2011). In a trust game both senders and receivers were willing to purchase a photo of their counterparts. Those who bought the picture sent more than those who did not. Interestingly, when a photo appeared involuntary, subjects did not differentiate in their trust compared to the blind settings. Furthermore, decision-makers were willing to share their own photos, and even agreed to pay for that (Heyes and List, 2016). By revealing their own facial characteristics, they expected to affect the actions of counterparts.

Listed findings suggest that private facial information learned either from images of faces or during in-person meetings influences judgements about behavioral traits of the seen person. These judgments lead to the change in a pricing behavior of a decision-maker. Therefore, a set of certain facial characteristics can be used as a tool for behavioral manipulation, allowing to turn the decision in a favorite venue. Being influenced by the revealed facial information about the partner, the decision-maker reconsiders his or her own utility and deviates in the choice from the optimum. Under the assertion that facial human features impact the supplier's pricing decision, we state Hypothesis 1.

Hypothesis 1. *People are not indifferent to the facial information of their counterparts. The wholesale price w offered in a context of shown faces deviates from w offered in a context of blind decision.*

In our research we explore the deviation in the choice of w offered by a supplier within two types of contracting settings—(1) no private facial information about a retailer is available to a supplier (Blind), and (2) a face image of a retailer is shown to a supplier (Face). With a purpose to identify the face effect in the supply chain contracting on its aggregate level, we allocate and measure the difference in the average w offered within two contexts.

3.2. Facial Traits Effects on Pricing Behavior

Behavioral economics suggests using attractiveness and trustworthiness to explain the variation in effects of facial traits on a trust (Wilson and Eckel, 2006, Eckel and Petrie, 2011). Studies of the individual's facial characteristics find a significant association of trustworthiness and dominance with the leadership potential (Dietl et al., 2018, Re and Rule, 2016). While the role of these three facial traits have been widely explored within the socio-economic settings, to our knowledge, no studies have been conducted within a supply chain contracting scenario. However, specific facial characteristics of a business partner are an essential source of information, which a supply chain manager uses to form the behavioral expectations about the partner. For the purpose of our research, we examine influences of shown faces by manipulating their facial traits; in particular, we chose to explore the effects of the three facial traits: attractiveness, trustworthiness, and dominance. The impacts of these three facial dimensions have been recently studied in various business settings *(*Krumhuber et al., 2007, Fruhen et al., 2015, Linke et al., 2016, Todorov et al., 2015*)*. The literature suggests the importance of these traits to judgments of a decision-maker, which implies the necessity to investigate their capacity in a context of operations management. We note that the effects of other facial characteristics can be also important to study, but leave them for the further research. In our experiment we gather the informational impact of counterpart's facial characteristics on a choice variance in pricing behavior of a supplier. Additionally, we observe the impact of individual's beliefs about own facial traits on the economic choices.

1. *Attractiveness.*

In a classic social psychology, Dion at al. (1972) find that attractive individuals are more successful than unattractive. The social stereotype, associated with physical attractiveness, is tied to positive benefits in many spheres of life. Attractive people are given hiring preferences over unattractive ones (Cash and Kilcullen, 1985, Chiu and Babcock, 2002, Ruffle and Shtudiner, 2014). A candidate's physical attractiveness is a strong predictor for the electoral success (Laustsen, 2014, Berggren et al., 2010, Hart et al., 2011, King and Leigh, 2009, Rosar et al., 2008). Attractive borrowers receive a tolerant attitude from lenders in financial transactions (Jin et al., 2017). A good-looking defendant is charged with a more lenient sentence for burglary (Sigall and Ostrove, 1975). These are just a few of the positive benefits associated with physical attractiveness demonstrating the "beauty premium" effect. However, contrary to the "beauty premium" effect, attractive people may be punished by the "beauty penalty". Beautiful trustees earn less on the second stage in a trust game (Wilson and Eckel, 2006). Attractive female applicants are hired less favourably for managerial positions (Heilman and Saruwatari, 1979, Heilman and Stopeck,1985, Ruffle and Shtudiner, 2014). When a crime is related to the use of physical beauty, an attractive defendant receives a harsher punishment compared to an unattractive defendant (Sigall and Ostrove, 1975).

Researchers started to recognize the importance of physical attractiveness from the mid-1960s - early 1970s (Berscheid and Walster, 1974; Hatfield and Sprecher, 1986). By consensus, the measure of beauty was identified by use of judges; each judge was asked to provide his or her independent rating for the physical attractiveness of the subject on a scale from 1 to 10. The reported measures were averaged by subject, and the resulting score is called the objective physical attractiveness (Walster et al., 1966). After a wide recognition of correlation of objective physical attractiveness with personality traits, popularity, cognitive and social abilities, the measure of self-rated or subjective physical attractiveness became of interest (Murstein, 1972). Several studies find that the subjective physical attractiveness is correlated with cognitive and affective abilities, and social skills (Cash et al., 1983; Lerner and Karabenick, 1974; Major et al, 1984, Baumeister et al., 2003).

To explain the deviation in supplier's decisions about w, we consider the effect of physical facial attractiveness A of both supply chain partners—a retailer and a supplier. We differentiate subjective evaluative judgments about attractiveness of others A^o and self-esteem attractiveness A^s. The supplier j evaluates the facial beauty of the retailer n by assigning the score A^o_{jn} and own attractiveness by self-reporting A^s_j . From the dual nature of the attractiveness effect (Wilson & Eckel, 2006) we expect to observe both beauty effects: a "beauty penalty" and a "beauty premium". By pleasing a supplier with his or her beauty, an attractive retailer will be awarded by a "beauty premium"—an offer with a lower w compared to an unattractive retailer. However, self-judgments about own beauty may influence a supplier either to recognize an attractive retailer as a "beauty competitor" or to make him/her jealous of other's attractiveness (Ruffle and Shtudiner, 2014). In this case, an attractive retailer will be punished by a "beauty penalty"—offered less appealing contract terms with a higher w. Following the assertion of dubious outcomes for attractive faces we formulate controversial Hypotheses 2a and 2b.

Hypothesis 2a. *A retailer with a high facial attractiveness rating is offered a lower wholesale price w compared to a retailer with a lower attractiveness score featuring the presence of a "beauty premium" effect. A supplier who reports a highly scored self-attractiveness offers a lower w than a supplier with a low self-reported attractiveness featuring the reciprocate "beauty premium" effect.*

Hypothesis 2b. *A retailer with a high facial attractiveness rating is offered a higher wholesale price w compared to a retailer with a lower attractiveness score featuring the presence of a "beauty penalty" effect. A supplier who reports a highly scored self-attractiveness offers a higher w than a supplier with a low self-reported attractiveness featuring the reciprocate "beauty penalty" effect.*

2. *Trustworthiness.*

Trustworthiness is typically associated with positive benefits. Trustworthy looking people have higher chances to obtain a loan and pay a lower interest rate (Duarte et al., 2012). Their offers are more likely to be accepted by businesses (Wu et al., 2018) and by consumers (Dean, 2017). Individuals with trustworthy-looking avatars receive larger amounts in a trust game (Tingley, 2014).

To understand the effect of trustworthiness on the pricing behavioral solution of a supplier, we study the facial trustworthiness T of both partners. Following the same concept as used to determine attractiveness, we differentiate subjective evaluations of trustworthiness of others T^o and own trustworthiness T^s. The supplier j evaluates the facial trustworthiness of the retailer n by assigning the score T_{jn}^o and own trustworthiness by T_j^s . We expect that a trustworthy-looking retailer anticipates supplier's positive judgments, which add an unfavourable decision noise in a supplier's choice of w. In parallel, self-rated trustworthiness should also negatively influence the rationality of a supplier. Under the expectations of positive benefits for being trustworthy-looking we state Hypothesis 3.

Hypothesis 3. *A retailer with a high facial trustworthiness rating is offered a lower wholesale price w compared to a retailer with a lower trustworthiness score. A supplier who* *reports a highly scored self-trustworthiness offers a lower w than a supplier with a low self-reported trustworthiness.*

3. *Dominance.*

Contrary to trustworthiness, dominance is associated with a greater power and aggressiveness (Oosterhof and Todorov, 2008, Dietl et al., 2018). In the context of supply chain contracting we seek to explain the effect of facial dominance D on the supplier's decision about the wholesale price w. In line with the concept used to determine attractiveness and trustworthiness, we differentiate subjective judgments about dominance of others D^o and self-reported dominance D^s. The supplier j evaluates the facial dominance of the retailer n by assigning the score D_{jn}^o and own dominance by D_j^s . Judgments about trustworthiness and dominance approximate into two orthogonal dimensions used to evaluate faces (Oosterhof and Todorov, 2008). While trustworthiness relates to positive factor of warmth, dominance loads to the negative factor of power (Dietl et al., 2018). This anticipates the adverse to trustworthiness expectations for the dominance effect on the human behavior. We expect that greater ratings in both evaluations (self and others) of dominance encourages a supplier for an aggressive pricing behavior. Under the assertion of punishment of having a dominant look we state Hypothesis 4.

Hypothesis 4. *A retailer with a high facial dominance rating is offered a higher wholesale price w compared to a retailer with a lower dominance score. A supplier who reports a highly scored self-dominance offers a higher w than a supplier with a low self-reported dominance.*

4. Experimental Procedure

We borrowed the initial experimental design of a human-to-computer game from Kalkanci et al. (2014) and developed it by adding a social context component—face images of potential retailers. Human subjects played as the supplier, and computers were programmed as the retailer. In our experiment we used the within-subject design with two treatments:

- "blind" (Blind) game when subjects have no facial information about the retailer,

- "face" (Face) game with shown up of the retailer's face image on the screen along with the statement "Imagine that the person on the picture is your buyer".

The treatments were mixed and their order was randomized into 70 periods. Every participant had to make 16 offers blindly and 54 decisions facing an image.

In the experiment we applied the wholesale price contracting scenario. The supplier had to make a decision about a wholesale price as an optional offer to the retailer. A computer was programmed with an algorithm to maximize the retailer's profit. The choice distribution of a wholesale price w was limited to discrete numbers from 0 up to \$100. The market price and costs were kept constant at the rates of $p = \$100$ and $c = \$30$. The demand was generated randomly with the uniform distribution from 0 up to 150 units. We used the z-Tree software (*Fischbacher, 2007*) to program our experimental interface.

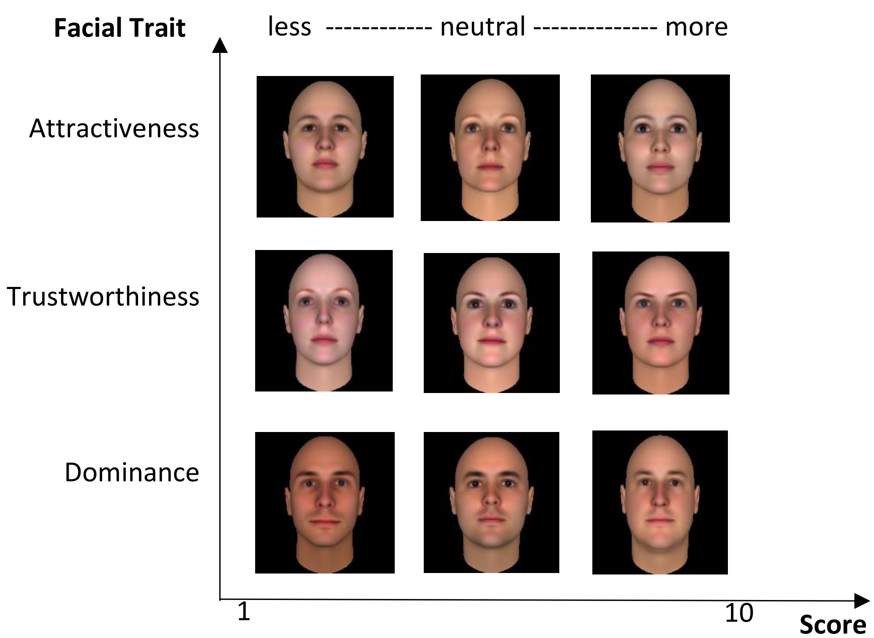
We performed two experimental sessions at the behavioral study laboratory of a major public U.S. university; 41 undergraduate students from the college of business were employed to participate in the supply chain contracting game. At the beginning of each experimental session, participants read the instructions at their individual stations; and then the instructions were read out loud with explanations of the game settings, and examples of the economic decisions made within the game. We informed the participants that they would be playing against the computerized buyers pre-programmed to make a decision about an order quantity which maximizes the expected profit of the computerized buyer. However, we did not discuss the specifics about social context in the experimental treatments. We explained the conversion of the individual earnings in the experiment into the final payment. Participants were compensated in proportion to their individual profits earned in the game, plus a fixed $5 participation fee. The average payment was $14. Each student participated only in one session.

4.1. Facial Context in Experiment

In Face treatments, an image of the face of a potential buyer appeared on the screen in front of subjects. The shown faces are not faces of real people. Figure 1 illustrates the example of face images. We selected 54 original computer generated faces from the database "300 Random Faces" provided by the Social Perception Lab at the Princeton University (https://tlab.princeton.edu/databases/). The database consists of 300 Caucasian faces randomly created in the Lab with computer models (Oosterhof and Todorov, 2008, Todorov and Oosterhof, 2011, Todorov et al., 2011). In order to avoid judgments affected by race stereotypes, the race control was set up to the face of European. All faces have a neutral emotional expression allowing also to control for judgments associated with anger, fear, sadness, and happiness. In addition, the mouth-shape, which can have the corners of the mouth up or down, was set up to neutral to further ensure that faces have a neutral expression. Each face has a black background on the image. The image dimensions are set up to a 400 x 400 pixels bitmap.

The computer models manipulated dimensions of nine facial traits—attractiveness, competence, trustworthiness, dominance, meanness, frightening, extraversion, threatening, and likability—to produce human faces. The scores of these nine facial traits, and the proportion of femininity, are reported for every face from the database. For our experiment, we selected 27 faces categorized as unambiguously male, and 27 faces categorized as unambiguously female. The faces were chosen based on the criteria to maximize, minimize, and average the scores of three facial traits—attractiveness, trustworthiness, and dominance (please, see examples of used faces in Figure 1). Every face from the total of 54 faces used in the experiment was shown to each subject once.

Figure 1. Examples of Faces Shown in Face Treatments



In addition to a decision about a wholesale price, in a Face treatment subjects were asked to evaluate the shown face of an imaginable retailer in terms of one of three facial traits (attractiveness, trustworthiness, dominance) on a scale from 1 (very unattractive, untrustworthy, nondominant) to 10 (very attractive, very trustworthy, very dominant). During the session, every participant evaluated 18 faces in attractiveness, 18 faces in trustworthiness, and 18 faces in dominance. At the end of the experiment participants were also asked to fill the questionnaire about self-identity (gender, age, ethnicity), their feelings during the game, and report scores of own attractiveness, trustworthiness, and dominance on a scale from 1 to 10 .

5. Experimental Results

We first check the effect of faces by comparisons of wholesale prices offered in Blind and Face conditions (Hypothesis 1). Next, we examine the effects of facial traits on the average w (Hypotheses 2-4). Additionally, we compare the density distributions of wholesale prices in low and high conditions of facial traits. Finally, we take an aggregate view on the shape of data distributions.

5.1. Wholesale Price Decisions in Blind and Face Treatments

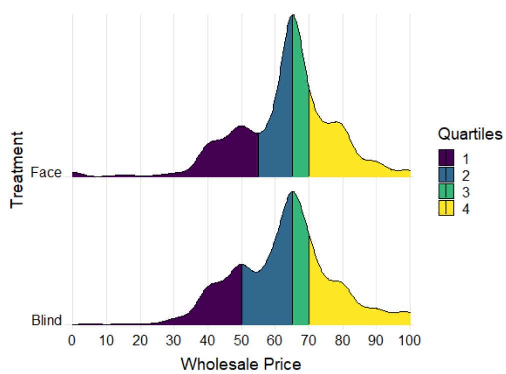
Table 1 provides a summary statistics of wholesale prices offered in Blind and Face (aggregate and across three facial traits) treatments. We observe systematic deviation of mean w below the equilibrium optimum of $65 and across treatments. However, Wilcoxon tests for the subject-average difference does not confirm that w in Blind treatment differ from w in Face treatments ($p > 0.05$).

Table 1. Offered Wholesale Price by Treatment and Primer

Treatment	Primer	Mean	St.Dev.	Min	Median	Max	n obs
Blind	-	62.99	14.83	5	65.00	100	656
Face	-	63.09	15.16	0	65.00	100	2214
	Attractiveness	62.81	16.24	0	65.00	100	738
	Trustworthiness	62.79	15.31	0	65.00	100	738
	Dominance	63.67	13.83	0	65.00	100	738

Comparing the aggregate decisions of w in Blind and Face conditions, the two-sided Kolmogorov-Smirnov test reveals that the two distributions are significantly different (p = 0.015). We find strong statistical evidence in support of Hypothesis 1. Therefore, the wholesale prices offered in treatments with shown faces deviates from the wholesale prices offered in treatments with no facial information. Figure 2 illustrates the distribution of w over all subjects in Face and Blind treatments.

Figure 2. Density Distribution of Wholesale Prices (Over All Subjects) in Blind and Face Treatments



5.2. Facial Traits Effect on Wholesale Price Decisions

To compare the effects of facial traits on the average wholesale price, we use regression analysis. We fit the data of w choices into a regression model with the independent variables for facial traits of others $Facial\ Trait^{o} \in (A^{o}, T^{o}, D^{o})$, evaluated by subject for every shown face, and self-reported facial traits $Facial\ Trait^{s} \in (A^{s}, T^{s}, D^{s})$:

$$w_{it} = \beta_o + \beta_1 Facial\ Trait^{o} + \beta_1 Facial\ Trait^{s} + \varepsilon_{it} \tag{1}$$

We apply the random effects model as the most robust compared to pooled and fixed effects (Hausman Test: $p > 0.05$, Breusch-Pagan Test: $p < 0.01$). However, the results for all three effects are consistent. The estimated parameters in Table 2 inform that some of the three facial traits have a significant impact on average w :

1) Attractiveness. We find strong significant evidence of the positive effect of attractiveness of shown faces ($p < 0.01$) in support of Hypothesis 2b. A retailer with more attractive face is punished by a larger average wholesale price. This features the "beauty penalty" effect. However, the effect of self-attractiveness is weakly significant ($p < 0.10$) to support Hypothesis 2a.

2) Trustworthiness. The facial trustworthiness of others has a significant positive effect ($p < 0.01$) on the average wholesale price. However, we do not find statistical evidence of the effect of self-reported trustworthiness. Therefore, Hypothesis 3 is partially supported.

3) Dominance. Based on the regression analysis, the change in dominance of looks does not affect the choice of w. No evidence is found to support Hypothesis 4.

Table 2. Regression Results for Testing Facial Traits Effects in Decisions (Random Effects)

	Estimate (standard error)					
Variable	Wholesale price (w)					
Attractiveness of Others (A^o)	1.023***	(0.231)				
Self-Attractiveness (A^s)	-1.817*	(1.007)				
Trustworthiness of Others (T^o)			0.583***	(0.213)		
Self-Trustworthiness (T^s)			-0.375	(1.305)		
Dominance of Others (D^o)					-0.259	(0.196)
Self-Dominance (D^s)					-0.692	(0.740)
Constant	70.295***	(7.113)	63.128***	(11.655)	69.360***	(4.915)
Note:	*p < 0.1; **p < 0.05; ***p < 0.01					

Complimenting the analysis of the average wholesale price, we take an aggregate view on the data distribution of reported choices. We find that the distribution of w varies with a change in facial traits of shown faces. Figure 3 demonstrates the distributions of w in low and high conditions of appeared facial traits. The Kolmogorov-Smirnov test confirms the difference in effects of low (1-3) and high (8-10) scores of some of the three facial traits, considering others $Facial\ Trait^o \in (A^o, T^o, D^o)$ and self-reported $Facial\ Trait^s \in (A^s, T^s, D^s)$:

1) Attractiveness. The suppliers with low self-reported attractiveness offer different wholesale prices compared to the suppliers with high confidence in own attractiveness (p = 0.001). Yet, no significant difference in w is found for low and high scores of attractiveness of others.

2) Trustworthiness. The data does not provide sufficient evidence to testify the effect of score-difference in trustworthiness of others on w. The subjects reported own trustworthiness either neutral or above it ($T^s \geq 5$).

3) Dominance. The effects of low and high dominance on pricing behavior are significantly different for others (p = 0.018) and self-reported (p = 0.022) scores.

Figure 3. Variations in Distribution of Wholesale Prices (Over All Subjects) for Others and Self-Reported Facial Traits

5.3. Multimodality in Aggregate Distributions of Wholesale Price Decisions

By visual inspection of Figures 2 and 3, we observe that the entire pricing probability distribution is multimodal, what features about the grouping tendency in selected decisions. The data of w is shaped with multiple peaks in both Face and Blind treatments, and in low and high conditions of facial traits. To test unimodality of distributions of w, we applied the excess mass and dip statistics. Three non-parametric tests including Hartigan's, Cheng and Hall, and Ameijeiras–Alonso provide strong evidence that the true number of modes is greater than one ($p < 0.0001$) in distributions of the pooled data and across treatments. A Gaussian finite mixture model confirms that it is significantly unlikely that choice distributions are unimodal ($p < 0.0001$). The expectation maximization algorithm identifies the split of density distributions into several components which represent decision choice intervals. Table 3 reports decision components identified in a structure of two distributions by using a Gaussian mixture model. We observe three decision components in a Blind treatment and eight components in a Face treatment. For comparison, we compound eight Face components into three intervals with the means close to means of Blind components. Interestingly, the proportion of components with the mean close to the optimum choice ($65) is higher in a Face condition (compound to 0.51) that in a Blind one (0.28).

Table 3. Decision Intervals Identified by a Gaussian Mixture Model

	Blind		Face		Face	
Component	Mean	Mixing Proportion	Mean	Mixing Proportion	Mean Interval	Mixing Proportion
1	49.94	0.38	6.01	0.02	(6.01-50.17)	0.27
2	65.53	0.28	39.57	0.09	(65.22-65.29)	0.51
3	75.77	0.34	50.17	0.17	(78.48-92.96)	0.22
4			65.22	0.08		
5			65.24	0.33		
6			65.29	0.10		
7			78.48	0.17		
8			92.96	0.05		

Multimodal distribution of w appears on both the aggregate and individual data levels. Figure 4 illustrates that the decision distributions of individual subjects across periods have multiple peaks. It appears from Figure 4 that individuals choose w from several decision intervals. For instance, subjects 4 and 40 frequently select w from two intervals, but subjects 21 and 27 are likely to range their choices within three intervals (please, see Figure 5). Nonparametric excess mass test reports that up to 54% of subjects demonstrate the multimodal decision choices (p <

0.05). A Gaussian finite mixture model identifies that 83% of participants ($p < 0.05$) are likely to pick w from several decision intervals.

Figure 4. Density Distributions of Wholesale Prices of Individuals across All Periods

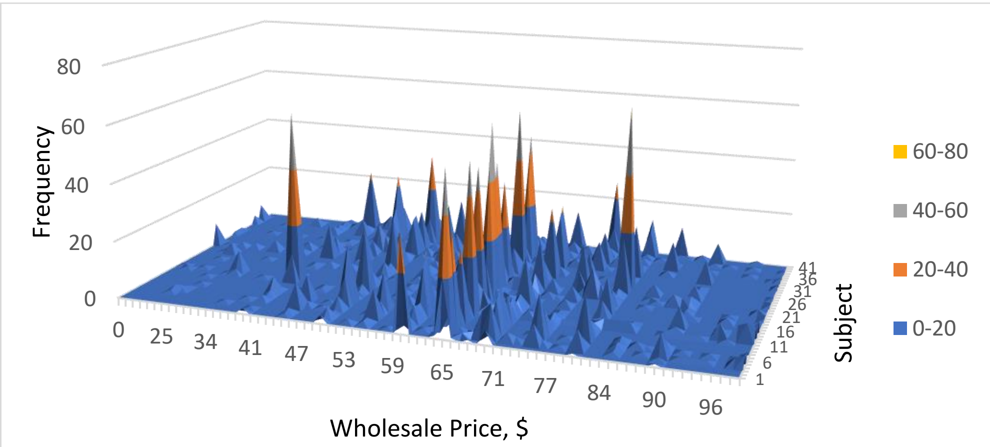
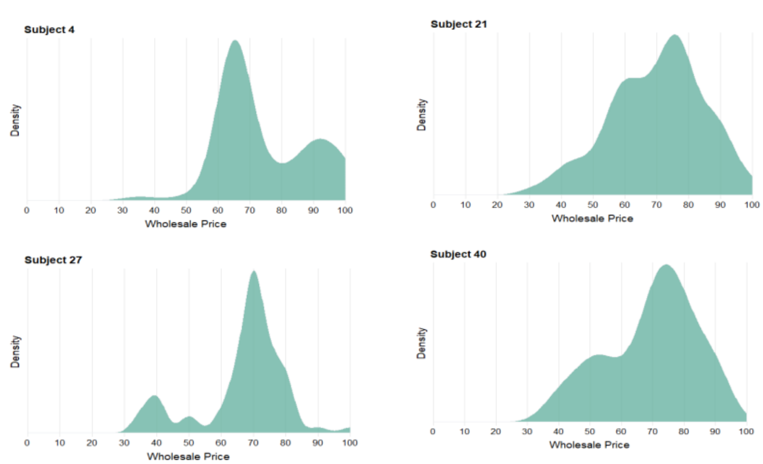


Figure 5. Density Distributions of Wholesale Prices of Subjects 4, 21, 27 and 40



In summary, the empirical analysis of experimental data reveals complicated patterns of observed behaviors. In particular, the decision distributions are multimodal and the dependencies on facial traits do not follow a simple pattern. To navigate these observations, we summarize our empirical results in Table 4. The phenomenon of multimodal distributions of experimental decisions has been observed before in newsvendor decisions by Wu and Chen (2014). We agree with their argument that “the traditional theory, which generates single-point predictions, is not able to explain” the behavioral patterns (Wu and Chen, 2014, p.259), and requires the new design of the traditional framework. In the next section, we develop a behavioral model to capture the underlying decision process.

Table 4. Summary of Empirical Evidences

Hypothesis/Effect	Average Wholesale Price (Wilcoxon test, Regression Analysis)	Distribution of Wholesale Prices (Kolmogorov-Smirnov Test)	Distribution of Wholesale Prices (excess mass and dip statistics, Gaussian finite mixture model)
Hypothesis 1: Face vs Blind	No evidence	Different ($p < 0.02$)	Multimodal ($p < 0.0001$)
Hypothesis 2a and 2b: Attractiveness effect Others Self	 Positive ($p < 0.01$) Negative ($p < 0.10$)	 No evidence Present ($p < 0.01$)	Multimodal ($p < 0.0001$)
Hypothesis 3: Trustworthiness effect Others Self	 Positive ($p < 0.01$) No evidence	 No evidence No evidence	Multimodal ($p < 0.0001$)
Hypothesis 4: Dominance effect Others Self	 No evidence No evidence	 Present ($p < 0.02$) Present ($p < 0.03$)	Multimodal ($p < 0.0001$)

6. Behavioral Model

We developed a behavioral model, motivated by discussed empirical observations, using a modified version of the popular quantal response framework (McKelvey and Palfrey, 1995, *Li et al., 2019*) and incorporating the impact of facial traits into the utility function. The key insight is that the multimodal distribution suggests a hierarchical decision-making process where an individual first decides on a “rough range” before zeroing-in on the actual decision. This idea is, in spirit, similar to the block decision[1] in Lim and Ho (2007). In that paper, a quantal response framework is also used to capture a decision process where the individual decides on which block first, and then picks a quantity within the block. There are two key differences between their model and ours. First, their block structure applies to the retailer quantity decision, while ours applies to the supplier's wholesale price decision. Second, their block structure is exogenous to the decision-maker as it is embedded in the contract, our block structure is endogenous to the strategic thinking of the decision-maker.

6.1. Hierarchical Quantal Choice Model nested on Pricing Strategies

We model the decision as a two-step process. Figure 6 demonstrates the hierarchical structure of a supplier's pricing decision process. First, an individual picks one of the three decision blocks, defined as intervals in wholesale prices. We recognize the structure of three decision intervals using a Gaussian Mixture Model (please, see Table 3 for details) and associate these decision blocks with pricing strategies: cooperation, competition and aggressive (biased) overcharge. These three strategies cover the entire possible range of wholesale prices. At the second step, a supplier decides about the wholesale price from the price interval of selected strategy.

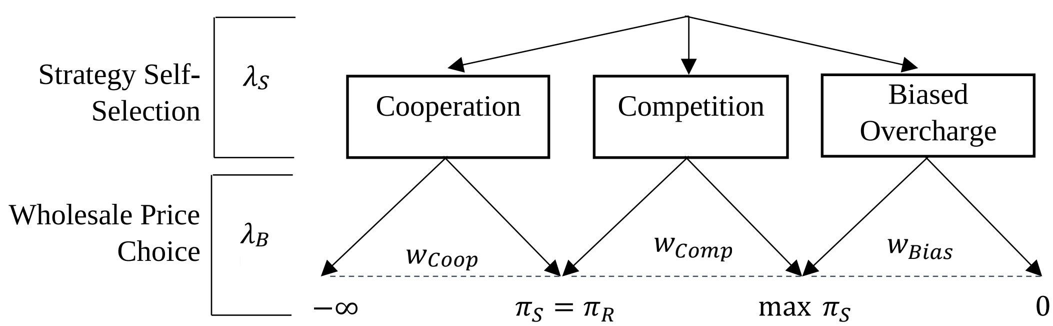
The proposed hierarchical pricing process is, in spirit, similar to the nested logit discrete consumer choice model popular in the marketing literature. These kinds of models assume that consumers make purchasing decisions by successively narrowing down their choices. For example, a consumer may first select a category of products before narrowing down his or her

[1] In Lim and Ho (2007) a block is defined as a range of order quantity for a retailer.

choice to a single product within the category (Guadagni and Little, 1998, Elshiewy et al., 2017). Li and Huh (2011) proposed to adapt the nested logit model for pricing solutions, which we did.

One key issue is to determine the intervals used in the first stage of the decision process. We turn to Rao and Kartono (2009) for inspiration. In that paper, based on surveys of 199 firms operating in the United States, Singapore, and India, 19 pricing strategies are identified. While there is no one-to-one mapping from the Rao and Kartono (2009) classification of pricing strategies to the three that we use, there are some conceptual similarities. For example, what we call the "cooperation" strategy is, in spirit, similar to "break-even" and "perceived value pricing" where retailers receive favorable prices. Similarly, their "premium pricing" and "leader pricing" are similar to our "aggressive" strategy.

Figure 6. Hierarchical Block Structure of a Pricing Decision



To incorporate the supplier's behavioral preferences into the strategic pricing model we refer to the classical Quantal Choice Model (Luce, 1959). In the experiment we observe that a supplier, when facing the alternatives to generate higher profit, does not always choose the best option in the selected strategic block which maximizes own profit. All possible decision choices are the candidates for selection, but more appealing alternatives are chosen with higher probabilities. Therefore, the probabilistic choice model proposes the superior descriptive approach to theoretical resolution of the supplier's behavior compared to the normative approach of solving the optimization of supply chain game (Su, 2008). The probabilistic choice model implies that players may make suboptimal decisions, which adds the decision noise to the model. But the decision, which leads to the higher profit, will be chosen more frequently or with a larger probability.

Following the popular literature approach, we use the logit quantal response equilibrium (QRE) framework, developed by McKelvey and Palfrey (1995). QRE specifies the probability of choosing alternative i from a decision space I which is proportional to e^{π_i}, where π_i is the profit given the decision i

$$P_i = \frac{e^{\lambda_B \pi_i}}{\sum_{i \in I} e^{\lambda_B \pi_i}} \tag{2}$$

where λ_B accounts for the decision error and is often called a bounded rationality. The observed λ_B has two limits. First, when $\lambda_B \to \infty$ the player makes fully rational decisions. Second, when $\lambda_B = 0$, the distribution of choices approaches the uniform distribution, meaning that all alternatives are chosen with the same probability. Given the assumption that demand D follows the uniform distribution over $D[a, b]$, a retailer orders a quantity q with mean $\mu_q = b - \frac{w}{p}(b - a) = q^*$ and a supplier offers the wholesale price w with mean $\mu_w = \frac{b}{2(b-a)} p + \frac{c}{2} = w^*$ (please, for details see Chapter 2 Appendix 1).

We develop the classic QRE (equation 3) into the hierarchical quantal choice model. To model the self-selection of pricing strategy, we enlarge the QRE framework by adding the second decision error λ_S and name it a strategic bias. We interpret λ_S similar to λ_B, at $\lambda_S = 0$ the individual is completely random in a choice among three strategic decision blocks. When $\lambda_S \to$

∞, the player demonstrates the fully rational strategic choice. Once we assume the stochastic structure of a decision mechanism (illustrated by Figure 5), we can estimate the observation-wise choice probabilities for the pricing strategy selection P_S for every $Strategy \in (Cooperation,$ $Competition,\ Biased\ Overcharge)$ and the wholesale price choice $P_B(w_i)$ for any λ_S and λ_B. For the wholesale price contract the probability density functions of a supplier's pricing decision are:

$$P_B(w_i) = \frac{e^{\lambda_B \pi_S}}{\sum_{w \in (0,\mathbb{R})} e^{\lambda_B \pi_S}} = \frac{e^{\lambda_B q(w_i - c)}}{\sum_{w \in (0,\mathbb{R})} e^{\lambda_B q(w_i - c)}} \tag{3}$$

$$P_S(w_i) = \frac{e^{\lambda_S E\pi_{Strategy}}}{e^{\lambda_S E\pi_{Coop}} + e^{\lambda_S E\pi_{Comp}} + e^{\lambda_S E\pi_{Bias}}} \tag{4}$$

The restriction of the decision space to discrete numbers, applied in the experiments, allows us to use a summation, instead of an integration, in both equations (3) and (4).

Our model assumes that an individual makes two consecutive decisions by selecting the decision block from the three available choices first, followed by a wholesale price choice conditioned on the selected decision block. We extend modeling to cover alternative assumptions. We model a process of simultaneous decisions when a wholesale price is selected from unrestricted decision space. This model is based on the classic (one step) QRE model. Additionally, we test the alternative number of decision blocks (two blocks instead of three) in the hierarchical QRE model. We find that the proposed nested three-blocks QRE model fits the data better than the classic QRE and other alternatives. The detailed discussion is presented in section 6.4.

6.2. Facial Traits in Strategic Model of Pricing Behavior

We specify the utility of the profit function of the supplier j with facial traits of shown faces in Face treatments.[2] Our purpose is to determine how retailer's facial characteristics affect supplier's pricing behavior. We consider subjective scores of attractiveness, trustworthiness and dominance $Facial\ Trait_{jn}^{o} \in (A_{jn}^{o}, T_{jn}^{o}, D_{jn}^{o})$ of shown face of the retailer n reported by subjects along with a choice of a wholesale price. Additionally, we evaluate the shift in pricing behavior dependent on self-reported facial traits $Facial\ Trait_{j}^{s} \in (A_{j}^{s}, T_{j}^{s}, D_{j}^{s})$. To incorporate the facial scores we model the utility of the supplier's profit function as follows:

$$u_j(w_i) = \big(\pi_j + \big(a_0 + a_1 Facial\ Trait_{jn}^{o} + a_2 Facial\ Trait_{j}^{s}\ \big) w_i\ \big)\lambda_B \tag{5}$$

To numerically estimate QRE, we maximize the log-likelihood of the experimental observations over the participants pool by using the likelihood function:

$$L\ (\lambda_S, \lambda_B | Coop, Comp, Bias) = \sum_{w \in Coop} P_{Coop}\, P_{Bi} + \sum_{w \in Comp} P_{Comp}\, P_{Bi} + \sum_{w \in Bias} P_{Bias}\, P_{Bi} \tag{6}$$

6.3. Estimation and Results

We estimate the strategic model of pricing behavior by the maximum-likelihood method (applied to equation 6) and use the likelihood ratio to determine which behavioral parameters of the model (equations 3 and 4) are statistically significant. The resulting estimates of the hierarchical QRE model over all subjects are reported in Table 5.

[2] In addition to the utility function, we tested bounded rationality and fairness as functions of the facial traits. The model with proposed utility function provides a better fit for the data based on the likelihood ratio test.

Table 5. Aggregate Behavioral Parameters of Facial Traits for Strategic Pricing Model

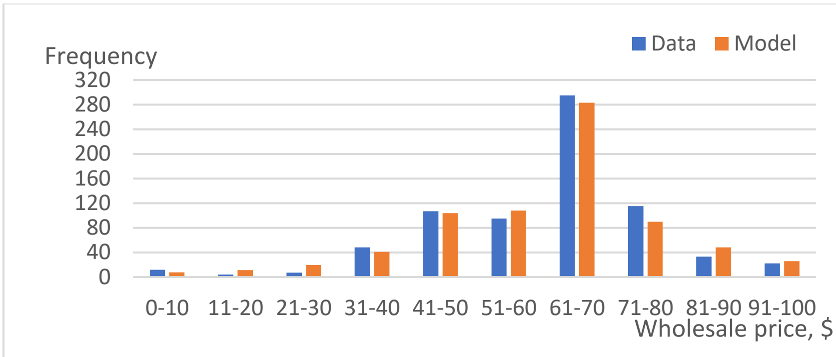
		Facial Primer		
Pricing Strategy	Variable	Attractiveness	Trustworthiness	Dominance
Cooperation	Intercept	45.077	2.908***	1.199***
	Facial Trait^o	42.298***	0.476***	0.005***
	Facial Trait^s	(-5.677)***	(-0.427)**	(-0.188)***
Competition	Intercept	1118.683***	(-9.798)*	3.057***
	Facial Trait^o	(-5.848)	(0.559)***	(-0.101)***
	Facial Trait^s	(-55.649)**	(1.998)***	(-0.027)***
Aggressive (Biased) Overcharge	Intercept	(-29.734)**	(-0.406)	0.065***
	Facial Trait^o	(-1.816)***	(-0.053)**	(-0.001)***
	Facial Trait^s	(-14.623)***	(-0.083)	(-0.002)***
	λ_S	0.004**	0.017***	0.023***
	λ_B	0.045***	3.347***	14.315***
	Log-likelihood	-2926.6	-2833.1	-2799.3

Note: *p < 0.1; **p < 0.05; ***p < 0.01

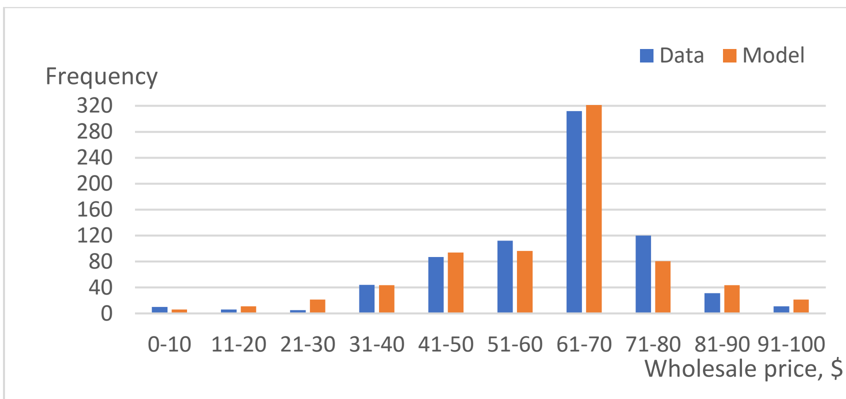
The models parameters are estimated with the normalized w from the initially observed range [0,100] into the range [0,1]. Taking into account that the expected q is a function of w, the expected profit becomes double normalized. The effect of parameters on the expected utility expressed in dollars should be calibrated by dividing the estimates by 10,000.

To visually illustrate the goodness of fit of the proposed hierarchical behavioral QRE model, we plot the observed and predicted decision distributions for each of three facial conditions. Figure 7 demonstrates that the proposed behavioral model has a good fit to the data in all three facial trait subsets.

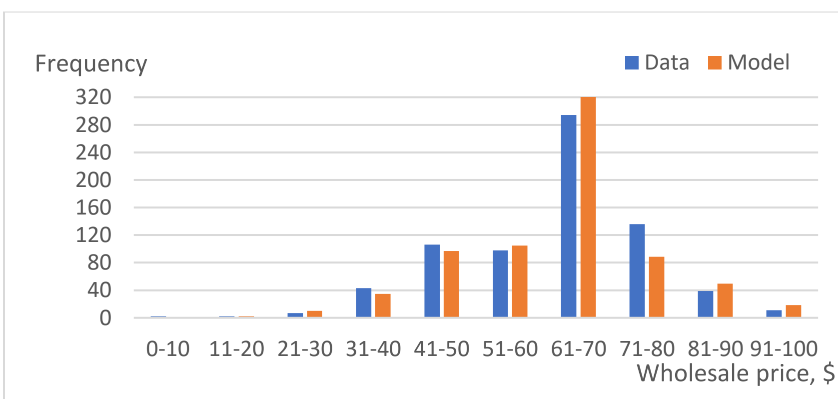
Figure 7. Model Fit for Face Treatments



(a) Attractiveness



(b) Trustworthiness



(c) Dominance

To navigate the discussion of the results, we first focus on the effect of subjective judgements of the partner's facial traits, and then discuss the effect of a self-evaluation of own facial traits.

6.3.1. Effects of Partner's Facial Traits

For all three facial traits, parameters of partner's facial scores are statistically significant ($p <$ 0.05, 0.01) except attractiveness in a competition strategy. The behavioral model explains that facial traits are associated with both effects in supplier's pricing behavior—the "penalty" by increasing the wholesale price, and the "premium" by lowering the offer. Faces with higher scores in attractiveness were offered a higher w in cooperation (42.298, $p < 0.01$), what is consistent with a beauty penalty effect, but a lower w in biased overcharge (-1.816, $p < 0.01$) features a beauty premium effect. Trustworthy-looking retailers were penalized with an increase in w in cooperation (0.476, $p < 0.01$) and competition (0.559, $p < 0.01$), yet experienced the opposite reaction in biased overcharge (-0.053, $p < 0.05$). Dominant looks are associated with a higher w only in cooperation (0.005, $p < 0.01$).

Overall, when cooperation is selected, the supplier positively responses to all three facial traits exhibiting "punishment" of a higher w on the retailer for his or her appearance. If the supplier choses to compete, the pricing behavior varies across the facial traits: trustworthiness is punished and dominance is benefited. Within an aggressive overcharge strategy, the supplier negatively reacts to each of three facial traits by lowering the wholesale price. Comparing the magnitudes of impacts of three facial traits, physical attractiveness relates to the strongest effect.

6.3.2. Effects of Own Facial Traits

All parameters for self-perceived facial characteristics are statistically significant ($p < 0.05$, 0.01), with the only exception for self-trustworthiness in an aggressive (biased) overcharge strategy. In all decision blocks, a higher self-esteem of own attractiveness and dominance has a negative effect on the supplier's utility function which makes a supplier offer a lower wholesale price. Only trustworthiness plays a dual impact on a supplier's pricing behavior: it is positively related with w offered in competition (1.998, $p < 0.01$) but negatively affects w in cooperation (-0.427, $p < 0.01$).

Therefore, we observe that stronger self-esteem of own facial traits is associated with a lower wholesale price. Such pricing reaction imposes "benefits" for the retailer across all strategies, but punishes own (supplier's) interests in cooperation and competition. However, when the supplier choses to compete, a high self-scored trustworthiness relates with a larger wholesale price choice which maximizes own pay-offs. Comparing the magnitudes of three facial traits effects, self-judged attractiveness unveils the strongest effect across all pricing strategies.

6.4. Model Robustness

For all three facial characteristics, the model nested on three decision blocks provides a superior explanation of the variance in wholesale prices. We evaluate and compare performances of the proposed three-blocks behavioral model with the reduced one-block (classic QRE) and two-blocks models (hierarchical QRE). For two-blocks design we consider six possible options to split the decision space. Table 6 summarizes the log-likelihoods of the full and reduced models. The detailed comparison tables with parameter estimates and likelihood ratio tests are available in Chapter 2 Appendix 2. For every facial trait, the likelihood-ratio test between the full model and any of other seven reduced models yields χ^2-statistics over 100 ($p < 0.0001$), suggesting that the full model nested on three blocks has a better fit to the experimental data. This result statistically justifies consideration of three pricing decision blocks (i.e., pricing strategies) to explain the pricing behavior.

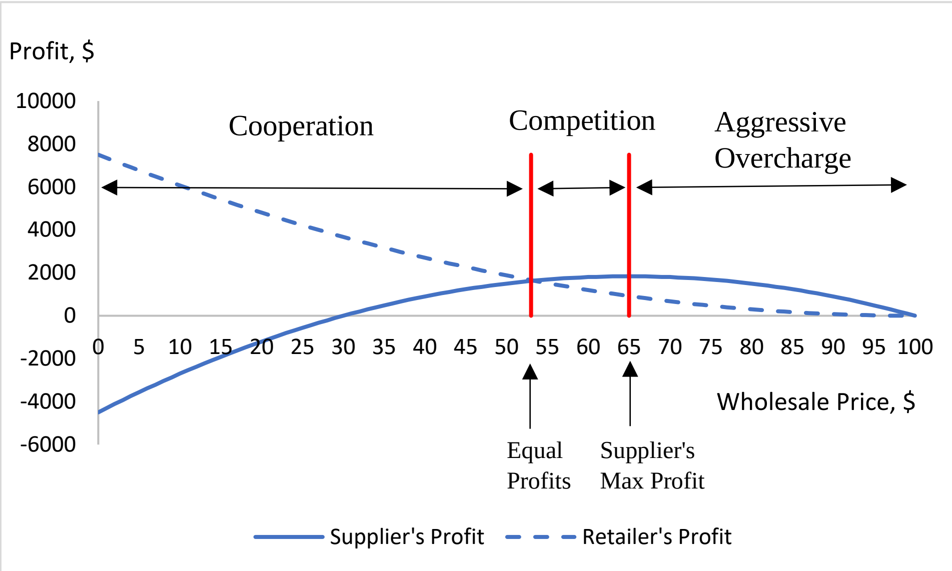
Table 6. Log-Likelihoods of Full and Reduced Models Under Face Conditions

	Decision Blocks	Attractiveness	Trustworthiness	Dominance
Log-Likelihood of full model with 3 blocks, L_{full}	[0, 53] & [54, 65] & [66, 100]	-2,926.5	-2,833.1	-2,799.3
Log-Likelihood of reduced model with 2 blocks, $L_{reduced}$:	[0, 40] & [41, 100]	-3,042.5	-3,007.6	-2,963.6
	[0, 50] & [51, 100]	-3,045.3	-3,019.6	-2,954.5
	[0, 53] & [54, 100]	-3,053.7	-3,020.9	-2,966.4
	[0, 60] & [61, 100]	-3,039.8	-2,982.1	-2,958.1
	[0, 65] & [66, 100]	-2,985.2	-2,901.5	-2,879.1
	[0, 70] & [71, 100]	-2,987.6	-2,948.9	-2,941.2
Log-Likelihood of reduced model with 1 block, $L_{reduced}$:	[0, 100]	-3,081.9	-3,051.4	-2,976.7

7. Strategic Implications of a Face Effect

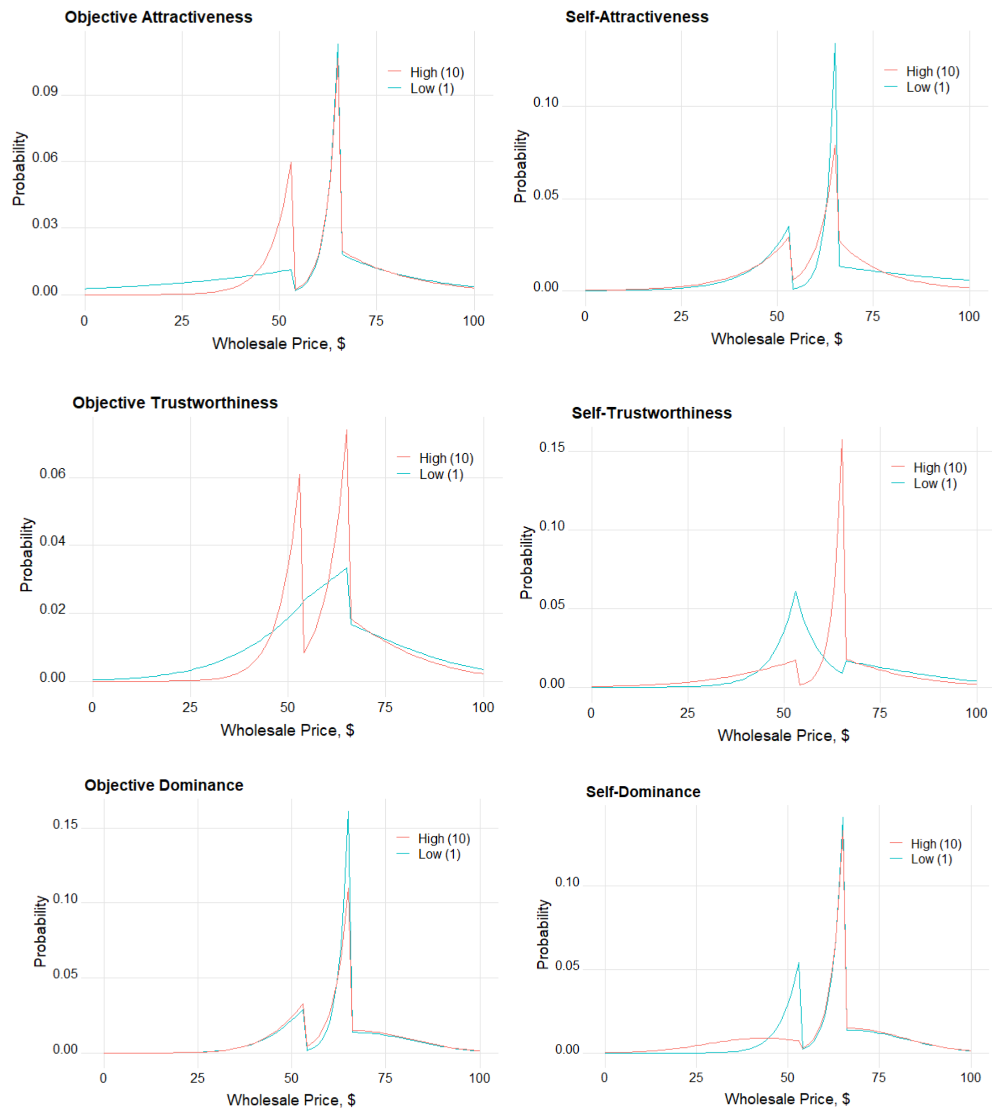
In our research we design the supplier's utility function with facial traits parameters to explain the main empirical conclusion that seeing a counterpart's face influences a human decision-maker to change a wholesale price. Facial traits are essential factors for differences in supplier's pricing behaviors. In this section, we discuss the implications of the proposed behavioral model from the perspective of the three pricing strategies. To illustrate these strategies we use the numerical example and graph expected profit curves of a supplier and a retailer as a function of w in the wholesale price contract (illustrated by Figure 8).

Figure 8. Expected Profit Curves (The Numerical Example)



We numerically compute the hierarchical QRE nested on three strategies for the low (score = 1) and high (score = 10) conditions of facial attractiveness, trustworthiness and dominance, with the effect of paired variable (self or others) set up neutral (score = 5). Note that the low and high conditions differ only on w; other parameters ($p = \$100, c = \$30, D \sim U[0,150]$) are fixed. Figure 9 demonstrates how different two distributions are for the low and high ratings of the same facial trait.

Figure 9. Wholesale Price Distributions for the Low and High Scores of Facial Traits



7.1. Cooperation is More Effective for a Supplier Facing a Retailer with Highly Rated Facial Traits.

A firm decides to cooperate by sacrificing a share of own profit in a favour of a partner. In this case, the pricing decision space is ranged from zero (e.g., sharing a product or service for free, giving test samples, etc.) up to the point of equal payoffs. In Figure 8, the cooperation block includes wholesale prices within the range [0, $53]. Since the supplier's profit function is constantly increasing within this range, the optimal supplier's choice is the highest price, which is the interval's upper boundary ($53). By choosing the optimum, a supplier fairly and equally divides the supply channel profit with a retailer.

The behavioral pricing model reports that in a cooperation strategy a supplier selects the optimum with a higher probability when a retailer's face looks more attractive, trustworthy, or dominant to a supplier (please, see the left graphs in Figure 9). However, high self-esteem of own facial traits negatively impacts a supplier's choice. Individuals with low self-perceived facial traits select the optimum more frequently compared to highly confident participants (please, see the right graphs in Figure 9). Such behavioral reaction to self-perception could be explained by stereotypes. Human self-judgements about own face activate stereotypical thinking to "act for good of others". Among three facial traits, self-confidence in own attractiveness is the fastest leverage to deviate from the optimal choice.

7.2. Competition is Leveraged by Trustworthiness.

With a goal to ultimately maximize own profit, a firm is expedient to compete in a partnership. In this case, the supplier's decision block is ranged from the point somewhat over of equal payoffs up to the maximum profit. As illustrated in Figure 8, the competition block includes wholesale prices within the discrete interval [$54, $65]. The supplier's profit function is constantly increasing up to the upper boundary ($65), which is the optimal decision for the competition strategy.

The Rational Choice Theory implies that on the open market a supplier, oriented to maximize own profit, should not differ in a choice preference for the best selling price under any environmental conditions. Nevertheless, the behavioral pricing model demonstrates that certain facial characteristics affects a supplier's choice. Trustworthy and dominant looks are associated with the largest gap in distribution of w and influence the opposite pricing behaviors. A supplier selects the optimum more often when seeing highly trustworthy and non-dominant faces (please, see the left graphs in Figure 9). A high self-perceived trustworthiness also positively affects the supplier's decision to select a larger w (please, see the right graphs in Figure 9). Surprisingly, trustworthiness does not trigger supplier's "sympathetic" judgments to lower the wholesale price and share payoffs with a trustworthy-looking retailer. Instead, trustworthiness empowers a supplier to compete. This phenomena can be explained by an individual's awareness about a possibility of manipulation by facial features, exploited to cause a certain psychological reaction. An intriguing effect is associated with a self-reported attractiveness. A high beauty self-esteem relates with a "softening" in pricing behavior which fosters a deviation from the maximum profit.

7.3. Aggressive (Biased) Overcharge is Less Harmful for a Confident in Own Attractiveness Supplier.

An aggressive competition stimulates for a biased overcharge in supply chain contracting. A supplier overestimates his market power over a retailer and increases a wholesale price above the best choice ($65). Such "a hunger for a larger stake" results in the profit loss. Figure 8 illustrates the decreasing slope of a supplier's profit curve for any wholesale price larger than the best response of $65. Thus, the optimum for the aggressive overcharge block is the lower boundary of the discrete interval [$66,$100].

The behavioral pricing model reports that higher ratings of three facial traits of both looks, a counterpart's and own, trigger a supplier to choose the optimum price (please, see Table 5). However, the largest gap between low and high conditions is at self-reported attractiveness (please, see the upper right graph in Figure 9). An individual with a stronger confidence in own facial beauty selects an optimum more frequently. Overall, judgments about seeing faces enhance supplier's self-control over aggressive pricing ambitions and helps to compete more effectively.

7.4. Differences in Supplier's Performance

We numerically estimate the supplier's expected profit based on the subject behavior. We follow the same assumptions we use for numerical computation of the wholesale price probability distribution (provided above in Figure 9). To differentiate the impact of facial traits we apply the low (score = 1) and high (score = 10) conditions of attractiveness, trustworthiness and dominance; while keeping the paired (self or others) variable neutral (score = 5). The expected profits are recorded for w with fixed parameters: $p = \$100, c = \$30, D \sim U[0,150]$. Results across three strategic blocks and the aggregate are presented in Table 7 with the highlighted largest profit between low and high conditions.

Table 7. Supplier's Expected Profit Conditioning on Facial Traits

		Aggregate		Cooperation		Competition		Biased Overcharge	
Facial Trait	Score	Low (1)	High (10)	Low (1)	High (10)	Low (1)	High (10)	Low (1)	High (10)
Attractiveness	Others	1093.7	1566.2	-38.6	1389.6	1823.2	1821.7	1435.9	1466.7
	Self	1439.6	1449.7	1120.5	954.6	1827.6	1812.0	1327.7	1568.9
Trustworthiness	Others	1335.0	1581.6	787.7	1402.4	1780.2	1807.1	1432.4	1495.1
	Self	1494.0	1416.7	1366.5	700.5	1742.4	1826.3	1415.3	1513.0
Dominance	Others	1592.6	1575.2	1261.2	1277.5	1825.6	1817.1	1500.1	1505.0
	Self	1627.9	1386.4	1437.9	468.5	1823.3	1821.1	1498.9	1506.4

At an aggregate level, both positive facial traits of the retailer, attractiveness and trustworthiness, stimulate the supplier for a higher expected profit in contrast to dominance. We observe that the biggest change in the expected profit is driven by attractiveness. When seeing a very attractive face (score = 10), subjects improve their performance up to 43% from the expectations with seeing a very unattractive face (score = 1). A trustworthy-looking retailer (score = 10) motivates a supplier for an increase in the expected pay-off of 18% comparatively to facing an untrustworthy retailer (score = 1). However, the change in the expectations conditioning on low and high dominance is very moderate (below 2%).

The aggregate results show that subjective judgments about self-perceived beauty have a small influence (near 1%) on the supplier's expected profit. Whereas, self-attractiveness has a reverse effect on a supplier's profitability across strategic blocks. Thus, a supplier with a low beauty self-esteem is expected to have a higher profit in cooperation (+17%), but a lower gain in aggressive overcharge strategy (-15%) compared to the performance of a subject with a high beauty self-esteem. The aggregate expected gains are higher for a supplier with low self-reported trustworthiness (+5%) and dominance (+17%); yet these results are driven mostly by low pricing behaviors of trustworthy and dominant subjects in the cooperation decision block.

In addition to the supplier's expected profit, Table 8 reports the QRE probability distribution of choosing one of the three strategic decision blocks conditioning on facial traits. We highlight the choices with the largest weights. These results show that subjects are more likely to select the decision interval corresponding to the competition strategy regardless of the facial traits conditions with a single exception for low self-trustworthiness. However, the estimated probabilities are not largely different.

Table 8. Probability of a Strategy Choice Conditioning on Facial Traits

		Aggregate		Cooperation		Competition		Biased Overcharge	
Facial Trait	Score	Low (1)	High (10)	Low (1)	High (10)	Low (1)	High (10)	Low (1)	High (10)
Attractiveness	Others	1.000	1.000	0.325	0.330	0.355	0.352	0.319	0.318
	Self	1.000	1.000	0.324	0.332	0.358	0.348	0.318	0.320
Trustworthiness	Others	1.000	1.000	0.336	0.333	0.343	0.376	0.321	0.291
	Self	1.000	1.000	0.369	0.289	0.296	0.442	0.335	0.269
Dominance	Others	1.000	1.000	0.256	0.279	0.472	0.428	0.271	0.293
	Self	1.000	1.000	0.277	0.254	0.450	0.456	0.274	0.290

8. Conclusion

In this paper, we study how facial traits impact supply chain contracting decisions. We find that the distribution of wholesale price decisions changes depending on whether individuals see (face treatment) or not see (blind condition) faces. More importantly, facial traits, measured by self-reported subjective evaluations of the individual supplier (self) and the retailers (others), have significant impact on wholesale prices set by the supplier. Surprisingly, subjects, in the role of the supplier, respond to faces, even though they were informed that retailers are played by software, and the faces are obviously computer generated imaginary. We speculate that much of the responses are driven by system 1 (*Kahneman, 2011*) type decision making process without conscious deliberation. It is, however, beyond the scope of this paper to probe into the detailed inner mechanism of the related cognitive processes.

The pattern of how decision behaviors are dependent on facial traits is complex, and we find evidence that it is consistent with a hierarchical decision process. We develop a behavioral model, adapted from the popular quantal response framework, to explain these findings. We model a decision process where individuals first divide the possible wholesale price range into three intervals, decide on an interval, before picking a specific wholesale price out of the chosen interval. We provide convenient labels (cooperation strategy, competition strategy and aggressive overcharge strategy) to the three intervals. We show that the effects of facial traits (self and others) vary across these three strategies. An attractive retailer is penalized with a higher wholesale price if the supplier decides to cooperate—the beauty penalty effect—but is benefited with a lower offer if the supplier first chooses the competition strategy —the beauty premium effect. However, the supplier with a high self-perceived attractiveness offers a lower wholesale price across all three strategies.

In addition, we conduct a numerical analysis of the profitability of the supplier (please, see Table 6) and find that the estimated model suggests that the supplier has higher expected[3] profit facing a more attractive retailer. This outcome is mostly driven by higher wholesale prices if the supplier chooses to "cooperate". In this strategy supplier's behavior is consistent with the beauty penalty effect discussed earlier. Similarly, the supplier has higher expected profits if the retailer is more trustworthy, again the differences driven mainly by the cooperation strategy. Conditioned on the supplier choosing to cooperate, he or she tends to cooperate "less" if the retailer looks more trustworthy or more attractive. Finally the dominant trait of the retailer does not seem to have a big impact (less than 2%) to the supplier's expected profit.

From a managerial perspective, we dispel the myth that face-to-face meetings are good for everyone. Even in the limited setting with no true interactions, seeing faces with certain traits can impact profitability. These reactions are likely not conscious choices, and we speculate that

[3] The expectation is taken over the quantal response probabilities of the wholesale price. Note that, in game theory, the supplier is not facing any uncertainly as long as the retailer is rational and picks the equilibrium quantity.

decision-makers may not even be aware. It is beyond the scope of this paper to investigate how to manage these reactions, and even if such management is possible.

This study is not without limitations. This study only addresses how looks impact supply chain decision-making. In practice, social interactions are believed to also play important roles with respect to business outcomes. That constitutes a natural direction, with a rich canvas, for future research.

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Chapter 2 Appendix 1.

$\max \pi_R = p * \min(D, q) - w * q$

$\max\ \pi_S = (w - c) * q$

$D \sim U[a, b]$

Solution:

1. Best response for the retailer

$$E[\min(D,q) = \int_a^q \min(D,q)\, dF(D) + \int_q^b \min(D,q)\, dF(D) = \int_a^q Df(D)dD + \int_q^b qf(D)dD$$

$$= DF(D)\Big|_a^q - \int_a^q F(D)dD + q\int_q^b f(D)dD$$

$$= qF(q) - aF(a) - \int_a^q \frac{D-a}{b-a}dD + qF(D)\Big|_q^b = -\frac{q^2}{2(b-a)} + \frac{aq}{b-a} - \frac{a^2}{2(b-a)} + q$$

$$\max_q \pi_R = \max\left(p * (-\frac{q^2}{2(b-a)} + \frac{aq}{b-a} - \frac{a^2}{2(b-a)} + q) - qw\right)$$

$$\frac{\partial}{\partial q} = -\frac{pq}{b-a} + \frac{pa}{b-a} + p - w = 0,\ q^* = b - \frac{w}{p}(b-a)$$

2. Best response for the supplier

$$\max_w \pi_S = \max(w-c) *(b - \frac{w}{p}(b-a)) = \max(wb - \frac{w^2 b}{p} + \frac{w^2 a}{p} - cb + \frac{wbc}{p} - \frac{wac}{p})$$

$$\frac{\partial}{\partial w} = b - \frac{2wb}{p} + \frac{2wa}{p} + \frac{bc}{p} - \frac{ac}{p} = 0,\ w^* = \frac{c}{2} - \frac{pb}{2(a-b)} = \frac{c}{2} + \frac{pb}{2(b-a)}$$

3. Supply Chain Coordination:

$$q_{SC}^* = b - \frac{\frac{c}{2} - \frac{pb}{2(a-b)}}{p}(b-a) = \frac{b}{2} - \frac{c}{2p}(\mathrm{b}-\mathrm{a})$$

$$\pi_R = p * \left(-\frac{q^2}{2(b-a)} + \frac{aq}{b-a} - \frac{a^2}{2(b-a)} + q\right) - qw = p * \left(-\frac{\left(\frac{bp-(b-a)c}{2p}\right)^2}{2(b-a)} + \frac{a\frac{bp-(b-a)c}{2p}}{b-a} - \frac{a^2}{2(b-a)} + \frac{bp-(b-a)c}{2p}\right) - \frac{bp-(b-a)c}{2p} * \frac{bp+(b-a)c}{2(b-a)},$$

$$\pi_S = \left(\frac{bp+(b-a)c}{2(b-a)} - c\right) * \frac{bp-(b-a)c}{2p}, \quad \pi_{SC} = \pi_R + \pi_S.$$

Chapter 2 Appendix 2.

Table 2.1. Estimation Results of Attractiveness Effect

		Full Model	Reduced Models						
Decision Blocks	Variable	[0, 53] & [54, 65] & [66, 100]	[0, 40] & [41, 100]	[0, 50] & [51, 100]	[0, 53] & [54, 100]	[0, 60] & [61, 100]	[0, 65] & [66, 100]	[0, 70] & [71, 100]	[0, 100]
A	Intercept	45.077	(-1.596)***	(-0.858)***	(-1.076)***	2.148***	526.452***	770.742***	0.282***
	Facial Trait^o	42.298***	(0.215)***	0.183***	0.144***	0.428***	38.384***	42.353***	0.017**
	Facial Trait^s	(-5.677)***	0.017***	(-0.018)***	0.017***	(-0.327)**	(-41.279)***	(-51.336)***	(-0.061)***
B	Intercept	1118.683***	0.297***	0.387***	0.237***	(-2.302)***	(69.670)***	297.237	
	Facial Trait^o	(-5.848)	0.013***	0.022***	0.025***	0.019	(-1.195)	8.046	
	Facial Trait^s	(-55.649)**	(-0.049)***	(-0.064)***	(-0.057)***	0.014	(-52.941)***	(-110.382)***	
C	Intercept	(-29.734)**							
	Facial Trait^o	(-1.816)***							
	Facial Trait^s	(-14.622)***							
	λ_S	0.004**	0.284***	0.226***	0.300***	(-0.091)***	0.064***	0.179***	
	λ_B	0.045***	20.271***	17.287***	14.577***	2.827***	0.022***	0.012***	12.054***
Likelihood-ratio test against full model	Number of Blocks	3	2	2	2	2	2	2	1
	Log-likelihood	-2926.5	-3042.5	-3045.3	-3053.7	-3039.8	-2985.2	-2987.6	-3081.9
	Difference, L_{full} - $L_{reduced}$	-	116.1	118.8	127.2	113.3	58.7	61.2	155.5
	χ^2		232.1	237.6	254.4	226.6	117.4	122.3	311.0
	p-value		*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*
A	n obs	184	71	178	184	273	461	568	738
B	n obs	277	667	560	554	465	277	170	
C	n obs	277							
	Total n obs	738	738	738	738	738	738	738	738

Note: *p < 0.1; **p < 0.05; ***p < 0.01

Table 2.2. Estimation Results of Trustworthiness Effect

		Full Model	Reduced Models						
Decision Blocks	Variable	[0, 53] & [54, 65] & [66, 100]	[0, 40] & [41, 100]	[0, 50] & [51, 100]	[0, 53] & [54, 100]	[0, 60] & [61, 100]	[0, 65] & [66, 100]	[0, 70] & [71, 100]	[0, 100]
A	Intercept	2.908***	(-3.450)***	(-0.657)***	(-0.502)***	41.762***	1092.966***	1227.097***	(-0.039)
	Facial Trait^o	0.476***	0.116***	0.128***	0.141***	2.644***	70.421***	69.979***	0.018**
	Facial Trait^s	(-0.427)**	0.247***	(-0.045)***	(-0.033)	(-4.002)***	(-80.535)***	(-73.872)**	(-0.012)
B	Intercept	(-9.798)*	(-0.104)***	(-0.094)***	(-0.423)***	(-18.944)**	(-498.229)*	(-833.777)*	
	Facial Trait^o	0.559***	0.007***	0.012***	0.049***	(-0.415)	(-2.018)	6.522	
	Facial Trait^s	1.998***	0.009	0.010***	(-0.013)***	0.088***	5.048***	4.171	
C	Intercept	(-0.406)							
	Facial Trait^o	(-0.053)**							
	Facial Trait^s	(-0.083)							
	λ_S	0.017***	0.258***	0.156***	14.458***	(-0.066)***	0.074***	0.155***	
	λ_B	3.347***	21.805***	23.021***	9.928***	0.396***	0.014***	0.008***	13.524***
Likelihood-ratio test against full model	Number of Blocks	3	2	2	2	2	2	2	1
	Log-likelihood	-2833.1	-3007.6	-3019.6	-3020.9	-2982.1	-2901.5	-2948.9	-3051.4
	Difference, L_{full} - $L_{reduced}$	-	174.4	186.5	187.8	149.0	68.4	115.8	218.3
	χ^2		348.9	373.1	375.5	298.0	136.8	231.6	436.5
	p-value		*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*
A	n obs	156	65	152	156	264	488	576	738
B	n obs	332	673	586	582	474	250	162	
C	n obs	250							
	Total n obs	738	738	738	738	738	738	738	738

Note: *p < 0.1; **p < 0.05; ***p < 0.01

Table 2.3. Estimation Results of Dominance Effect

Decision Blocks	Variable	Full Model [0, 53] & [54, 65] & [66, 100]	Reduced Models [0, 40] & [41, 100]	[0, 50] & [51, 100]	[0, 53] & [54, 100]	[0, 60] & [61, 100]	[0, 65] & [66, 100]	[0, 70] & [71, 100]	[0, 100]
A	Intercept	1.199***	(-0.425)***	0.091***	(-0.028)***	0.314***	159.288***	1.363***	0.159***
	Facial Trait^{o}	0.005***	0.033***	0.036***	0.019***	(-0.002)***	(-4.081)**	(-0.016)***	(-0.011)
	Facial Trait^{s}	(-0.188)***	0.067***	(-0.079)***	(-0.067)***	(-0.056)***	(-7.784)**	(-0.114)***	(-0.021)***
B	Intercept	3.057***	0.101***	0.170***	0.171***	(-0.058)***	(-27.350)	0.050***	
	Facial Trait^{o}	(-0.101)***	(-0.006)	(-0.003)***	(-0.006)***	(-0.003)***	(-1.797)	(-0.025)***	
	Facial Trait^{s}	(-0.027)***	(-0.012)	(-0.011)***	(-0.015)***	(-0.023)***	(-1.429)	(-0.044)**	
C	Intercept	0.065***							
	Facial Trait^{o}	(-0.001)***							
	Facial Trait^{s}	(-0.002)***							
	λ_S	0.023***	0.589***	0.133***	0.144***	3.434***	0.073***	0.354***	
	λ_B	14.315***	19.319***	27.994***	25.410***	14.158***	0.128***	7.944***	17.091***
	Number of Blocks	3	2	2	2	2	2	2	1
	Log-likelihood	-2799.3	-2963.6	-2954.5	-2966.4	-2958.1	-2879.1	-2941.2	-2976.7
Likelihood-ratio test against full model	Difference, L_{full} - $L_{reduced}$	-	164.3	155.2	167.1	158.8	79.9	141.9	177.4
	χ^2		328.6	310.4	334.3	317.7	159.7	283.9	354.8
	p-value		*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*
A	n obs	166	54	160	166	258	482	552	738
B	n obs	316	684	578	572	480	256	186	
C	n obs	256							
	Total n obs	738	738	738	738	738	738	738	738

Note: *p < 0.1; **p < 0.05; ***p < 0.01

Chapter 3

Does Looking Trustworthy Facilitate Forecast Sharing in a Supply Chain? An Experimental Study

Abstract

Information is crucial to the supply chain performance because it provides the foundation for managerial decisions. Inventory decisions often depend on the private forecast shared by retailers. Facing uncertain demand, suppliers tend to rely on nonverifiable retailers' reports known as "cheap talk". Problems of misreporting and mistrust can arise. With a purpose to motivate trust and honesty (i.e., trustworthiness) in supply chain contracting, our study investigates social factors affecting decision-makers. In controlled experiments, we explore the effect of human faces on the retailer's information-sharing behavior and supplier's inventory responses. We observe that the channel efficiency improves when facial identities of retailers are revealed to the supplier. However, the change in profitability is linked to the difference in facial trustworthiness. The experimental data evidence an increase in forecast distortion by trustworthy-looking retailer conditioning on untrustworthy look of a competing counterpart. Whereas trusting supplier still allocates inventory favoring trustworthy look over untrustworthy or hidden face.

1. Introduction

Since the Covid-19 pandemic hit, business practices rely on online meetings more than ever before. According to Priori Data, global downloads of videoconferencing applications (i.e., conference calls over Zoom, Microsoft Teams, Skype) increased dramatically in March 2020. For instance, Zoom was downloaded nearly 27 million times in March, while in January it was just 2.1 million times (Richter, 2020). Video calls have become a great alternative to the face-to-face interactions. While technology-enabled meetings do not fully replace the benefits gained through in-person connections, they offer communication attributes which are important for building trustful relationships. In particular, virtual calls make possible to observe the partner's face during a meeting. However, frequently participants do not turn the webcam on and choose not to share their live video. Instead, only their avatar pictures are available to see for the counterparts. The choice—to show or not to show own face—determines individual's social preferences which may not align with expectations of another party. Does this choice affect trust and cooperation among business partners?

The role of trust has gained a wide attention in the recent operations management literature (Ozer et al., 2011, Firouzi et al., 2016, Ebrahim-Khanjari et al., 2012). Researchers uniformly agree on the importance of trust for the cooperation. However, to the best of our knowledge, no studies have been done yet to explore the social factors that may motivate truth-telling and trusting behaviors. In this study, we experimentally investigate how the facial identity and facial trustworthiness influence supply chain transactions over the forecast communications.

Information is crucial to the supply chain performance because it provides the foundation for managerial decisions. Sharing information among supply chain members may bring numerous benefits, including inventory reduction and efficient inventory management, cost reduction, optimized capacity utilization, significant reduction of bullwhip effect, and others (Lotfi et al., 2013). In our study, we focus on sharing of private forecasts which is also known as "cheap talk". Since this information is often nonbinding and nonverifiable, the issue of trust arises.

The goal of our study is to discover how shown human faces impact truth-telling, trust and reciprocity in a supply chain which all together affect the resulting channel efficiency. We use a sequential mover game in which a supply chain consists of two retailers (she) and a single supplier (he) (Spiliotopoulou et al., 2016). Retailers have an advantage to observe private market forecasts and choose what numbers to share with the supplier. The supplier relies on the reported information to build enough inventory prior market demand is realized. We make three changes in this design. First, we add photos of human faces shown for either one or both retailers. By revealing retailers' facial identities, we seek to manipulate retailer's forecast sharing behavior and supplier's subjective judgements about truthfulness of received reports. Second, we use the special case scenario in which two retailers act on two separate markets with perfectly correlated (i.e., identical) demands. This case makes possible for the supplier to detect the false report. Third, the supplier selects own scheme for inventory allocation among retailers. Contrary to the prior literature, we do not apply a predetermined allocation rule.

Our analysis reveals that facial information systematically influences both retailer's and supplier's decisions. Seeing faces of all retailers drives up supply chain performance and overall efficiency. The distinct facial trustworthiness maintains mutually beneficial actions from both sides—while retailers tend to misreport, the supplier relies less on shared forecasts. We find that trustworthy-looking retailers are likely to report with a greater distortion when they know that another retailer looks untrustworthy. However, the trusting supplier allocates a greater quantity to trustworthy-looking retailers than to retailers with no shown photo or looking untrustworthy.

Next, we review related literature in behavioral economics, supply chain contracting, and psychology in section 2. In section 3, we describe theoretical insights and state hypotheses for experimental investigation. The experimental design and procedures are presented in section 4. Section 5 reports the analytical results of experimental data, followed by the analysis of data from validation experiments in section 6. Section 7 summarizes our results and recommends future research extensions.

2. Literature Review

2.1. Trust in Forecast Information Sharing

Demand information asymmetry may cause a moral hazard in supply chain performance. When the shared forecast information is costless, nonbinding, and nonverifiable, problems of misreporting and mistrust can arise (Ozer et al., 2011). In controlled laboratory experiments researchers observed that manufacturers, who know the private forecast, tend to inflate shared reports, and suppliers still rely their capacity decisions on cheap-talked forecasts disregarding that received information is not credible. However, suppliers do not fully trust retailers' reports. Nonetheless, the limited trust among players significantly affects the aggregate channel profit and improves its efficiency. Ozer, Zheng, and Chen (2011) proposed the trust-embedded model which incorporates factors of trust and trustworthiness of decision-makers in cheap-talk forecast communication.

By contrast to the single interaction study of Ozer et al. (2011), Ebrahim-Khanjari, Hopp, and Iravani (2012) found that in the long-term relationships in order to maintain trust of a supplier, a manufacturer deflates shared forecasts and sacrifices own payoffs. Authors extended the study of trust in forecast sharing by differentiating on personal characteristics of decision-makers—motives and interpersonal skills of the information holder, and social behavior of the information seeker. They demonstrated that a gain of trust depends on personalities of both involved parties.

Firouzi, Jaber, and Baglieri (2016) proposed the analytical solution of the manufacturer's optimal order quantity in the one-term interaction when the supplier has a private forecast of yield risk and decides whether to share its truthfully or not to share. Authors modelled and numerically compared supply chain profits for two scenarios—the manufacturer trusts the shared report and it does not trust. The results indicated that it is beneficial for the manufacturer not to trust the shared information with no matter whether it is true or false.

Spiliotopoulou, Donohue, and Gurbuze (2016) added an additional layer of complexity to the initial information sharing game with a single-period setting. They extended the structure of the supply chain from initially considered two players (single manufacturer - single supplier) to the multiple regional managers (i.e., retailers) who compete for common inventory which is determined by the central planner (i.e., the supplier) (multiple retailers - single supplier). By doing so, researchers shifted the focus on co-dependence of incentives of regional managers when they share demand information. They employed a framework of the integrated supply chain where all players belong to the same company. The inventory is allocated among regional managers based on the proportion of reported private forecasts to the total shared demands. Since the central planner has an objective to maximize the total system profit and no individual financial interests, the behavioral incentives to misreport the private information should change. However, the laboratory results demonstrate that the information distortion is not reduced.

Strategic concerns over the peer players (other regional managers) lead to the greater deviation in shared forecast than strategic concerns over the centralized supply chain.

Our study adopts similar to Spiliotopoulou et al. (2016) supply chain structure with multiple retailers and a single supplier, but differs in the sense that all players have personal financial interests and are not parts of the single centralized supply chain. Additionally, the allocation of inventory among retailers is delegated to the supplier who decides how much of inventory to deliver to each retailer. The retailers act on the separate markets but their demands are perfectly correlated (i.e., identical marker demands). This allows the possibility for the supplier to detect untruthful reports. Furthermore, we extend the information sharing game by adding the social context such as facial photos of retailers.

2.2. Trust and Face Effect

The body of experimental literature on the trust issues in information sharing and supply chain performance has been growing over the last decade. However, a little attention has been given to the role of social factors in supply chain settings (Ebrahim-Khanjari et al., 2012). We find more evidence of social context effects on trust in the studies of behavioral economics. In a trust game, Eckel and Petrie (2011) demonstrated the positive shift in trust and consequent cooperation of responders when they saw the photos of senders. Subjects were strongly willing to see the photo of their counterparts and even purchased the photo for a positive price. Moreover, Heyes and List (2016) experimentally revealed that players are choosing to pay to show their own photo to the other party. These findings imply that human faces have an indigenous economic value. In the absence of other information, decision-makers form expectations about future actions of their counterparts from the observed facial identities and facial trustworthiness in particular. These subjective judgements shape behavioral choices of decision-makers.

People detect trustworthiness from strangers' faces automatically. This process is effortless and encapsulated (Bonnefon et al., 2013). In a trust game, faces that appear untrustworthy are less likely to be trusted and attract lower economic investments than trustworthy faces (Ewing et al., 2015). When given a choice, subjects select more trustworthy-looking images for their avatars with a purpose to gain more trust from partners (Tingley, 2014). Moreover, people continue to rely on facial trustworthiness and invest more in trustworthy-looking partners even in the presence of reputational information (Rezlescu et al., 2012).

This motivation encouraged us to study the face effect on trust and honesty[4] (i.e., truth-telling) in supply chain scenario. Following the examples of behavioral economists, we add the facial photos to signal about human traits and trigger subjective judgements in the forecast sharing experiment. The settings of our study differ from the prior behavioral research on trust in supply chain. First, we use photos of human faces with distinct facial trustworthiness to manipulate supplier's subjective judgements about truthfulness of retailer's shared forecast. Second, we apply a special case scenario with multiple retailers acting on separate markets with identical demands. Third, we allow the supplier to choose the inventory allocation scheme.

[4] Prior behavioral literature on information sharing in supply chain (Ozer et al., 2011, Spiliotopoulou et al., 2016) use trustworthiness to define the truth-telling behavior of the information holder. However, with a purpose to avoid possible confusion of terms "trustworthiness" and "facial trustworthiness", we use the term "honesty" in place of "trustworthiness".

3. Theory and Hypotheses

3.1. Information Sharing Game

We introduce the information sharing game in decentralized supply chain consisting of n retailers and a single supplier. They interact under a wholesale price contract. Each retailer $i \; \forall \; i \in (1, n)$ sells the common product on her market for the market price p per unit and pays the wholesale price w per unit to the supplier. The retailers act on separate markets. Before demand is realized the supplier builds total inventory I of the common product at a cost c per unit to satisfy all order quantities Q_i placed by retailers. Demand at each market is given by $D_i = A_i + \epsilon_i$, where A_i is the private demand forecast observed by each retailer i and ϵ_i is the market i uncertainty.[5] The retailers are facing the demand uncertainty ϵ_i but the supplier is exposed to uncertainty enlarged with the number of markets $\sum_{i \in (1,n)} \epsilon_i$. All players know that ϵ_i is zero-mean random variable with cumulative distribution function $G_i(\cdot)$, probability density function $g_i(\cdot)$, and support on[$\underline{\epsilon_i}, \overline{\epsilon_i}$]. It is known fact that due to her proximity to the local market, each retailer possesses the abilities and skills to produce the demand forecast. This information is privately available to retailers and noted with A_i in the demand model. All players know that A_i is the random variable with the mean μ_i, the cumulative distribution $F_i(\cdot)$, probability density function $f_i(\cdot)$, and support on [$\underline{A_i}, \overline{A_i}$]. Retailers have a power to signal the supplier about A_i by sharing the report B_i.

Figure 1. describes the structure of the forecast sharing game with three players—two retailers and one supplier. The sequential actions in the game are as follows: (1) each retailer

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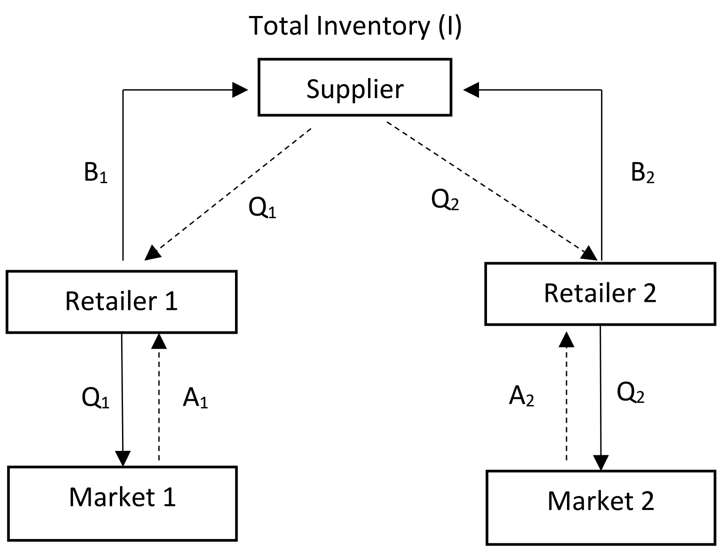
[5] Ozer et al. (2011) proposed the demand model $D = \mu + \varepsilon + \epsilon$, where μ is the positive constant average demand known to all parties, ε is the retailer's private forecast, and ϵ is the market uncertainty. We adopt the simplified version of this demand model by summing up μ and ε into $A = \mu + \varepsilon$.

privately observes the demand forecast A_i and shares it with the supplier via her report B_i; (2) the supplier receives all reports B_i and builds the total inventory of common product I at unit cost $c > 0$; (3) market demands D_i are realized and revealed to all parties; (4) the supplier decides how much inventory $Q_i \leq D_i$ to allocate for each retailer for the unit wholesale price $w > 0$; (5) the retailers receive and realize on the market the order quantities Q_i for the market price p; (6) the profits of all players are calculated and finalized.

Figure 1. Structure of Forecast Sharing Game with 3 players



Given I, Q_i and ϵ_i, the expected profits for the retailer i and the supplier are defined as follows:

$$\pi_{R_i}(A_i, I) = (p - w)\mathbb{E}_{\epsilon_i} \min(A_i + \epsilon_i, Q_i(I)\,) \tag{1}$$

$$\pi_S(A, I) = w\mathbb{E}_{\epsilon_i} \min[\sum_{i\in(1,n)} (A_i + \epsilon_i)\,, I] - cI, \tag{2}$$

where $Q_i(I)$ is the supplier's allocation function used to determine the inventory split among retailers. The literature suggests the proportional allocation scheme—the retailer i receives the quantity that is proportional to her order (i.e., shared forecast B_i): $Q_i(I) = \frac{B_i}{B_i+B_{-i}} I$ (Chen et al., 2012), or to her market demand: $Q_i(I) = \frac{D_i}{D_i+D_{-i}} I$ (Spiliotopoulou et al., 2016). Additionally we consider the equal inventory split among retailers: $Q_i(I) = \frac{1}{n} I$. However, neither of three rules is dominant in the equilibrium. Since we do not use any allocation scheme with a prior set up in the game, the supplier has a freedom to choose any allocation rule $Q_i(I)$.

The theory predicts that only uninformative equilibria are possible in the forecast sharing game (Ozer et al., 2011). The supplier does not rely on the shared reports B and determines the optimal inventory based on the prior belief:

$$I^* = (F_1 \circ F_2 \ldots \circ F_n \circ G_1 \circ G_2 \ldots \circ G_n)^{-1} \left(\frac{w-c}{w}\right) \quad (3)$$

Given the supplier knew A, he would optimize the newsvendor problem with the total demand equal to a convolution of the distributions of all retailers' demands. Equation (2) would be maximized by setting

$$I(A) = \sum_{i \in (1,n)} (A_i) + (G_1 \circ G_2 \ldots \circ G_n)^{-1} \left(\frac{w-c}{w}\right). \quad (4)$$

The problem is that the supplier does not observe the actual market demand forecast A_i. This incentivizes him to rely on the private information communicated by retailers. The shared forecast cannot be verified by the supplier and is cost free for the retailers. The retailers are motivated to misreport the private forecast. If the supplier fully trusts the retailers, he will set up the inventory

$$I_{trust}(B) = \sum_{i \in (1,n)} (B_i) + (G_1 \circ G_2 \ldots \circ G_n)^{-1} \left(\frac{w-c}{w}\right). \quad (5)$$

However, all supplier's inventory solutions (Equations (3)-(5)) are independent of the allocation scheme. The supplier has a freedom to choose any quantity to deliver to each retailer with no change in own profit if $I < \sum_{i\in(1,n)}(D_i)$. This may anticipate more pronounced inflation in the shared reports.

3.2. Strategic Concerns and Perfectly Correlated Market Demands

Seeking to observe behavioral patterns in supplier's decisions $Q_i(I)$ we apply the special case scenario of market demands D being perfectly correlated $D_i = D_{-i}$ (i.e., identical for all markets). The private forecasts A observed by retailers are also identical $A_i = A_{-i}$. Consequently, the retailers are expected to report the highly correlated B_i and B_{-i} to the supplier. With no coordination among retailers it is unlikely that the shared information will be identical. This implies the possibility that the distortion of private forecast can be detected by the supplier at the stage of inventory decision. However, not knowing the actual A the supplier may rely on any of received reports or its mean estimate. After the demand is realized, the supplier will have more "evidence" to detect the greater misreport among reported B_i and B_{-i}. If reports are significantly different, supplier will form negative judgements about trustworthiness of the retailer with the greater deviation in reported B. These negative judgments will lead to the change in supplier's decision behavior at the inventory allocation stage. The retailer with lower trustworthiness will be punished with the lower order quantity Q leading to the lower retailer's profit. However, this will hold true only when the realized market demand is greater than the total inventory. Given $I < \sum_{i\in(1,n)}(D_i)$, the supplier has multiple choices of inventory split among retailers while keeping the aggregate delivery at the level of total inventory: $I = \sum_{i\in(1,n)}(Q_i)$. Otherwise, when the realized market demand is less or equal than the total inventory $I \geq \sum_{i\in(1,n)}(D_i)$, the rational supplier equally splits the total inventory among retailers.

3.3. Face Effect

The operations management literature suggests that cooperation among partners depends on trust within a channel (Ozer et al., 2011, Ebrahim-Khanjari et al., 2012) and the strategic environment they operate in (Spiliotopoulou et al., 2016). To gain a further insight into what might drive retailer's forecast sharing behavior and supplier's trust and reciprocity (i.e., inventory allocation), we consider the social environment effect on economic decisions. Social preferences systematically affect decision making and may help to achieve channel coordination in supply chain (Loch and Wu, 2008). Specifically, we focus on the effect of human faces. We make two assumptions. First, with no other information available in a one-period decision the supplier's trust in the shared private forecast and reciprocity can be motivated by facial information (Eckel and Petrie, 2011). Second, the retailer's reporting behavior is triggered by facial trustworthiness. To investigate the effect of human faces on a cooperation within a system, we examine a set of special cases. These include (a) adding one or more photos of human faces, and (b) manipulating photos based on their facial trustworthiness.

To quantify the cooperation within a channel we use four measurements—channel efficiency, retailer's honesty (i.e., trustworthiness), supplier's trust, and reciprocity. Eckel and Petrie (2011) found that in a trust game seeing the faces of counterparts increases trust and results in greater investments. When the photo is available to see the level of investor's reciprocity is significantly greater compared to the case with no photo. By showing own face, a retailer shares privacy about her identity with a supplier. This signals about retailer's intentions to add credibility to her actions towards building relationships with a supplier. Thus, by revealing the personal identity the retailer anticipates a greater trust in shared private forecast, and the supplier is expected to response with a larger inventory. Altogether, they determine a greater resulting channel efficiency. Based on these predictions, we develop the following directional hypotheses.

3.3.1. Channel Efficiency

Hypothesis 1. *Channel efficiency should be higher in the treatment when photos of the retailers i and $-i$ are shown to the supplier, compared to the treatments with no shown photos or with a single photo (i.e., the cooperation is greater when the facial identities are revealed).*

To estimate the resulting channel efficiency we compare the expected profit of a supply chain $[\pi_S(A, I) + \sum_{i\in(1,n)} \pi_{R_i}(A_i, I)\ ]$, in which I observed in the experiment, to the theoretically predicted expected profit of a channel $\pi_{Th}(A, I^*) = p\mathbb{E}_{\epsilon_i} \min[\sum_{i\in(0,n)}(A_i + \epsilon_i)\ , I^*] - cI^*$, in which $I^*$is the best response of the supplier with zero trust. We expect the positive treatment effect of shown photos on the channel efficiency $E = \ [\pi_S(A, I) + \sum_{i\in(1,n)} \pi_{R_i}(A_i, I)\ ]/ \pi_{Th}(A, I^*)$.

To explain the differences in expected channel profit and resulting efficiency, we refer to the subject behavior. In particular, we explore retailer's honesty in forecast sharing and supplier's trust in received reports. To conclude, we analyze the possible consequences of detected misreports through supplier's reciprocity at the inventory allocation.

3.3.2. Retailer's Honesty / Trustworthiness

Hypothesis 2. *The positive correlation between retailer's report B and observed forecast A is lower in the treatment when a photo of the retailer is shown to the supplier, compared to the treatments with no shown photos (i.e., retailer's honesty is lower when the facial identity is revealed).*

We speculate that the retailer relies on the facial positive effect and expects a greater trust in shared reports when her facial identity is revealed. Moreover, this effect can be signified when several photos are revealed simultaneously. For instance, if the retailer evaluates own face as looking more trustworthy compared to other faces, she may rely on the facial positive effect to a large extent. This will lead to a greater distortion in the reported private forecast from the actually observed one.

Hypothesis 2a. *The trustworthy-looking retailer i reports B_i with a greater forecast distortion $(B_i - A_i)$ compared to the report of untrustworthy looking retailer and a retailer with unshown photo (i.e., the trustworthy-looking retailer reports with lower honesty).*

3.3.3. Supplier's Trust

Hypothesis 3. *The positive correlation between supplier's decision I and retailers' reports B_i and B_{-i} is greater in the treatment when photos of retailers i and $-i$ are shown to the supplier, compared to the treatments with no shown photos or with a single photo (i.e., trust is greater when the facial identities are revealed).*

Hypothesis 3a. *When a photo of the retailer i is shown to the supplier, the supplier's inventory decision I is more positively correlated with the private forecast B_i shared by the retailer i compared to the private forecast B_{-i} shared by the retailer with no shown photo (i.e., the retailer is judged with greater trustworthiness if the facial information is revealed).*

We expect the positive correlation of supplier's total inventory decision I with each shared private forecast B_i $\forall\ i \in (1, n)$ (Ozer et al., 2011, Spiliotopoulou et al., 2016). However, the correlation effect should be stronger in the treatment when retailers' photos are shown, and consequently a greater trust is anticipated. Human faces become the source for subjective judgements and expected behavioral intentions (Engell et al., 2007, Rezlescu et al., 2012, Todorov et al., 2009). In the case when a facial photo of a single retailer is revealed, we expect a greater correlation between inventory decision I with shared private forecast of that retailer whose photo is seeing by the supplier. Thus, in a group with asymmetric facial information the supplier will trust more the retailer with a photo.

What happens when face images of more than one retailer are available? Several retailers reveal their facial identities with a purpose to increase cooperation and reciprocity. The supplier simultaneously receives multiple credibility signals and has to choose whom to trust. Facial trustworthiness is automatically evaluated (Bonnefon et al., 2013). An individual associates a greater trust with a greater facial trustworthiness what leads to consequent economic benefits (Ewing et al., 2015, Tingley, 2014). Thus, we hypothesize that it is likely that trustworthy-looking retailers are trusted more.

Hypothesis 3b. *When photos of several retailers are shown to the supplier, the positive correlation of the supplier's inventory decision I is greater with the private forecast B_i shared by trustworthy-looking retailer i compared to the private forecast B_{-i} shared by untrustworthy-looking retailer (i.e., the trustworthy-looking retailer is trusted more than the untrustworthy-looking retailer).*

3.3.4. Supplier's Reciprocity

The supplier reciprocates to the retailers' forecast sharing behavior at the inventory allocation stage. The possibility to detect a report with a greater distortion increases after the demand is realized and informed to the supplier. The special case of perfectly correlated market demands creates the ground for comparison. A greater misreport will evoke negative judgements about the reporting retailer and may cause a negative reciprocity in supplier's actions. However, the supplier's negative response to the false report can be mitigated by the facial trustworthiness of the retailer. The trustworthy-looking retailer enjoys greater economic benefits compared to untrustworthy-looking counterpart (Ewing et al., 2015, Tingley, 2014). Conditioning on inventory shortage, the supplier reciprocates by allocating to deliver a larger order quantity to the more trusted retailer, who is likely looking trustworthy.

Hypothesis 4. *The supplier allocates a larger Q_i for the trustworthy-looking retailer i compared to Q_{-i} allocated for untrustworthy-looking retailer $-i$ (i.e., the trustworthy-looking retailer is trusted more than untrustworthy-looking retailer).*

Note that Hypothesis 4 interacts with retailers' information sharing behavior. In particular, a greater distortion in reports $(B_i - B_{-i})$ and $(B_{-i} - B_i)$ will negatively affect supplier's reciprocity in allocation of Q_i and Q_{-i}. This effect is likely to hold for all retailers.

4. Experimental Design and Procedures

We conducted a series of controlled experiments with human participants to investigate our hypotheses. We choose to use the three players supply chain structure (trio structure)—two retailers and a single supplier (described in Figure 1). We developed four treatments, as summarized in Table 1. Each treatment is labeled according to the setting of facial information provided to the participants: NF represents no facial photos, HT_NF – a high trustworthy face is shown for a single retailer and no photo for another retailer, NF_LT – low trustworthy face is shown for a single retailer and no photo for another retailer, HT_LT – high trustworthy face is shown for one retailer and low trustworthy face is shown for another retailer.

Table 1. Experimental Design

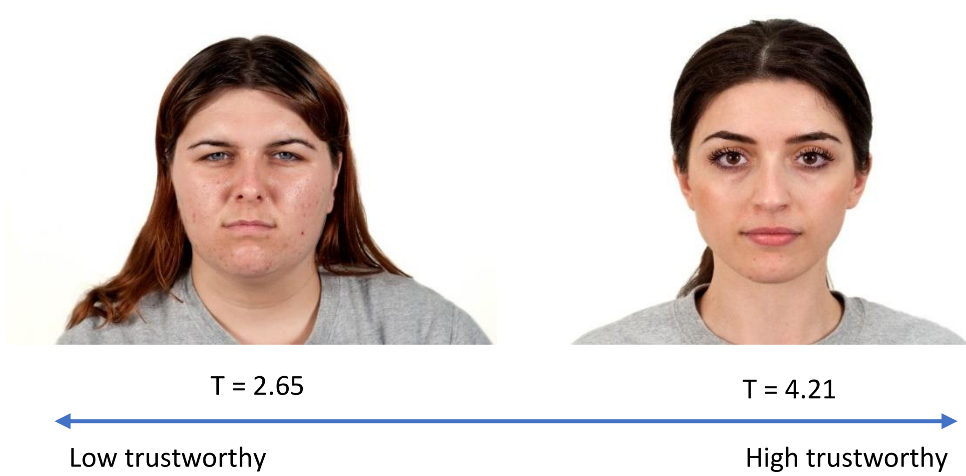
Treatment	Description	No. of Photos	Facial Trustworthiness	No. of Participants	No. of Groups
NF	No Face	0	-	306	102
HT_NF	1 Retailer Face	1	High	216	72
NF_LT	1 Retailer Face	1	Low	234	78
HT_LT	2 Retailers Faces	2	High and Low	234	78

The experiment was programed and conducted with the software SoPHIE. We recruited participants through the crowdsourcing platform Amazon's Mechanical Turk (MTurk) but restricted their geographic location to the United States (Lee et al., 2018). 990 subjects (330 groups) participated in the experiment. We used a between-subject design to assign individuals to treatments. Every subject participated in a single treatment and was involved in a single supply chain group. To participate individuals were required to pass a quiz after reading the instructions for the experiment. If the subject passed the quiz, the two practice rounds were played before the actual experiment. In the first practice round individuals were assigned the role of a retailer, and in the second practice round – a supplier. In both practice rounds they played with the programmed computer. After the practice rounds, participants entered the treatment and were randomly assigned the role of either one of the two retailers or a supplier. Every three participants were randomly and anonymously assigned to a supply chain group. Each treatment consisted of a single round.

We conducted all experimental treatments with the following parameters: $A_i \sim U[100,400]$, $\epsilon_i \sim U[-75,75]$, $p = 100$, $w = 75$, $c = 60$. These parameters represent the setting with a high inventory cost and a high market uncertainty, which was described by Ozer et al. (2011) as the case with the lowest observed trust and channel efficiency compared to other settings. We choose to apply this setting with an intention to solicit a greater deviation in trust and improve channel efficiency.

In treatments with facial information, we added photographs of female faces provided by Chicago Face Database (CFD) (Ma et al., 2015). CFD is a free of charge source of photographs available for non-commercial research purposes. It provides standardized photos with extensive norming data, which includes physical attributes (e.g., face dimensions, gender) and subjective scores of facial traits rated by independent judges (e.g., trustworthiness). In order to avoid judgments affected by race, gender and age stereotypes, we set the control to the face of white European female within 25-30 years age category. In addition, we use the photos of faces with neutral emotional expression. Figure 2 demonstrates face images used in the experiment. The faces are reported by CFD with the trustworthiness scores on the Likert-type scale from 1 (very untrustworthy-looking) to 7 (very trustworthy-looking) averaged over the surveyed independent responders. The face on the left was judged with the lowest trustworthiness score of 2.65 and the face on the right—with the largest trustworthiness score of 4.21 within assigned category.

Figure 2. Face Images Shown in Experiment



The photos of retailers appeared on the supplier's screen with the introductory phrase "Imagine that this is a photo of Retailer 1/2". However, all participants were informed about shown facial photos. The retailers saw the screenshot of what facial information is shown to the supplier. It appeared with the phrase "The following is shown to the Supplier: ". The introductory phrase is the common in the literature approach to set the condition which is necessary for the experiment (Loch et al., 2013, Loch and Wu, 2008). We provide the examples of experimental screens in Chapter 3 Appendix 1.

The facial representation of retailers was randomized and reordered in all experimental treatments. For example, in some rounds of HT_LT the first retailer was introduced to the supplier with a highly trustworthy face and the second retailer with a low trustworthy face, but in other rounds the order was reversed. For the clarity of the analysis, we structured the collected experimental data by treatment with the first retailer i described by the first two letters from treatment notation and the second retailer $-i$ described by the last two letters from treatment notation.

At the end of each experiment, the participants were asked to complete a questionnaire. The questionnaire was designed to collect the participants' demographics (gender, age, ethnicity), self-reported scores of own facial trustworthiness and subjective evaluations of trustworthiness of shown photos on a Likert-type scale from 1 (very untrustworthy-looking) to 7 (very trustworthy-looking), and comments about the experiment. Participants were compensated in proportion to their individual profits earned in the experiment plus a fixed $0.5 participation fee. The average payment was $1.21 per subject. On average participants spent 15 minutes on the experiment.

5. Experimental Results

We analyze the experimental data and present the results with respect to the hypotheses introduced in section 3.

5.1. Channel Efficiency

We first check the effect of faces on channel efficiency by comparing it across treatments (Hypothesis 1). Table 2 presents summary statistics and Wilcoxon rank sum test two-sided comparison results. Fist, we observe that the median channel efficiency is the highest in HT_LT compared to other treatments. Only in HT_LT treatment the median of supply chain profits is greater the theoretical prediction, pointing on the opportunity to increase the channel profitability. Second, the two-sided Wilcoxon test confirms that E is significantly different in HT_LT compared to NF, NF_LT (p-values < 0.05) and HT_NF (p-value < 0.08).

Table 2. Summary Statistics and Comparison of Channel Efficiency by Treatment: Wilcoxon Rank Sum Test Results (two-sided)

Treatment	E (%)			Comparison p-value		
	Avg	[med]	(SD)	HT_NF	HT_LT	NF_LT
NF	96.5	96.5	21.8	0.434	0.015	0.803
HT_NF	92.1	96.4	19.6		0.080	0.660
HT_LT	94.3	105.1	24.1			0.027
NF_LT	89.7	96.5	23.5			

Note: "Avg", "med", and "SD" stand for average, median, and standard deviation, respectively

Additionally to comparisons, we use the regression analysis to test Hypothesis 1. To determine the treatment effect on E, we use the linear regression model defined as follows,

$$E_j = \beta_0 + \beta_1 A + \beta_2 HT\_NF + \beta_3 HT\_LT + \beta_4 NF\_LT + \varepsilon_j \tag{6}$$

where subscript j denotes the index for a supplier, HT_NF, HT_LT and NF_LT are treatment indicators with NF used as the reference, and ε_j is the independent error component across observed supplier's decisions. Regression results are reported in Table 3. The coefficient for HT_LT is positive and statistically significant (p-value < 0.05), suggesting that the average E is greater when both retailers' photos are available to the supplier. Thus, we find evidence in support of Hypothesis 1. The channel efficiency is higher when facial identities of both retailers are revealed to the supplier compared to no facial information (Regression, Wilcoxon test) and one retailer's face (Wilcoxon test) effects.

Table 3. Regression Results for Testing Treatment Effect on Channel Efficiency

	Estimate (standard error)	
Variable	*E (%)*	
A	-0.076***	(0.01)
HT_NF	1.317	(3.30)
HT_LT	6.730**	(3.23)
NF_LT	0.659	(3.22)
Intercept	108.122***	(4.03)

*Note: *p < 0.1; **p < 0.05; ***p < 0.01*

We next provide intuition to explain the observed differences in the resulting channel efficiency across treatments. We start from the analysis of distortion in reports of retailers (Hypotheses 2 and 2a) and continue with the exploration of supplier's reliance on shared forecasts (Hypotheses 3, 3a-b). To finalize the story, we check the behavioral consequences via the supplier's inventory allocation responses (Hypothesis 4).

5.2. Retailer's Honesty / Trustworthiness

Summary statistics on the forecast distortion $(B - A)$ and the simple regression slopes of B on A are reported in Table 4. The reports B appear to be highly correlated in all treatments. This confirms the earlier findings (Ozer et al., 2011, Spiliotopoulou et al., 2016). However, we find the pronounce difference in the regression slopes across treatments. The positive correlation between B and A decreases as facial information is revealed with the lowest correlation coefficient in HT_LT. The two-sided Fisher's combined probability test confirms that the Pearson correlation coefficient of B on A in HT_LT is significantly lower (p-value < 0.01) than in other treatments (presented in Table 5).

Table 4. Summary Statistics of Forecast Distortion by Treatment

Treatment	|B - A|			B - A	B > A	B < A	B = A	Simple regression	
	Avg	[med]	(SD)	Avg	%	%	%	Slope B on A	Standard Error
NF	37.7	24.0	41.4	18.6	64.7	28.9	6.4	0.822***	0.041
HT_NF	42.0	23.5	53.6	22.5	66.0	25.7	8.3	0.710***	0.056
HT_LT	55.7	23.5	65.8	1.9	53.2	37.8	9.0	0.446***	0.075
NF_LT	43.2	19.0	57.8	12.0	61.5	25.6	12.8	0.665***	0.061

Note: *p < 0.1; **p < 0.05; ***p < 0.01

"Avg", "med", and "SD" stand for average, median, and standard deviation, respectively

Table 5. Comparison of Correlation Coefficients between A and B: Fisher's combined probability test (two-sided)

Treatment	*Cor (A,B)*	Comparison p-value		
		HT_NF	HT_LT	NF_LT
NF	0.815	0.052	0.000	0.001
HT_NF	0.729		0.000	0.263
HT_LT	0.432			0.003
NF_LT	0.662			

To examine the variation in $(B - A)$ by the facial trustworthiness on photos, we grouped experimental observations into three categories: NF represents no facial information, HT – the reports of retailers with high trustworthy face, and LT – the reports of retailers with low trustworthy face. Table 6 presents summary statistics of the deviation in reported forecast by facial trustworthiness type. The positive Pearson correlation of B on A is significantly lower for both HT and LT compared with NF (Fisher's combined probability test: p-value < 0.001) which supports Hypothesis 2.

Table 6. Summary Statistics of Forecast Distortion by Facial Trustworthiness

Facial Information	|B - A| Avg	[med]	(SD)	B - A Avg	B > A %	B < A %	B = A %	Simple regression: Slope B on A	Standard Error
NF	39.4	22.0	47.7	20.4	63.6	27.7	8.8	0.761***	0.033
HT	50.2	22.5	62.7	6.1	60.0	34.0	6.0	0.551***	0.067
LT	49.2	21.5	60.7	6.9	58.3	29.5	12.2	0.607***	0.068

Note: *p < 0.1; **p < 0.05; ***p < 0.01

"Avg", "med", and "SD" stand for average, median, and standard deviation, respectively

To further test Hypotheses 2, which predicts that the facial information affects the behavioral deviation in $(B - A)$, we use the linear regression models defined as follows,

$$(B_n - A_n) = \beta_0 + \beta_1 A_n + \beta_2 HT\_NF + \beta_3 HT\_LT + \beta_4 NF\_LT + \beta_5 A_n \cdot HT\_NF + \beta_6 A_n \cdot HT\_LT + \beta_7 A_n \cdot NF\_LT + e_n \quad (7)$$

$$(B_n - A_n) = \beta_0 + \beta_1 A_n + \beta_2 HT + \beta_3 LT + \beta_4 A_n \cdot HT + \beta_5 A_n \cdot LT + \tau_n \quad (8)$$

where subscript n denotes the index across all retailers i and $-i$, in Equation (7) HT_NF, HT_LT and NF_LT are treatment indicators, and in Equation (8) HT and LT indicate the facial trustworthiness with NF used as the reference in both equations. The terms e_n and τ_n are the independent error components across observed retailer's decisions. Chapter 3 Appendix 2 provides a definition of variables and error terms used in the regression models.

Regression results are summarized in Table 7. The coefficient for HT_LT is positive and statistically significant (p-value < 0.01), suggesting that on average $(B - A)$ is greater when photos of all retailers are shown to the supplier. However, in HT_LT the distortion in reports diminishes with a larger private forecast at a faster rate. The coefficient for main effect of HT is significantly positive (p-value < 0.05) but the coefficient for main effect of LT is not statistically significant. Observed effects imply that retailers inflate shared reports accounting on two necessary conditions: (1) they know that the photo on their behalf is shown to the supplier, and

(2) the face on the photo looks trustworthy. This finding partially supports Hypothesis 2, suggesting that retailers behave less honest and report partially informative forecast relying on the value of facial information but conditioning on facial trustworthiness.

Table 7. Regression Results for Testing Treatment Effect on Forecast Distortion

	Estimate (standard error)							
Variable	*B* - *A*				B_i - A_i		B_{-i} - A_{-i}	
A	-0.178***	(0.05)	-0.239***	(0.04)	-0.093	(0.07)	-0.262***	(0.07)
HT_NF	25.698	(19.56)	—		45.775*	(26.90)	5.621	(28.38)
HT_LT	88.575***	(22.09)	—		125.223***	(30.37)	51.927	(32.04)
NF_LT	33.144	(20.28)	—		66.335**	(27.89)	-0.047	(29.42)
A · HT_NF	-0.112	(0.08)	—		-0.199*	(0.11)	-0.025	(0.11)
A · HT_LT	-0.376***	(0.08)	—		-0.527***	(0.11)	-0.226*	(0.12)
A · NF_LT	-0.157**	(0.08)	—		-0.251**	(0.11)	-0.064	(0.11)
HT	—		39.376**	(18.51)	—		—	
LT	—		30.429	(19.17)	—		—	
A · HT	—		-0.210***	(0.07)	—		—	
A · LT	—		-0.154**	(0.07)	—		—	
Intercept	62.692***	(13.28)	78.775***	(9.92)	37.904**	(18.27)	87.481***	(19.27)

*Note: *p < 0.1; **p < 0.05; ***p < 0.01*

"—" indicates that the independent variable is not in the model. Value in parentheses are the standard errors.

Next, we test Hypothesis 2a, which predicts how the misreporting behavior varies across types of facial trustworthiness. To determine which retailer reports with a greater distortion, we apply the regression model from Equation (7) to the datasets restricted to reports of one retailer from each supply chain groups and compare the treatment effects. The regression results are summarized in Table 6. We observe the significant positive effect of treatments HT_LT and NF_LT (p-value < 0.05) on the forecast distortion of the retailer i and no treatment effect for another retailer $-i$. Note that the retailer i is presented with a high-trustworthy looking face in HT_LT and no face in NF_LT, and the retailer $-i$ is presented with a low-trustworthy face in both treatments. This suggests that the retailer is likely to misreport on a larger scale when another retailer who competes for the supplier's trust looks untrustworthy. However, this effect decreases with a larger forecast. Thus, we find the partial evidence in support of Hypothesis 2a.

5.3. Supplier's Trust

We next examine the inventory decisions made by suppliers across treatments. Table 8 reports the summary statistics of the differences between observed inventory decisions and the suggested inventory given the mean of retailers' reports ($I - I_{trust}(\bar{B})$). The simple regression slopes of I on the total of two reports ($B_i + B_{-i}$) suggest the strong positive correlation in all treatments except HT_LT. The two-sided Fisher's combined probability test confirms that the Pearson correlation coefficient of I and B in HT_LT is significantly lower (p-value < 0.01) compared to the other treatments (presented in Table 9). This finding contradicts to Hypothesis 3 and suggests a lower supplier's trust in information shared by retailers with distinct facial trustworthiness.

Table 8. Summary Statistics on Supplier's Inventory Decision

Treatment	$\lvert I - I_{trust}(\bar{B}) \rvert$			$I - I_{trust}(\bar{B})$	$I > I_{trust}(\bar{B})$	$I < I_{trust}(\bar{B})$	$I = I_{trust}(\bar{B})$	Simple regression	
	Avg	[med]	(SD)	Avg	%	%	%	Slope I on (B_i+B_{-i})	Standard Error
NF	101.7	90.0	72.0	43.3	79.4	20.6	0.0	0.771***	0.069
HT_NF	92.8	90.0	60.3	48.8	80.6	19.4	0.0	0.855***	0.077
HT_LT	107.4	89.0	95.4	14.0	71.8	26.9	1.3	0.592***	0.126
NF_LT	84.7	88.0	48.6	40.4	75.6	24.4	0.0	0.968***	0.070

Note: *p < 0.1; **p < 0.05; ***p < 0.01

"Avg", "med", and "SD" stand for average, median, and standard deviation, respectively

Table 9. Comparison of Correlation Coefficients between I and B: Fisher's combined probability test (two-sided)

Treatment	*Cor (I,B)*	Comparison p-value		
		HT_NF	HT_LT	NF_LT
NF	0.682	0.822	0.000	0.548
HT_NF	0.695		0.000	0.733
HT_LT	0.351			0.000
NF_LT	0.715			

Next, we use linear regression models to further test treatment and facial trustworthiness effects on the supplier's trust in shared forecast described by Hypotheses 3, 3a and 3b:

$$\bar{I}_j = \beta_0 + \beta_1 B_n + \beta_2 HT\_NF + \beta_3 HT\_LT + \beta_4 NF\_LT + \beta_5 B_n \cdot HT\_NF + \beta_6 B_n \cdot HT\_LT + \beta_7 B_n \cdot NF\_LT + \gamma_j \quad (9)$$

$$\bar{I}_j = \beta_0 + \beta_1 B_n + \beta_2 HT + \beta_3 LT + \beta_4 B_n \cdot HT + \beta_5 B_n \cdot LT + \omega_j \quad (10)$$

where subscript j denotes the index for a supplier, in Equation (9) HT_NF, HT_LT and NF_LT are treatment indicators, and in Equation (10) HT and LT indicate the facial trustworthiness with NF used as the reference in both equations. The terms γ_j and ω_j are the independent error components across observed supplier's decisions (definition of regression variables is provided in Chapter 3 Appendix 2). We approximate the equality in inventory build for every from two markets and assign $\bar{I} = \frac{1}{2} I$.

Table 10 reports regression results. The results of both models provide insights on the reliance of suppliers in the inventory decision on the retailers' reports. The coefficients for B in two models are significantly positive but are less than 1 (Linear hypothesis test: p-value < 0.001). This implies that suppliers partially rely on the shared reports (Ozer et al., 2011). The coefficient for interaction $B \cdot HT\_LT$ is negative and significant (p-value < 0.001), suggesting that suppliers place a lower trust in reports of retailers with shown faces which are directly opposite in facial trustworthiness. However, the significant positive main effect of HT_LT refers to the positive benefits from seeing faces for supplier's trust. Thus, we find the evidence partially supporting Hypothesis 3 and pointing on the facial trustworthiness as the necessary condition in supplier's reliance.

Who is trusted more—a retailer with a trustworthy face or a retailer with an untrustworthy face? To explore the difference in trust we refer to the results of the second model in Equation (10) reported in Table 10. The coefficients for interaction $B \cdot HT$ and $B \cdot LT$ are both negative and statistically significant (p-value < 0.01 and p-value < 0.05 respectively), suggesting that suppliers rely less on the reports of retailers with shown faces. However, the main effect of HT is significantly positive (p-value < 0.05) and the main effect of LT is weakly significant (p-value < 0.1) with no significant difference among them in HT and LT effects on $\bar{I}$ (Linear hypothesis test: p-value = 0.595). These findings suggest that seeing a face of a retailer has a positive effect on supplier's trust compared to no shown face retailer. But this effect diminishes with a larger forecast. The observed effect does not differ for high trustworthy and low trustworthy faces. Thus, we find the partial support of Hypothesis 3a and fail to support Hypothesis 3b.

Table 10. Regression Results for Testing Treatment Effect on Inventory Decision

Variable	Estimate (standard error) $\bar{I}$			
B	0.650***	(0.05)	0.668***	(0.04)
HT_NF	-2.744	(21.35)	—	
HT_LT	75.427***	(22.32)	—	
NF_LT	-13.293	(21.31)	—	
$B \cdot HT\_NF$	-0.001	(0.08)	—	
$B \cdot HT\_LT$	-0.325***	(0.08)	—	
$B \cdot NF\_LT$	0.04	(0.08)	—	
HT	—		49.417**	(19.72)
LT	—		36.182*	(19.68)
$B \cdot HT$	—		-0.199***	(0.07)
$B \cdot LT$	—		-0.155**	(0.07)
Intercept	69.942***	(14.11)	62.274***	(10.90)

*Note: *p < 0.1; **p < 0.05; ***p < 0.01*

"—" indicates that the independent variable is not in the model. Value in parentheses are the standard errors.

5.4. Supplier's Reciprocity

We conclude our story by analyzing the supplier's reciprocity as the consequence to retailer's sharing behavior. After the demand is realized and available to all players, the greater forecast distortion is possible to detect. The optimal supplier has numerous alternatives of inventory allocation scheme when the realized demand is greater than inventory. To test Hypothesis 4, which predicts that the supplier allocates inventory with the preferences for trustworthy-looking retailer, we next apply our analysis to the experimental data restricted to $I < (D_i + D_{-i})$. Table 11 presents descriptive statistics of differences in order quantities $(Q_i - Q_{-i})$ allocated respectively to the retailers i and $-i$. The two-sided Wilcoxon rank sum tests show that $(Q_i - Q_{-i})$ in HT_NF is significantly different from $(Q_i - Q_{-i})$ in NF_LT (p-value = 0.029) and $|Q_i - Q_{-i}|$ in HT_LT is different from $|Q_i - Q_{-i}|$ in NF with a weak statistical significance (p-value = 0.07). The difference across treatments points on the varying reciprocity in supplier's behavioral choices. The regression slopes of $(Q_i - Q_{-i})$ on $(B_i - B_{-i})$ are all significantly positive (p-value < 0.01), suggesting a strong positive correlation between differences in reports and differences in quantities of two retailers in favor of the first retailer i, who is introduced with highly trustworthy face in HT_LT and HT_NF and no face in NF_LT. Note that the order effect was eliminated in experimental design of treatments with shown faces (described in details in section 4).

Table 11. Summary Statistics on Supplier's Inventory Allocation Decision

Treatment	No. of Rounds	$\lvert Q_i - Q_{-i}\rvert$			$Q_i - Q_{-i}$	$Q_i > Q_{-i}$	$Q_i < Q_{-i}$	$Q_i = Q_{-i}$	Simple regression	
		Avg	[med]	(SD)	Avg	%	%	%	Slope $(Q_i - Q_{-i})$ on $(B_i - B_{-i})$	Standard Error
NF	42	38.0	5.5	62.0	-3.1	31.0	21.4	47.6	0.654***	0.170
HT_NF	33	37.6	20.0	47.6	-17.6	27.3	42.4	30.3	0.336***	0.107
HT_LT	45	56.9	30.0	74.8	2.5	40.0	33.3	26.7	0.431***	0.102
NF_LT	33	33.6	20.0	43.8	14.5	48.5	21.2	30.3	0.342***	0.072

Note: *p < 0.1; **p < 0.05; ***p < 0.01
"Avg", "med", and "SD" stand for average, median, and standard deviation, respectively

We apply a set of the linear regression models to test Hypothesis 4:

$$(Q_i - Q_{-i})_j = \beta_0 + \beta_1(B_i - B_{-i}) + \beta_2\, HT\_NF + \beta_3 HT\_LT + \beta_4 NF\_LT \\ + \beta_5 dR_i + \beta_6 dR_i \cdot (B_i - B_{-i}) + \alpha_j \quad (11)$$

$$(Q_i - Q_{-i})_j = \beta_0 + \beta_1(B_i - B_{-i}) + \beta_2 HT + \beta_3 LT \\ + \beta_4(B_i - B_{-i}) \cdot HT + \beta_5(B_i - B_{-i}) \cdot LT + \theta_j \quad (12)$$

In Equations (11-12) we use subscripts i and $-i$ to denote individuals in the role of retailers, and subscript j as the index for a supplier. We include the difference in reports $(B_i - B_{-i})$ as an independent variable to inspect the effect of differences in retailers' reports on the supplier's choice to allocate different quantities for two competing retailers. We account for the treatment effect through the treatment indicators HT_NF, HT_LT, and NF_LT in Equation (11), and HT and LT in Equation (12) with NF used as the reference in both equations. Additionally, we include the indicator of the retailer i (dR_i) in a supply chain group in Equation (11). The error terms α_j and θ_j are independent error components across observed supplier's decisions (definition of regression variables is available in Chapter 3 Appendix 2).

Regression results are reported in Table 12. The coefficients for $(B_i - B_{-i})$ and interaction effect $dR_i \cdot (B_i - B_{-i})$ are statistically significant (p-value < 0.001) and have opposite signs. This suggest that the difference in retailers' reports is not treated equally by the supplier. When retailer i overreports forecast, she is likely to receive a greater order quantity (positive correlation) than another retailer $-i$. However, when retailer $-i$ overreports forecast, she is likely to receive a smaller order quantity (negative correlation) than the retailer i. Note that retailers i were introduced to the supplier with eighter high trustworthy face or no face, and retailers -i —with eighter low trustworthy face or no face. In addition, the coefficients for HT_LT treatment effect is significantly positive (p-value < 0.05). This implies that the difference in order quantities is larger when two opposite in facial trustworthiness images are shown to the supplier.

To examine the impact of facial trustworthiness, we refer to the second model in Table 12. The reported coefficients for interaction effects $(B_i - B_{-i}) \cdot HT$ and $(B_i - B_{-i}) \cdot LT$ are both statistically significant (p-value < 0.01) and have different signs, suggesting contrary effects of HT and LT on $(Q_i - Q_{-i})$. Thus, our findings imply that the retailer with high facial trustworthiness is likely to receive a larger order quantity compared to the retailer with no facial information and to the retailer looking untrustworthy (Linear hypothesis test: p-value < 0.001), which supports Hypothesis 4.

Table 12. Regression Results for Testing Treatment Effect on Inventory Allocation Decision

	Estimate (standard error)			
Variable	$(Q_i - Q_{-i})$			
$(B_i - B_{-i})$	-0.415***	(0.05)	0.048	(0.07)
HT_NF	-2.290	(10.33)	—	
HT_LT	19.009**	(9.55)	—	
NF_LT	9.659	(10.29)	—	
dR_i	0.000	(7.14)	—	
$dR_i \cdot (B_i - B_{-i})$	0.831***	(0.08)	—	
HT	—		5.314	(9.53)
LT	—		10.605	(9.41)
$(B_i - B_{-i}) \cdot HT$	—		0.356***	-0.102
$(B_i - B_{-i}) \cdot LT$	—		-0.440***	-0.098
Intercept	-7.371	(7.70)	-2.927	(5.54)

*Note: *p < 0.1; **p < 0.05; ***p < 0.01*
"—" indicates that the independent variable is not in the model. Value in parentheses are the standard errors.

5.5. Robustness Check

Thus far we have identified several behavioral patterns linked to the facial trustworthiness. Specifically, these behavioral regularities depend on the observed difference in facial trustworthiness between retailers. In the experiments we used two facial images which are reported with distinct trustworthiness scores by CFD (presented in Figure 2). With a purpose to investigate the subjective perception of shown faces, we asked participants to evaluate seeing images on facial trustworthiness on the Likert-type scale from 1 (very untrustworthy-looking) to 7 (very trustworthy-looking)[6]. Table 13 displays the average scores of facial trustworthiness reported by CFD and rated by participants in the experiment. We find that facial trustworthiness scores for HT are significantly greater than scores for LT (Welch Two Sample t-test: p-value <

[6] The same Likert-type scale from 1 (very untrustworthy-looking) to 7 (very trustworthy-looking) was used in survey conducted for Chicago Face Database (Ma et al., 2015).

0.001) in HT_LT treatment, and this difference is consistent across all assigned roles (Pairwise Welch Two Sample t-test: p-value < 0.001). For instance, suppliers rate the HT face with a greater score than the LT face which confirms that suppliers see two distinct faces and differentiate them on facial trustworthiness. The same hold true for both retailers.

Table 13. Comparison of Facial Trustworthiness Scores: Welch Two Sample t-test

Treatment	CFD		Experiment		
	HT	LT	HT	LT	Comparison p-value
HT_NF	4.01		5.23		
HT_LT	4.01	2.65	5.76	3.49	0.000
NF_LT		2.65		3.32	

6. Validation Experiments

To validate the behavioral patterns in retailer's sharing actions and supplier's responses, we conducted several additional treatments where we manipulated the shown faces. In treatment HT_LT, we (1) used another low trustworthy face and (2) replaced highly trustworthy face with low trustworthy face. We choose to use the same new photo with the low facial trustworthiness score 2.8 reported by CFD. The first validation treatment is denoted HT_LT(2.8) and the second treatment LT(2.8)_LT. A similar number of supply chain groups were run (51 in HT_LT(2.8) and 52 in LT(2.8)_LT), with participants recruited using the same crowdsourcing platform and incentives as previous treatments.

To test the results we follow the methodology employed in sections 5.2 and 5.3. We use the linear regression models in Equations (7) and (8) with the treatment indicators HT_LT(2.8) and LT(2.8)_LT to test retailer's reporting behavior. To explore supplier's trust, we modify the linear regression model in Equation (9) by excluding interaction effects and adding the treatment indicators HT_LT(2.8) and LT(2.8)_LT. NF is applied as the reference in all models. Table 14 provides the regression results. We observe a significant positive treatment effect of showing faces which are distinct in trustworthiness on forecast distortion (p-value < 0.01). However, this effect diminishes with an increase of private forecast. Knowing that the face shown for her to the supplier looks highly trustworthy compared to another retailer's face, the retailer inflates reported forecast greater than the retailer with no facial information (p-value < 0.01). Pairwise Wilcoxon rank sum test confirms that HT retailer inflates shared forecast significantly more than LT retailer (p-value = 0.019). Interestingly, we observe similar effect in a treatment with two low trustworthy looking photos. The positive treatment effect in LT(2.8)_LT can be explained by a slight difference in facial trustworthiness (CFD reports 2.8 and 2.6 trustworthiness score for photos in LT(2.8)_LT treatment). This finding confirms our original results in section 5.2. Also, we find the positive treatment effect of seeing two contrary in trustworthiness faces on supplier's inventory decision. However, this effect is weakly significant (p-value = 0.067).

Table 14. Regression Results for Testing Treatment Effect on Forecast Distortion and Inventory Decision in Validation Experiments

	Estimate (standard error)					
Variable	*B - A*				$\bar{I}$	
A	-0.178***	(0.05)	-0.178***	(0.05)	—	
B	—		—		0.637***	(0.03)
HT_LT(2.8)	57.077***	(22.04)	—		12.738*	(6.95)
LT(2.8)_LT	36.613*	(20.70)	—		2.046	(6.91)
A · HT_LT(2.8)	-0.217***	(0.08)	—		—	
A · LT(2.8)_LT	-0.177**	(0.08)	—		—	
HT	—		91.573***	(28.17)	—	
LT	—		32.620*	(18.60)	—	
A · HT	—		-0.302***	(0.10)	—	
A · LT	—		-0.164**	(0.07)	—	
Intercept	62.692***	(12.88)	62.692***	(12.79)	73.387***	(9.44)

*Note: *p < 0.1; **p < 0.05; ***p < 0.01*
"—" indicates that the independent variable is not in the model. Value in parentheses are the standard errors.

In addition to discussed above treatments, we conducted treatments with the same faces shown for both retailers. We refer the interested readers to Chapter 3 Appendix 3 for full information.

To further examine factors influencing the retailer's sharing behavior, we test the importance of knowing how another retailer looks. In particular, we test whether retailers compare own look with facial trustworthiness of a competing retailer. We conducted HT_LT treatment with a change in information revealed to retailers. The participants were informed only about the photo shown on their behalf to the supplier but not about the face shown for another retailer. All other procedures remained unchanged. We run 50 supply chain groups with participants recruited using the same crowdsourcing platform and incentives as previous treatments. To test the treatment effect we applied the regression model in Equation (7) with an indicator for treatment HT_LT and NF as the reference. Regression results are reported in Table 15. We do not observe a significant treatment effect on the distortion in reports of both retailers. Next, we compare the correlation coefficients between actual private forecast and shared reports of retailers in original and limited settings (presented in Table 16). Both retailers reported with a greater honesty when they did not know about asymmetry in facial trustworthiness of shown photos (Fisher's combined probability test: p-value < 0.001). Thus, we find supporting evidence that decision-makers rely on the comparison of facial trustworthiness.

Table 15. Regression Results for Testing Treatment Effect on Forecast Distortion

	Estimate (standard error)			
Variable	$B_i - A_i$		$B_{-i} - A_{-i}$	
A	-0.093*	(0.05)	-0.262***	(0.06)
HT_LT	21.641	(23.42)	-18.927	(28.39)
$A \cdot HT\_LT$	-0.065	(0.09)	0.075	(0.11)
Intercept	37.904***	(13.44)	87.481***	(16.29)

*Note: *p < 0.1; **p < 0.05; ***p < 0.01*

Table 16. Comparison of Correlation Coefficients between A and B in HT_LT treatments: Fisher's combined probability test (two-sided)

	Cor (A, B)		
	Original	Limited	Comparison p-value
Retailer _ HT	0.371	0.842	0.0000
Retailer _ LT	0.494	0.820	0.0009

7. Discussion and Conclusion

This study examines whether the facial identity impacts cooperation between partners in a supply chain. We experimentally analyze forecast information sharing in a multiple players setting—two retailers and a single supplier—under a linear wholesale price contract using various exposure of retailers' facial information. Although the game theory pursues that rational decision-makers ignore social considerations when choosing among alternatives, our experimental data suggests the opposite. We find that retailer's reporting behavior and supplier's trust and reciprocity systematically deviate from the theoretical predictions. These behavioral patterns are attributed to social preferences and facial stereotypes. In particular, we find that facial photos impact both retailer's and supplier's choices. Moreover, the supply chain efficiency increases when facial identities of all retailers are revealed to the supplier. We believe that understanding and managing the social environment effect is important in a supply chain contracting.

To explain an increase in a supply chain profitability, we analyze the change in the retailer's forecast sharing and supplier's trust under four conditions: (1) no facial information is available, (2) highly trustworthy looking face is shown for a single retailer, (3) low trustworthy looking face is shown for a single retailer, and (4) highly trustworthy and low trustworthy faces are shown for one and another retailers respectively. Our experimental results suggest that retailers report with the greatest distortion when both retailers' faces are available with trustworthy looking retailers deviating significantly more. However, the retailer with a trustworthy look is likely misreport knowing that another retailer looks untrustworthy. This insight shows that the retailers' truth-telling depends not only on own facial effect but on a comparison of own facial look to the face of another player. On the supplier's side, we observe the lowest reliance on forecast information shared by retailers with distinct facial trustworthiness in addition to positive benefits of revealed faces. Thus, in a supply chain both the face and the facial trustworthiness impact players' judgments which trigger retailer's honesty and supplier's trust. To conclude the story, we inspect the supplier's reciprocity conditioning on the ability to detect false reports. The data suggests that suppliers allocate inventory unevenly between retailers. Retailers with an untrustworthy face benefit less than their counterparts with either unshown or trustworthy-looking face.

This paper offers two contributions to the behavioral operations literature. First, we demonstrate that social preferences, such as the facial identity and facial trustworthiness, are important to predict a decision-maker's behavior in a supply chain contracting. Moreover, revealed facial information affects directional changes in behavioral decisions and enhances a channel performance, whereas facial trustworthiness can induce trust and reciprocity but compromise honesty. Second, our findings add to the exploration research venue of trust and trustworthiness issues in operational contexts by pointing on the value of facial information. We determine that facial identity can be used to facilitate trust and positive reciprocity in a supply chain.

We believe that this research could be extended in numerous ways. In this study, we focus exclusively on the value of facial information and control for the effect of reputation. One could further explore the effect of facial trustworthiness on cooperation through the repeated interactions. It would be interesting to investigate which of two effects—facial trustworthiness or reputation—has a greater impact on trust. Other important and interesting future research directions would be to explore the effect of faces across genders, ages, and cultures, which are highly relevant to the current context of operations management via virtual communication. Providing empirical answers to these questions would enhance business practitioners with practical knowledge of how to increase cooperation and facilitate trust in a supply chain.

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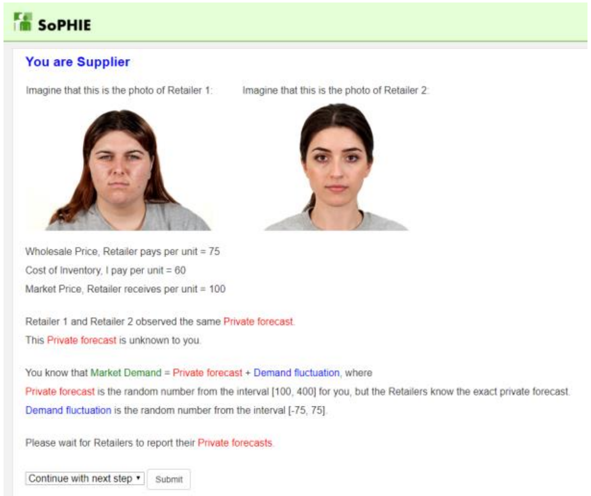
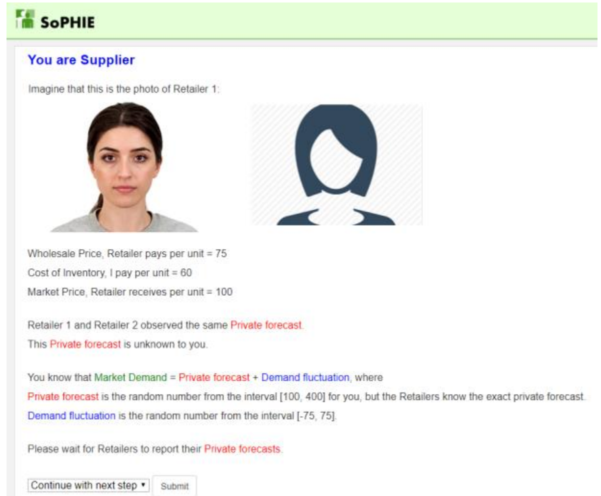
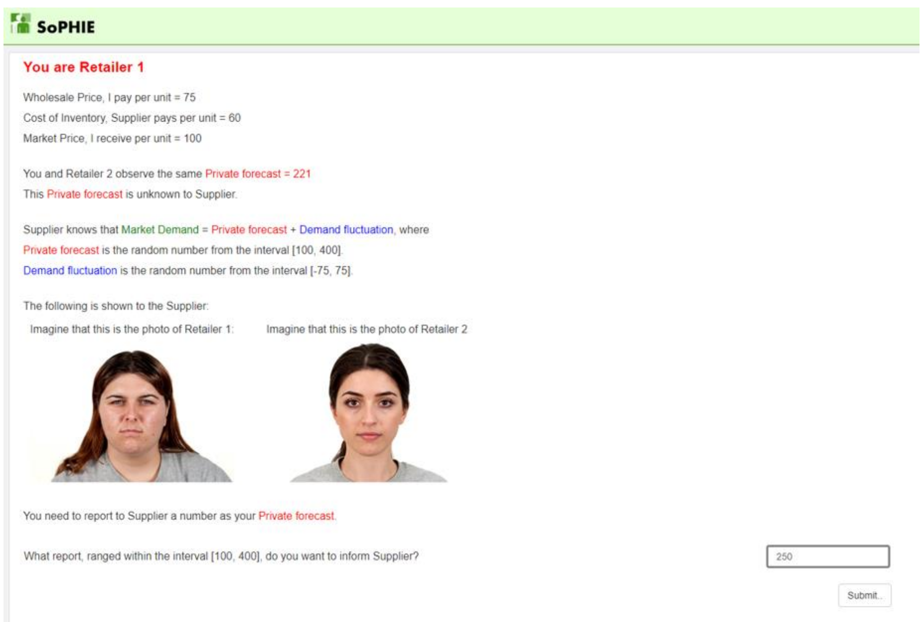
Chapter 3 Appendix 1. Examples of Experimental Screens

Supplier's screens in HT_LT and HT_NF treatments:





Retailer' screens in HT_LT and HT_NF treatments:



Chapter 3 Appendix 2. **Definition of Variables used in Regression Models**

Variable	Definition
Dependent variables	
E_j	Channel efficiency for a supply chain with supplier *j*
$(B_n - A_n)$	Distortion of reported forecast from actually observed by retailer *n*
$\bar{I}_j$	Inventory built by supplier *j* for each from two markets, inventory equality is assumed
$(Q_i - Q_{-i})_j$	Difference between the order quantities determined by supplier *j* to deliver to retailers *i* and *-i*
Treatment dummies	
HT_NF	Indicator variable for a treatment when a high trustworthy face is shown for retailer *i* and no photo for retailer *-i*; *HT_NF* = 1 if the data are from *HT_NF* treatment and 0 otherwise
HT_LT	Indicator variable for a treatment when a high trustworthy face is shown for retailer *i* and a low trustworthy face is shown for retailer *-i*; *HT_LT* = 1 if the data are from *HT_LT* treatment and 0 otherwise
NF_LT	Indicator variable for a treatment when no face is shown for retailer *i* and a low trustworthy face is shown for retailer *-i*; *NF_LT* = 1 if the data are from *NF_LT* treatment and 0 otherwise
Facial Trustworthiness dummies	
HT	Indicator variable for a high facial trustworthiness of a photo shown for retailer *i*; *HT* = 1 if the data are from *HT* face condition and 0 otherwise
LT	Indicator variable for a low facial trustworthiness of a photo shown for retailer *-i*; *LT* = 1 if the data are from *LT* face condition and 0 otherwise
Other independent variables	
A_n	Private forecast observed by retailer *n*
B_n	Forecast report provided by retailer *n* to supplier

B_i	Private forecast report provided by retailer *i* to supplier
B_{-i}	Private forecast report provided by retailer -*i* to supplier
$(B_i - B_{-i})$	Difference between forecast reports provided by retailers *i* and -*i* involved in the same supply chain group
dR_i	Indicator of the retailer *i* : $dR_i = 1$ if data are from retailer *i* and 0 otherwise
Interactions	
$A_n \cdot HT\_NF$	Interaction between the actual private forecast observed by retailer *n* and the treatment HT_NF
$A_n \cdot HT\_LT$	Interaction between the actual private forecast observed by retailer *n* and the treatment HT_LT
$A_n \cdot NF\_LT$	Interaction between the actual private forecast observed by retailer *n* and the treatment NF_LT
$A_n \cdot HT$	Interaction between the actual private forecast observed by retailer *n* and HT face
$A_n \cdot LT$	Interaction between the actual private forecast observed by retailer *n* and LT face
$B_n \cdot HT\_NF$	Interaction between the forecast report provided by retailer *n* and the treatment *HT_NF*
$B_n \cdot HT\_LT$	Interaction between the forecast report provided by retailer *n* and the treatment *HT_LT*
$B_n \cdot NF\_LT$	Interaction between the forecast report provided by retailer *n* and the treatment *NF_LT*
$B_n \cdot HT$	Interaction between the forecast report provided by retailer *n* and HT face
$B_n \cdot LT$	Interaction between the forecast report provided by retailer *n* and LT face
$dR_i \cdot (B_i - B_{-i})$	Interaction between the difference in forecast reports provided by retailers *i* and -*i* involved in one supply chain and the indicator of retailer *i*
$(B_i - B_{-i}) \cdot HT$	Interaction between the difference in forecast reports provided by retailers *i* and -*i* involved in the same supply chain group and HT face
$(B_i - B_{-i}) \cdot LT$	Interaction between the difference in forecast reports provided by retailers *i* and -*i* involved in the same supply chain group and LT face
Error terms	
ε_j	Independent error across observed decisions of supplier *j*
e_n, τ_n	Independent error across reports of retailers *n*
γ_j, ω_j	Independent error across inventory decisions of supplier *j*
α_j, θ_j	Independent error across decisions of supplier j about differences in order quantities determined to deliver to retailer *i* and -*i*

Chapter 3 Appendix 3. Treatments with Same Shown Faces

To examine the influence of facial trustworthiness on retailer's forecast sharing behavior and supplier's trust and reciprocity, we develop additional treatments where the shown faces are identical. Specifically, we run two treatments with the same shown face for both retailers. We used a photo of a face with a high trustworthiness for HT_HT treatment and a photo of a face with a low trustworthiness for LT_LT treatment, denoted HT_HT_same and LT_LT_same respectively. Participants were recruited using the same crowdsourcing platform and incentives as previous treatments with resulting number of supply chain groups 30 in HT_HT_same and 52 in LT_LT_same. Even that these treatments may be seen as unrealistic for the conservative reader, we did not receive any comments or complains about this issue from the participants.

To test the treatment effect we apply the methodology from sections 5.2 and 5.3. We use the linear regression models in Equations (7) and (9) with the new treatment indicators HT_HT_same and LT_LT_same, and NF as the reference. We simplify the models by excluding interaction among independent variables. Regression results are reported in Table C.1. We observe a significant negative effect of LT faces on both retailer's forecast distortion and supplier's reliance on received reports (p-value < 0.05). These findings conform with our original results in sections 5.2 and 5.3. Low trustworthy-looking retailers report with less pronounce distortion than retailers with no facial photo. However, suppliers rely less on their reports compared to shared forecast of retailers with unshown faces.

Table C.1. Regression Results for Testing Treatment Effect of Same Shown Faces

	Estimate (standard error)			
Variable	B - A		$\bar{I}$	
A	-0.266***	(0.04)	—	
B	—		0.608***	(0.04)
HT_HT	-11.417	(8.47)	2.518	(8.96)
LT_LT	-17.333**	(6.95)	-17.213**	(7.39)
Intercept	84.566***	(9.70)	81.155***	(10.89)

*Note: *p < 0.1; **p < 0.05; ***p < 0.01*

"—" indicates that the independent variable is not in the model. Value in parentheses are the standard errors.

Chapter 4

Clustering Behavior in Operational Choices (Meso Level). How Ideological Network Influences Terrorist Attack Tactics? An Empirical Study

Abstract

Global news reflects the inefficiency of the current counterterrorism strategy. The number of terrorist attacks worldwide continues to grow. Multiple studies have not yet discovered how the configuration of links among terrorists drives their choice of attack. Using “the starfish and the spider” framework, this empirical study examines both the centralized and decentralized structures of the terrorist network. We draw the network from operational tactics of different ideologies. Focusing on the types of attacks, we explore similarities in terrorist operations, discern clusters among ideological movements, and draw the structure of terrorist networks over time. The findings contribute to an improved understanding of the operational conception of violent groups. It was found that almost half of ideological movements connect through clusters with several links stable over decades. These networks transformed from a centralized (spider) hierarchy to a decentralized (starfish) structure and eventually evolved into the combination of two – a hybrid organization. These results provide insights for counterterrorism policy makers and strategic risk managers.

1. Introduction

In 2010, The U.S. Army launched a new pilot program titled "The Army's Starfish Program" with the intent "to promote decentralization as yet another tool to counter decentralized and networked threats" (Dempsey, 2010). The program involved the collaboration with Ori Brafman, one of the authors of the bestseller "The Starfish and The Spider: The Unstoppable Power of Leaderless Organizations" (Brafman and Beckstrom, 2006). Brafman and Beckstrom explore the implications of the rise of decentralized organizations in contrast to centralized ones. The authors used key metaphors to describe two different types of organizational structures. The spider represents the centralized organization and the starfish represents the decentralized network. Both a spider and a starfish have many legs coming from their bodies, which are the links within the organization network, but their sustainability towards disruptions is different. A spider is easy to kill by cutting its head. In contrast, a starfish does not have the central brain, and when cut in half, it will regenerate into a new starfish, making it resilient to threats.

Is the global terrorist network a spider or a starfish? A centralized organization, a spider, is efficient regarding its focused vision, fast execution of decisions, and high level of control and accountability over its operations. A decentralized network, a starfish, has advantages of flexibility and autonomy through control delegation to the lower-level leaders. The organizational dilemma is a trade-off between the benefits of a spider coordination and the resilience of a starfish (Harris and Raviv, 2002).

The answer to this question is key to managing a terrorist network. There are multiple ways to draw a network by using either social or functional relations. Primarily, from an operations perspective, we should seek to understand the terrorists' tactics. As we cannot directly observe the information transfer, we posit that similarities in attack types between terrorist groups evince channels for exchange of knowledge and information between them. In our study, we explore the structure of the global terrorist network built on tactical similarities of different ideological groups. This allows us to investigate the terrorists links through their operational interrelations on the aggregate, high-level network of these terrorist organizations. We perform network analysis to evaluate the network configuration. This technique allows us to understand the topology of the network and to measure its structural properties. By doing so, we analyze the network properties, detect communities among linked ideological groups, and compare their membership structure.

Of course, organizational structure may change over time. In response to new environmental pressures, operational strategies, or technological developments, the network structure may either shift from a spider to a starfish and vice-versa, or adjust the degree of its fragmentation. The challenge is to identify the change in organizational structure of a terrorist network in order to develop efficient counterterrorism strategies. By evaluating changes in the global terrorist network over time, we aim to provide a strategic guidance to governments. Should a government concentrate its efforts just on cutting the head off the terrorist network, or does a government need to develop a sophisticated plan to fight against each of the terrorists' "autonomous legs"? The answers are crucial for successful counterterrorism policy and managing risks of terrorist attacks.

Failure to understand the dynamics of "the starfish versus the spider" leads to fatal errors. The terrorist leader Osama Bin Laden was killed; yet, al Qaeda continued its violent operations: "Take away the catalyst [inspirational leader] and the starfish organization will do just fine. If anything, it'll be even stronger; if a catalyst is killed, the power shifts to the circles [norm based clusters], making the organization that much more decentralized" (Brafman and Beckstrom, 2006, p. 142).

On the one hand, decentralized structure explains the powerful sustainability of the terrorist network over time. After eight years of war, since the massive terrorist attacks in 9/11, The U.S. Army learned this lesson: in response to the decentralized threats they decentralized their own capabilities. Army leaders were retrained to think, act, and operate more decentralized (Dempsey, 2011). The launch of a new military program supports an assessment of the terrorist network as a fragmented, starfish-type organization. On the other hand, recent attacks are complex coordinated "acts of terrorism that involve synchronized and independent team(s) at multiple locations"(FEMA, 2018). The complexity of violent actions requires a well-planned scenario with critical details such as location, time, and magnitude of the incident. From the view of operations management practice, we know that the carrying out of extreme operations is possible only with managerial directives from a leading center which plans, organizes, directs, and controls the activities. These opposing viewpoints lead to the assumption that a terrorist network is neither a pure starfish nor a pure spider. Using data over a period of 46 years, we investigate the structural changes in the terrorist ideological network over time and explore the stability of the formed ties and clusters. Paradoxically, our analysis suggests the combination of characteristics of both types - centralized and decentralized – can be seen in the terrorist network.

The analysis of operational choices made by terrorists through their ideological root causes provides a new perspective on the network structure behind the violent operations. We have found that almost half of the terrorist ideological movements executed matching tactics in their operations. Some of the terrorist ties have been stable over decades. Network analysis revealed the evolution of the terrorist network structure from a centralized spider to a decentralized starfish with some spider elements. The organizational structure has significant implications on the network performance. The change in the network organization correlates with changes in the terrorist tactics. By studying these transformations, we seek to commit to a better understanding of the terrorist network structure and foresee the types of future threats. Analyzing the ideological terrorist network by its tactics exhibits strategic operational implications for counterterrorism policy makers and strategic risk managers.

The article is structured as follows. After the literature review and formulation of research questions we describe the data collection procedure. Next, we split our discussion into two streams. We examine (1) the network ties by structural properties and detect clusters among ideological groups, and (2) study the network transformation over time. Finally, we discuss results with managerial and policy implications.

2. Literature review

The peak in terrorism research came after the massive terrorist attacks on 9/11. The terrorism problem has been discussed from a variety of research perspectives. Root causes such as poverty, social inequality, demographic and political factors have been argued as direct conditions for terrorism (O'Neill, 2003, Stern, 2003, Ehrlich & Liu, 2002, Scruton, 2003, Denoeux, 2013, Juergensmeyer, 2017). The discussion was extended to arguments about why "root causes" are important in explaining terrorism. Edward Newman (2006) proposed the idea of "root causes" driving terrorism as a significant insight into how, where and why terrorist acts occur. A certain relationship exists between the underlying political, social, economic and demographic conditions and terrorist activities. He recognized two major streams in "root causes" which are (1) permissive structural factors such as poverty, demographics and urbanization, and (2) direct roots of grievances which include social inequality, human rights abuse, religious and other beliefs, values controversy, globalization and invasion. The authors agreed on the claim that "root causes" are helpful in understanding specific categories of terrorist attacks. Weinberg et al. (2004) emphasized the importance of ideological factors for the choice of behavior of a terrorist group. This argument leads to the assumption that terrorist activity conducted by a responsible terrorist organization is driven by a proclaimed ideology. Grounded on the relationship between operational tactics and ideology, the first research question emerges:

(Q1) Are there any methodical similarities in terrorist tactics of different ideological roots? Is there any terrorist ideology that is different from others in their methodology?

Several studies have been done in the area of terrorist operations (Strang & Alamieyeseigha, 2015, Oprescu, 2013, Rivinius, 2014) but few attempts were made to explore the relationship between terrorist tactics and ideology. Strang (2015) identified the ideology driving a terrorist attack based on the difference between nationalities of the terrorist group and the target society. The two-step cluster analysis revealed terrorism nationality and the choice on attack type are significantly interrelated in the patterns on the magnitude of the attack. Strang and Sun (2017) continued to analyze the link between terrorist ideologies and attack types through the integration of big data analytics with statistics. The researchers used Hadoop big data text analytics to collect the information of the ideological roots from the news media coverage. Based on the correspondence analysis, they found significant interrelation between ideologies and attack types. Following the direction of Strang and Sun, we extend the study of relationships between ideological roots based on deployed tactics. With the aim to do so we specify the list of ideological roots using the library of the Terrorism Research and Analysis Consortium and apply network analysis to reveal a clustering tendency among them. This directs us to our second research question:

(Q2) Is there any grouping tendency among terrorist ideologies based on similar tactics?

The tactical linkages among violent ideologies allows us to draw the terrorist network. Referring to the theory of organizations, network structure differentiates into two organizational types – centralized and decentralized (Hage, 1965). Brafnam and Beckstrom (2006) represented a centralized structure as a spider and a decentralized network as a starfish. For the ease of articulation we will use their typology. A spider is an organization with a strong hierarchy relying on a controlling leading center (or a leader). While a spider is efficient regarding the fast execution of operational decisions, it may suffer from a delay in the decisions accomplishment. A starfish is characterized by flexibility and greater autonomy delegated to the lower-level leaders. The diversity of expertise and knowledge benefits decision-making to handle various situations but may cause a conflict. It appears that both a spider and a starfish are similar in their look – many legs are coming from their bodies. But, upon closer inspection, we find that a starfish has no central brain. All its organs, including brain and memory, are distributed throughout the body. It is easy to kill a spider by cutting its head, but it is almost impossible to kill a starfish. When any parts of a starfish are cut, it can grow them back, or even replicate the entire body from just one piece. This makes a starfish organization powerful and highly resilient to many threats.

There are two venues in the literature that focus on the optimal structure of a terrorist network. Enders and Jindapon (2010) argued that decentralized decision-making is not efficient from the network perspective and a central leader is needed to coordinate the network operations. Brafnam and Beckstrom (2006) expressed the opposing view by exploring the implications of the rise of decentralized organizations. They noted the structure of al Qaeda as an example of a starfish. It is organized from the ordinary people united by the common ideological philosophy, who are fragmented into autonomous cells and spread all over the world. This structure was essential for al Qaeda to coordinate similar attacks over wide geographical distances (Krebs, 2002, Sageman, 2011). Thus, the third research question arises as:

(Q3) What is the organizational structure of the global terrorist network?

The terrorist network changes over time. It mutates, adjusting organizational structure to geographical expansion and new environmental pressures, which includes changes in counterterrorist policies. Recent studies, broadly categorized as defender-attacker problems, found that risk mitigating government strategies against terrorist risk can directly impact further terrorists' actions (Pourakbar and Zuidwijk, 2018, Insua, 2016). The rise in decentralization of terrorist networks was suggested as a response to the increase in government efforts to destroy them (Everton, 2012). Bier and Gutfraind (2019) proposed a concept of "defensibility which examines the changes in the system value in response to defense efforts". They found that defensibility depends not only on the values distributed within a network but on the nature of outside threats, suggesting the responsive property of terrorist networks.

With the goal to monitor structural changes in terrorist networks, Everton and Cunningham (2013) incorporated the longitudinal analysis into the network change detection. They found the shift in the Noordin Top terrorist network towards decentralized structure in a hostile environment. The follow-up study of al-Muhajiroun's networks identified a similar tendency (Kenney et al., 2017). Opposed to the prior focus on the individual or group level, our study contributes a holistic analysis of the structure of the global terrorist network, which includes the terrorist groups driven by various ideological reasons.

Assuming the potential of terrorist operations to change over time, emphasized by proactive risk management (Knemeyer et al., 2009) and reactive defensibility of terrorist networks, we developed the fourth research question:

(Q4) Has the structure of ties among terrorist groups changed over time or is it constant?

3. Data

To answer the research questions, we gathered data from two major sources and then integrated it into one sample. Historical information about terrorist attacks was collected from the Global Terrorism Database (GTD) and the ideologies of terrorism were retrieved from the Terrorism Research and Analysis Consortium (TRAC). We identified the primary root causes of every terrorist attack by linking it with the responsible terrorist organization (Newman, 2006).

The Global Terrorism Database (GTD) is the open-source database which includes the records of terrorist attacks from 1970 through 2016. On an ongoing basis, The National Consortium for the Study of Terrorism and Responses to Terrorism (START) (2016b) based at the University of Maryland collects, organizes and distributes the information about terrorist acts from a variety of available media resources. GTD carries a record of every single terrorist act in a separate line with up to 120 different attributes. The database, which we used for this study, contains more than 170,000 unique records of attacks and provides the description of each act including the incident date and location, the perpetrator group name, the tactics used in attacks, the nature of a target, types of weapons used, an indication of attack success, the total number of fatalities and injured people, and the amount of property damage.

GTD defines terrorism as "the threatened or actual use of illegal force and violence by a non-state actor to attain a political, economic, religious, or social goal through fear, coercion, or intimidation" (Codebook: Inclusion Criteria and Variables, 2016a, p. 9). For the incident's inclusion, three attributes must be present: (1) the incident must be intentional and (2) execute some level of violence or threat of violence, and (3) the perpetrators must be sub-national actors. The database does not include records of activities of state terrorists and legitimate warfare.

The Terrorism Research and Analysis Consortium (TRAC) represents the library of groups and individuals that execute, support, and condone violence. It provides information about more than 4,650 terrorist groups with a short description of historical development and identifies their ideological roots, targets, and tactics. More than 2,800 experts contribute to the TRAC library by reporting and updating news about acts of violence.

For the purpose of this study, the ideologies of terrorist organizations were scrapped from the TRAC website (https://www.trackingterrorism.org) by using the Beautiful Soup library in Python resulting in a total of 4,350 files. GTD identifies 3,454 organizations responsible for recorded terrorist acts. On the integration step, two datasets were synthesized and refined into one sample (we applied Jaccard similarity index > 0.6). The resulting sample contains records of 19,864 terrorist attacks affiliated with 864 terrorist organizations. According to their proclaimed ideology, the terrorist organizations were grouped into 31 ideological movements. The detailed description of each ideology is provided in Chapter 4 Appendix 1. Table 1 represents the descriptive distribution of ideological groups in the resulting sample.

Table 1. Distribution of Ideologies in the Sample

id	Terrorist Ideology	Terrorist Groups	Number of Attacks	Number of killed	Number of wounded
id	**Total of unique observations**	**864**	**19864**	**40837**	**39251**
i1	Separatist / New Regime Nationalist / Ethnic Nationalist	327	8956	20511	19035
i18	Transnational Crime and Terrorism / Organized Crime	40	8087	15562	9112
i9	Left Wing Terrorist Groups (Marxist)	123	6826	19266	4683
i6	Narcoterrorism	32	5334	14386	5633
i28	Terrorism and Governmental Policy	11	5221	12291	4915
i19	Political Responses to Terrorism: Kashmir	74	4603	5437	9633
i10	Extremist Right Wing Terrorist Groups	64	3359	2697	4947
i4	Cell Strategy and Terrorist Groups	7	3108	2408	4514
i8	Left Wing Terrorist Groups (Maoist/ Marxist/ Communist/ Socialist)	141	3036	3717	3673
i14	Diasporas and Terrorism	5	2958	2380	4607
i11	Jihadist Terrorist Groups - Religious (Islamic)	82	1861	5787	8835
i12	Ideological Sources of Radical Islam - Religious (Islamic)	84	1846	5307	7558
i17	Economic Terrorism and Extortion	32	1512	2163	2112
i30	Urban Terrorism	2	956	1773	2326
i3	Racist Terrorist Groups	52	760	831	1361
i2	Left Wing Terrorist Groups (Anarchist)	98	608	518	426
i22	State Sponsored Terrorism	17	599	1031	1772
i16	Comparative Religious Terrorist Groups (Christian/ Hindu/ Jewish/ Sikh)	39	461	563	555
i5	Current Regime Nationalists Terrorist Groups	32	437	2467	2713
i23	Quranic Understandings of Violent Jihad - Religious Terrorism (Islamic)	26	322	604	1019
i21	Environmental Terrorist Groups	21	230	94	28
i25	Terrorism and the Lone Wolf	4	192	0	12
i7	Third Party Combatants as a Tool of Terrorism	9	77	381	554
i13	Religious (all) and Cult Terrorist Groups	18	57	125	6978
i15	Terrorism International Law	1	49	77	121
i26	Policy Making within Transnational Terrorist Organizations	4	45	7	7
i24	Terrorism and Warlordom	6	34	312	87
i20	Radical Islam and Anti Globalization	3	7	16	42
i27	Differences between Islamic State (ISIS) and Nusra Front (JN)	1	2	0	0
i31	Evolutionary Process of Political Violence to Terrorism	1	2	4	1
i29	Deterring Terrorism	1	1	0	0

GTD determines tactics used by the perpetrator for every recorded attack. There are nine identified types of terrorist attacks: (1) armed assault, (2) assassination, (3) bombing / explosion, (4) facility/ infrastructure attack, (5) hijacking, (6) hostage taking (barricade incident), (7) hostage taking (kidnapping), (8) unarmed assault, and (9) unknown type. The detailed description of terrorist attacks types is given in Chapter 4 Appendix 2.

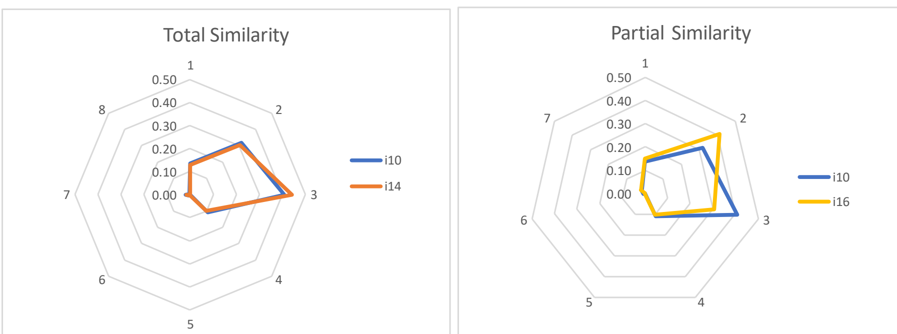
4. Analysis

In the resulting sample, we coded 31 ideologies with notations ranging from i1 to i31 (the code dictionary is given in Chapter 4 Appendix 3) and 9 attack types (see Chapter 4 Appendix 2 for the detailed description). Assessing the data with the purpose of finding patterns in attack methods of terrorist organizations, we decided to ignore the type nine stated as "Unknown" attack type. In the analysis, we focus on the eight types of attacks defined explicitly in GTD. The proportion of the most used tactics in the sample extracted from GTD aligns with the previous findings (Strang, 2015). Three attack types—armed assault, assassination, and bombing—account for over 70% of total operations in 27 of the ideological segments (see Chapter 4 Appendix 4).

Next, following the research questions structure, we split our discussion into two venues: (1) similarity in the frequency of deployed tactics among identified root causes of terrorists, structure of the terrorist network and community detection, and (2) transformation of network structure and community development over time.

We considered two types of classification methods to the data: a whole matching method to assess the total similarity of the choice frequency distribution of attack types (Chakrabarti et al., 2002) and a subsequent pairwise matching method to estimate partial similarity of the operational choices (Faloutsos et al., 1994, Sadahiro and Kobayashi, 2014). Figure 1 illustrates the difference between two methods. The total similarity method classifies ideologies i10 and i14 into the same group by considering the entire vector distribution of made choices (1-8). The partial similarity method identifies ideologies i10 and i16 into the same group by matching on three attack types (1,4, and 7).

Figure 1. Two Methods of Evaluation of Similarity between Ideologies



We find that the total similarity analysis is limited to the comparison of the vector distributions of eight attack types which makes this method inflexible for the network analysis. Since observed results of two matching methods, total and partial similarities, align to a large extent, we decided to examine the network from a partial similarity of terrorist tactics to draw further conclusions from the analysis. The total similarity analysis is presented in Chapter 4 Appendix 5. The analysis of partial similarity is discussed in details in the next part of the study.

4.1. Similarity: Structure of Terrorist Network and Community Detection

4.1.1. Partial Similarity

Partial similarity analysis explores the likelihood of choosing the same type of attack by two ideologies without limiting to the entire vector distribution of eight attack types. This method is based on the subsequent pairwise matching of every attack type choice (Faloutsos et al., 1994, Laub et al., 2006). With the purpose of revealing the maximum number of possible matches, we limited the length of subsequences to one attack type.

In order to detect similarity, we applied the two-side proportion test without corrections (Larntz, 1978) which detects the likelihood of similarity for every attack type between two ideologies. Based on the pairwise proportion comparison test (significance level $\alpha = 0.05$), pairs of ideologies with p-value > 0.05 were determined as having nonzero similarity in the choice of the attack type and were binary coded as having the link between them. Following this procedure, we identified similarity links for 465 pairs of ideologies and structured them into eight adjacency matrices for eight attack types. Next, we compounded all adjacency matrices into one matrix with the weights distributed from 0 to 8, reflecting the number of attack types when two ideologies were found to be similar. The resulting adjacency matrix was used for the network analysis. Similarities between nodes articulated via edges are the core concept of detecting relationships in the network.

4.1.2. Network Analysis

Network analysis (or social network analysis, NA) is an analytical tool built on graph theory (Freeman, 1978, Kirchherr, 1992). The social network is a way of thinking about relationships between actors within the system network (Borgatti et al., 2018). The actors in the system are called “nodes” or “vertices”. The existing relationships between actors are shown as links connecting two nodes and called “edges”. Ties among actors can be detected through explicit (direct relations) and functional (similarities, interactions, and flows) relations.

Initially, NA was developed for the analysis of different types of relationships within a certain community, such as friendships, acquaintanceships, family links, and other relative roles (Milgram, 1967, Atkin, 1977). However, an application of NA is not just limited to social relationships. It has been expanded to nonsocial interactions including diffusion of innovations (Abrahamson & Rosenkopf, 1997, Young, 2006), supply chain networks (Borgatti & Li, 2009, Kim et al., 2011), and strategic management (Mahmood et al., 2011, Larcker et al., 2013). Recently, NA has been widely used to study the relationships of terrorist groups and central actors (Ressler, 2006, Perliger & Pedahzur, 2011, Yang & Sageman, 2009) and was even introduced as an investigative tool for organized crimes (Van der Hulst, 2009). Using NA for prediction of terrorist attacks in 2014-2015, Tutun et all. (2017) achieved an accuracy of more than 90% compared to historical records. We take inspiration from NA and applied this technology to study nonsocial links in the global terrorist network.

Borgatti et al. (2018) stated: "Network analysis is about structure and position." Application of computational foundation from the graph theory allows the expression of structural network properties in mathematical terms. The qualitative description of the network is derived from node positioning and its graphical shape. A combination of methodologies to map, measure and analyze the relationships between actors differentiates NA from other methodologies. NA is well incorporated for the purpose of our study. We use the tactical similarity to draw the indirect informational connections among terrorist ideologies. This allows us to capture complex interactions among violent actors, which are terrorist ideologies (Tutun et al., 2017), with further detection of the formed communities. NA focuses on three levels of analysis: node, dyad, and network. We define the ideological terrorist network (or network) as the unit of analysis in our research.

The NA framework we applied is limited by its binary structure. We acknowledge that the robustness of the analysis may increase by adding weights for considered features and combining distance measures with the probability of frequency measure. Yet, the weighted (or valued) networks are limited in its community detection algorithms due to the computational complexity. “Few methods can handle link directions and weights, while we wanted to test a broad class of techniques.” (Hric, Darst, and Fortunato, 2014, p. 8). Thus, for the purpose of the current research, the binary method is beneficial because it provides a higher degree of computational power at the network level.

To transform the weighted adjacency matrix into the binary networks, we used the cut-off measures. The lower boundary of cut-offs are estimates of the similarity index (SI), which is the proportion of similar attack types to the total number of attack types. Following this procedure, we generated eight networks with nodes representing the terrorist ideologies and edges mapping the ties between nodes. An equal number of nodes (31) make networks comparative. Then, we analyzed the structure of developed networks by exploring their properties which are listed in Table 2. The network theory identifies the list of multiple properties measurements (Borgatti et al., 2018) but we consider several of them as attributable for the purpose of our analysis.

Table 2. Network Properties

		net_1	net_2	net_3	net_4	net_5	net_6	net_7	net_8
		no cut off	cut off < 2	cut off < 3	cut off < 4	cut off < 5	cut off < 6	cut off < 7	cut off < 8
Similarity Index		0.13	0.25	0.38	0.50	0.63	0.75	0.88	1.00
Number of Nodes		31	31	31	31	31	31	31	31
Number of Edges		165	43	12	2	1	0	0	0
Density		0.355	0.092	0.026	0.004	0.002	0.000	0.000	0.000
Centralization	Degree	0.345	0.174	0.141	0.029	0.031	0.000	0.000	0.000
Centralization	Closeness	0.058	0.044	0.012	0.002	0.002	0.000	0.000	0.000
Centralization	Eigenvector	0.511	0.744	0.927	0.931	1.000	0.000	0.000	0.000
Centralization	Betweenness	0.029	0.092	0.022	0.000	0.000	0.000	0.000	0.000
Clustering	Global	0.653	0.373	0.316	NA	NA	NA	NA	NA
Coefficient	Average	0.699	0.473	0.367	NA	NA	NA	NA	NA
Homophily		-0.072	0.054	-0.124	NA	NA	NA	NA	NA
Diameter		3	6	3	1	1	0	0	0

The network cohesion, or connectedness, is described by measurements of density, centralization, clustering coefficient and homophily (Freeman, 1978, Otte & Rousseau, 2002, Borgatti et al., 2018). It characterizes the structure of network ties and the degree of nodes' connectedness. *Density* is the simplest cohesion estimate which reflects the proportion of identified edges from the total number of possible edges. In other words, the density may be seen as the probability of the link between two randomly chosen nodes. The other widely used measurement is the network centralization.

Centralization reveals the tendency of some nodes in the network to be maximally centered while others minimally. Computed from the nodes centrality measures, the score of network centralization represents the variation in the nodes centrality adjusted by the maximum possible variation in centrality in a similar network or a network of the same size. We used four approaches to compute the score of network centralization: centralization degree, closeness, eigenvector, and betweenness. Degree centrality is based on the number of ties between nodes. Closeness centrality is the inverse measure of the node's average geodesic distance to other nodes. Eigenvector centrality describes the degree on which the node is connected to other central nodes and is proportional to the sum of connection centralities. Betweenness centrality applies the number of the shortest paths going through the node. Comparing five terrorist ideological networks (from the net 1 up to the net 5) both measures, centralization (accept eigenvector centralization) and network density, decrease with the stronger SI (please, see Table 2). The steepest change in degree centralization is between networks 1 (SI $\geq$ 0.13) and 2 (SI $\geq$ 0.25), but the shift between networks 2 (SI $\geq$ 0.25) and 3 (SI $\geq$ 0.38) is flat.

The measure of *clustering coefficient* identifies the network tendency to be denser in some parts. It measures the probability of ties formed by adjacent nodes. The estimates are based on the transitivity relation, which expresses the expectation of two unconnected nodes to form a tie between them if they are both linked to the same third node. Global clustering coefficient is the ratio of triangles (with the length of three edges) to connected triples (with the length of two edges). Average clustering coefficient is computed as the average ratio of local clustering coefficients or the ratio of triangles to connected triples each node is part of. Due to the networks sparsity, clustering coefficients are identified only for three terrorist networks: the net 1, 2 and 3 (SI ≥ 0.13, 0.25 and 0.38). Both global and average clustering measures decrease with the decline in network density (please, refer to Table 2).

The *homophily* score characterizes how similar the tied actors are. The homophily is measured based on the assortativity coefficient, or the correlation of degrees between connected vertices. The negative score determines a disassortative nature of a network, when high degree nodes (nodes with the larger number of ties) tend to connect with low degree nodes (nodes with the lower number of ties). The strongest homophily (-0.124) is reported for the net 3 (SI ≥ 0.38) (estimates are provided in Table 2).

Diameter is the longest geodesic distance within the network, where the geodesic distance is the length of the shortest path between two nodes. The diameters of all networks do not exceed 6 links, this implies that the structure of formed ties is dense and centered (please, refer for details to Table 2).

To test the significance of the identified network, we applied the quadratic assignment procedure (QAP) (Hubert, 1987). The QAP correlation test allows to compute the correlation between entries of two square matrices and access its statistical significance. The adjacency matrix of the network 3[7] was compared to the randomly permuted structure matrices (1000 permutations were applied). The procedure was bootstrapped 5000 times. The QAP correlation test indicated that no significant correlation was detected between the network 3 and the random networks (p-value = 0.96). Therefore, the identified structure of ties in the network of terrorist ideologies is significantly different from the random structure.

4.1.3. Community Structure Analysis

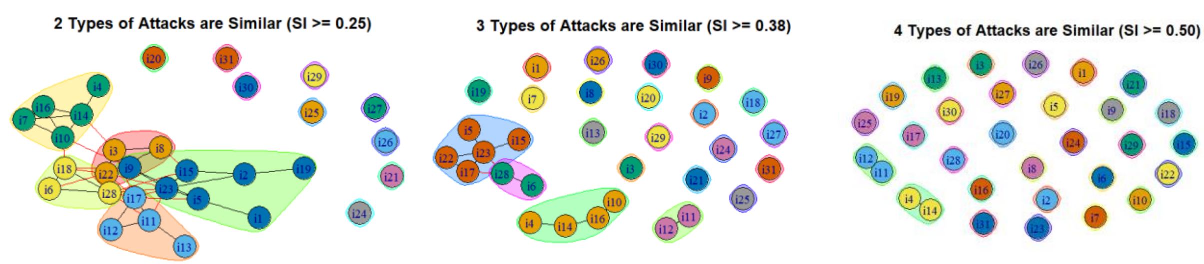
To further explore the similarity patterns of ideologies, we looked at the clustering tendency among nodes. Community structure displays the network as clustered vertices. Multiple community detection algorithms aim to separate clusters of densely connected nodes with fewer connections across other clusters. We applied seven community detection algorithm provided within the iGraph library (an R-Studio package): Walktrap, Fastgreedy, Newman-Girvan, Leading eigenvector, Label propagation, Multilevel, and Informap (Spinglass was omitted from analysis due to the computational limitations). While all algorithms derived similar patterns in the community formation, we found a deviation in the number of detected clusters (between 3 and 4). To identify the community structure, we compared algorithms modularity scores, which represent the degree of strength of division network into groups (Newman, M.E, 2006). The highest modularity score (0.489) was reported for four community detection algorithms: Fastgreedy, Newman-Girvan, Multilevel, and Label propagation. The first three of them determined identical community structures.

In order to choose the most adequate algorithm, we considered an additional accuracy parameter — the mixing parameter (μ) (Yang et al., 2016). The mixing parameter (μ) is defined

[7] We chose the network 3 for the QAP analysis as the representative network which is used for the further inferences in our study

as the proportion of the number of edges connecting two different communities to the total number of edges in the network. The accuracy of algorithms decreases with an increase in values of both network size and μ. In our analysis, the estimated μ is relatively small (μ < 0.5) for all algorithms and the network size is stable (n=31). Thus, the accuracy is relatively high for all algorithms. Considering that the results of Multilevel (Louvain) algorithm exhibited the highest degree of reliability (Yang et al., 2016), we applied Multilevel algorithm for our further analysis. Next, we detected communities for three networks (SI ≥ 0.25, 0.38 and 0.50) (Figure 2) and compared their membership structure (see Chapter 4 Appendix 6).

Figure 2. Network Communities



Networks 2 and 3 (SI ≥ 0.25 and 0.38) have a higher degree of density and form larger communities comparing to the sparse and dyadic network 4 (SI ≥ 0.50). The structure of community membership changes with an increase in SI, but two dyads are recognized in all three networks (Figure 2). The first dyad (i11-i12) is the link between two ideologies with Islamic Religious roots, Jihadist Terrorist Groups (i11) and Ideological Source of Radical Islam (i12). The second dyad (i4-i14) reveals the additional strong link between Cell Strategy and Terrorist Groups (i4) and Diasporas and Terrorism (i14).

Exploring the structure of detected communities in network 3 (at least three similar attack types), we found that the structure of defined clusters varies (see the middle graph in Figure 2).

There are two dyadic clusters which are not tied (i11-i12) or have weak connections (i28-i6) to other nodes. The third community (i4-i14-i16-i10) has a simple chain structure what indicates weak ties (indirect link through the third node) and bridges between nodes. Weak ties provide an advantage in spreading the information and creativity throughout the formed community, but bridges are critical for cutting the informational flows within the community (Ahuja, 2000). Network bridges point out the weakness (possible structural holes) in the network structure (Borgatti et al., 2018). From a counterterrorist perspective, discovered bridges are of the biggest interest as they are crucial points for the successful network disruption. The fourth community (i5-i15-i17-i22-i23) has a complex ("star" type) structure and is linked to the second dyad. Together they form a subnetwork with many weak ties, which makes this structure resilient to threats.

In addition to the detected communities, Figure 2 illustrates that 18 nodes in the network 3 (at least three similar attack types) are not associated with any other node, and those 18 nodes are fully autonomous within the terrorist network. The nodes depicted as having zero ties are called isolates (or outsiders). Some of them (i20, i27, i29, i31) may have fallen into the group of isolates due to the small sample size (please, see the last four rows listed in Table 1). Other isolates represent a considerably large number of attack records. Among them are Separatist / New Regime Nationalist / Ethnic Nationalist (i1), Transnational Crime and Terrorism / Organized Crime (i18), Left Wing Terrorist Groups (Maoist/ Marxist/ Communist/ Socialist) (i8).

4.1.4. Validating the Detected Communities: Facts from the Field

We validate detected results by listing the records of historical evidence. The observed collaboration among terrorist actors with different ideological beliefs confirms the results we draw based on NA. We believe that the history provides the strongest arguments for our findings.

The ideologies Cell Strategy and Terrorist Groups (i4) and Diasporas and Terrorism (i14) were categorized into the same community in all three considered networks which emphasizes the strength of this dyad (Figure 2 illustrates the networks). This type of connection was widely pictured in Canada. Canada, described sometimes as a cultural mosaic, "has a history of spillover effects from conflicts based in other countries" (Canadian Security and Intelligence Service, 1999). The flow of immigration in the early 1970s brought to Canada immigrants having strong political, religious, and ethnic-national beliefs at a time of growth in terrorist organizations with an implemented cell strategy. Among them were the *Irish Republican Army (IRA), Palestine Liberation Organization (PLO), Hezbollah, and Armenian Secret Army for the Liberation of Armenia (ASALA)*. The terrorist groups launched support and propaganda networks among diasporas in Canada and used them for fundraising, new hires, and channeling supply and logistics (Bell, 2009). Homeland terrorism took root in the 1980s when Turkish diplomats were shot in Ottawa after several assassination attempts by *ASALA*. Another known terrorist group *Liberation Tigers of Tamil Eelam (LTTE)* carried its activity in Toronto through the largest diaspora outside of its “home base” in Shri Lanka. They propagated terrorism fundraising for *Tamil Tigers* through thousands of demonstrators in Toronto. The growth in terrorist operations extended up to 2000. The fundraising network caused one of the biggest finance investigations in Canadian history. After 9/11, Canada began to reshape its counterterrorism policy by enacting the Antiterrorism Act and by strengthening National Security Enforcement.

The ideologies Terrorism International Law (i15) and Quranic Understanding of Violent Jihad -Religious (Islamic) (i23) are found related in networks 2 and 3 (SI $\geq$ 0.25 and 0.38) (please, refer to the graphs in Figure 2). Terrorist groups (*e.g., Black September*) that view legal agreements and treaties between countries as a restraint to national sovereignty are associated through the utilized methods of attacks with organizations (*e.g., Palestinian Islamic Jihad (PIJ), Hizbul Mujahideen (HM), Taliban*), that interpret the Quran for extension of their violence. The invasion of Afghanistan by the USSR and the US with a purpose to impose political concepts of communism and democracy faced the strong resistance from *Taliban*, fighting against the alien value systems (Dibb, 2010). *Taliban* saw these foreign concepts as an apostate religion that competes with Islam and threatens Islamic laws (Rogan, 2010).

4.1.5. Summary

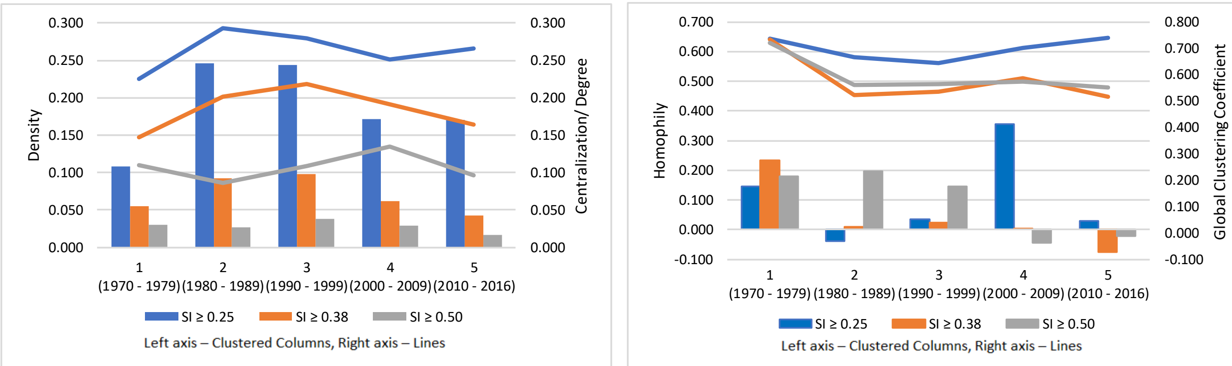
Our analysis reports that 13 ideological movements (network 3) were connected through 165 links either directly or through a third agent and 18 ideologies were fully autonomous. Within formed networks, players with a large number of connections grouped with players with a small number of links. Linked ideologies grouped into 4 clusters with different structures which include dyad, chain and subnetwork. A structural type describes possible weaknesses and strengths in the network. The chain points out opportunistic structural holes in the terrorist connections. In particular, an isolation of a key player or a break of a central link will negatively affect coordination within a cluster. However, the subnetwork is difficult to disrupt. Multiple weak ties enhance the resilience of information path. The nodes clustering tendency reveals an evidence of a network centralization. Yet, its sparsity indicates a decentralized structure. We assume that clusters represent a residual effect of the network structural mutation from a spider to a starfish with some remnants.

4.2. Stability of Similarities: Network Structure and Community Development Over Time

4.2.1. Network Analysis Over Time

We explored the structural dynamics of ideological terrorist network by examining three sets of networks (SI ≥ 0.25, 0.38 and 0.50) generated for different time periods. The sample was split into five subsamples corresponding to five time periods: (1) 1970 – 1979, (2) 1980 – 1989, (3) 1990 – 1999, (4) 2000 – 2009, and (5) 2010 – 2016. To check the robustness of our results, we created a matrix group of 55 networks by sequentially shifting boundaries of time frames by one year (illustrated in Chapter 4 Appendix 7.1). Through the means of shifted time frames, we captured valid longitudinal trends. To trace changes over time, we applied the structure analysis of networks properties (similar to the analysis in part 4.1.2) to every network from the matrix. The detailed graphs that illustrate shifts in the network cohesion properties are provided in Chapter 4 Appendix 7.2. These graphs describe the dynamics of four network cohesion properties—density, degree centralization, clustering coefficient and homophily—over time for three networks. To illustrate the changes, we plot the median point estimates (please, refer to the graphs on the left in Chapter 4 Appendix 7.2) and smooth mean estimates (please, refer to the graphs on the right in Chapter 4 Appendix 7.2) for moving time frames. By comparing trends over time in the network cohesion properties of smooth mean estimates for moving time frames (illustrated by the graphs on the right in Chapter 4 Appendix 7.2) and structural properties of networks with time frames fixed on the five decades — (1) 1970 – 1979, (2) 1980 – 1989, (3) 1990 – 1999, (4) 2000 - 2009, and (5) 2010 -2016 — (illustrated by Figure 3), we observe that changes in two analyzed network sets align. Thus, we decided to proceed in our analysis with the network with time frames fixed on the five decades.

Figure 3. Network Cohesion Properties Over Time



There are apparent patterns in the network's historical transformation. A significant growth in connectedness that occurred in the 1980s remained for two decades, up to 2000. The density coefficients of network sets 2 and 3 (0.244 - 0.246 and 0.092 - 0.098 accordingly) are reported higher in the 1980s than in the previous 1970s (0.108 and 0.055 respectively) (please, refer to the left graph in Figure 3). The measure of degree centralization relates to the rise in connections in the same periods—the score estimates in the 1980s and 1990s (0.280 – 0.294 and 0.201 – 0.219 for network sets 2 and 3 respectively) are comparatively larger than in the 1970s (0.255 and 0.148). Considering network set 3, the tendency of some nodes to have more connections over others achieves its highest point in the 1990s.

The highest global clustering coefficients (0.736, 0.734 and 0.721 for network sets 2, 3 and 4 accordingly) along with the significant homophily scores (0.147, 0.234 and 0.181) are noted in the 1970s (please, see the right graph in Figure 3). This implies that in the 1970s actors were likely to group with members similar to them. For the consecutive two decades 1980 – 1999, the variation in parameters suggests a relaxation in the network clustering tendency. The second wave of cluster tightening is reported in the 2000s (0.701, 0.588 and 0.572 for the net sets 2, 3 and 4 accordingly). In 2000 – 2016, a decline in homophily scores of strongest ties (network sets

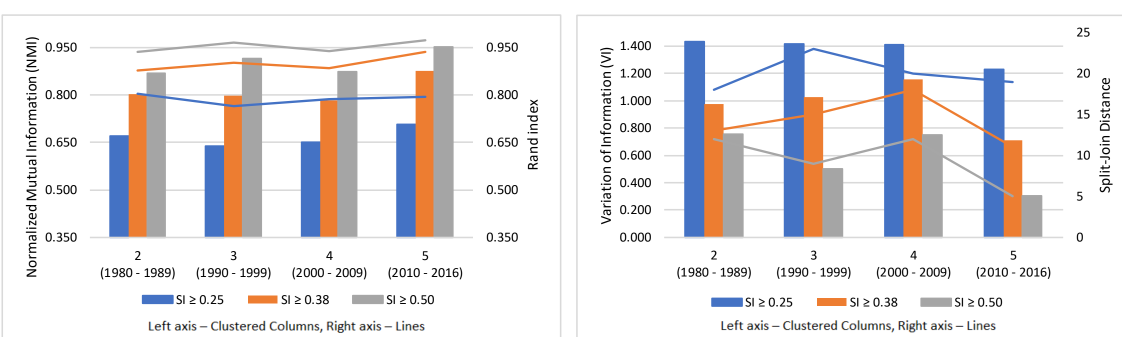
3 and 4) refers to the change in a nature of connections when connections between dissimilar actors became more likely.

We also examined changes over time with respect to a number of similar edges and harming distances—a number of different edges (see Chapter 4 Appendix 7.3). The results suggest the peak growth in stability of links among ideologies in the 1990s when the number of similar edges observed in two consecutive periods is the highest (73 for the net sets 2 and 18 for the net set 3). A slow decrease in stability of ties in the 2000s (56 for the net sets 2 and 10 for the net set 3) and 2010s (42 for the net sets 2 and 8 for the net set 3) supports the drop in network connectedness reported earlier (please, see the trends in Figure 3).

4.2.2. Community Structure Analysis Over Time

Along with structural transformations, the clustering tendency of terrorist networks changed over time (see Chapter 4 Appendix 7.4). We analyzed differences in community structures using four methods: the variation of information (Meilă, 2003), the normalized mutual information (Danon et al.,2005), the split-join distance (Van Dongen, 2000), and the Rand index (Rand, 1971).

Figure 4. Variation in Community Structure Over Time



The variation of information (VI) and the normalized mutual information (NMI) are based on the notion of information entropy associated with the average amount of information produced by the network data. VI measures the amount of information lost and gained in changing from clustering to clustering over time. The measure of NMI indicates what portion of information about the community structure in a recent period can be discovered from the community structure of a preceding period. NMI is based on a matrix partitions comparison and proposes a more discriminatory approach compared to VI. The detailed estimates for all time frames are provided in Chapter 4 Appendix 7.5. With some degree of variation, the analysis of VI and NMI reveals common trends in terrorist networks. Figure 4 demonstrates the change in VI and NMI measures compared to the previous period. In the 2000s, the analysis of networks 3 and 4 suggests an increase in VI (from 1.027 in the 1990s up to 1.159 in the 2000s for the network SI > 0.38 and from 0.500 in the 1990s up to 0.751 in the 2000s for the network SI > 0.50) with a simultaneous drop in NMI (from 0.797 in the 1990s down to 0.783 in the 2000s for the network SI > 0.38 and from 0.916 in the 1990s down to 0.873 in the 2000s for the network SI > 0.50). In the 2010s, the trend reversed into a steep decline in VI (down to 0.713 for the network SI > 0.38 and 0.302 for the network SI > 0.50) and an increase in NMI (up to 0.876 the network SI > 0.38 and 0.951 for the network SI > 0.50). Thus, we observe a directional shift in clustering behavior over time. After 2000, a stability of informational paths was distorted what lead to a change in communities membership. A decade later in the 2010s, the structure of formed clusters stabilized, which is reflected by a decrease in membership differences between clusters along with a rise in a portion of learning from the previous period.

Similar to NMI, Rand Index and Split-Join Distance measure a similarity between membership structures of communities. Rand Index depicts a number of correctly classified pairs of clusters' elements between two networks. When it equals 1, the clusters' structures are identical. Additionally, we examined the Adjusted Rand Index (Hubert and Arabie, 1985) computed as a difference between reported Rand Index and the expected value of randomly drawn clusters with the fixed number of clusters and elements (please, refer to Chapter 4 Appendix 7.5). Split – Join Distance (SJD) indicates a number of vertices that need to be moved to obtain one clustering from the other. Figure 4 illustrates the variation in Rand Index and Split-Join Distance compared to the previous period. All three indices suggest an increase in a stability of community membership structures in the 2010s after its drop in the 2000s. From all periods the smallest SJD is reported for the period of 2010s illustrating the formation of the strongest ties. Thus, analytical results of all methods applied to compare the structural changes in community membership over time coincide.

In order to detect consistent clusters, we draw the membership map and analyzed repetitive clusters and dyads (details are reported in Chapter 4 Appendix 7.6). In the further discussion, we report inferences based on network 3 ($SI \geq 0.38$) as capturing a majority of revealed longitudinal patterns.

4.2.3. Validating the Communities Detected Over Time: Facts from the Field

The communities in the ideological terrorist network, detected over time, are validated by historically recorded facts. While we have not assessed all the available facts relevant to the links and communities identified in our study (that is out of the scope of this study), we found enough records in the political science literature and media to validate the proposed approach. [8]

[8] An anonymous reviewer suggested using the collection of records and facts from political science literature for the analysis of network changes over time instead of the approach proposed in this article. We agree with this suggestion and believe it has a potential for the future extension of the study. For the moment of our analysis such data was not available.

The ideologies Jihadist Terrorist Groups - Religious (Islamic) (i11) (e.*g., al-Qaeda, Hezbollah, Armed Islamic Group (GIA) etc*.) and Ideological Sources of Radical Islam - Religious (Islamic) (i12) (*e.g., Mujahideen Youth Movement (MYM), Hezbollah, Popular Resistance Committees etc.)* have been tied within the same community for more than 45 years (1970-2016). The terrorist groups, rooting their actions on the Islamic religion, are frequently associated with both ideological movements (please, see the descriptive statistics in Chapter 4 Appendix 8). In the 1990s, a number of terrorist groups following both Islamic ideologies doubled compared to previous decades and declined after the antiterrorism enforcement in the 2000s and 2010s. They are responsible for 83% of the conducted violence with its peak in the 1990s (97% of the total attacks).

Furthermore, in the 2000s and 2010s, two Islamic terrorist ideologies (i11 and i12) have clustered with the ideology Political Responses to Terrorism: Kashmir (i19). The Kashmir crisis, which initially began as the confrontation between supporters of independence of Kashmir from one side and supporters of Indian government from another side, turned to the Islamic religious-based conflict maintained by Jihadist movements (*e.g., Hizbul Mujahideen (HM), Palestinian Islamic Jihad (PIJ), Runda Kumpulan Kecil (RKK) etc*.). This transformation demonstrates the new form of "hybrid terrorist organizations", which unites multiple dimensions not only in the root ideology but also in their violent tactics and criminal behavior (Hoffman, 2010).

Hezbollah (i11 and i12) was initially founded in 1982 as a "revolutionary vanguard" terrorist organization, aiming to fight against American and Israeli imperialism and for the freedom of Southern Lebanon. Believing in the unionization of all Muslims (the concept of the global Ummah), the group widely supported all national movements (Muslims and non-Muslims). Later, in 1991, the organization *Hezbollah – Kashmir* (i19), also known as *Kashmiri Hizballah*, emerged. Currently, *Hezbollah* has transformed to a hybrid terrorist - political movement with a focus on social injustice and religious education (Azani, 2013). Hybrid wars, as a convergence of different types of conflicts, became a challenging concept of warfare and require a change in the combating response. Groups such as *Hezbollah, Hizbul Mujahideen (HM), and Chechen rebels* have adopted elements of multidimensionality. They use both conventional and unconventional operational tactics in their criminal activities. By adopting informational sources, hybrid terrorist organizations execute physical and psychological methods in their attacks. Thus, *Hezbollah* has exploited media resources to gain the political and ideological effects in Israeli. In July and August 2013, the terrorists caused panic and terror by intentionally misdirecting the short-range missiles (Panã, 2016). From a military evaluation, *Hezbollah* success is rather controversial. However, other terrorist groups are observed to be learning from *Hezbollah* successful operations (Johnson, 2011). Among them is *Hamas*, also known as *the Islamic Resistance Movement*, which claimed the establishment of the Islamic Palestinian State in place of Israeli.

The ideologies Extremist Right Wing Terrorist Groups (i10) and Transnational Crime and Terrorism / Organized Crime (i18) were clustered into the same community for 40 years (1970 – 2009). *The Provisional Irish Republican Army (PIRA or IRA)* (i10) emerged in the early 1970s after the split of the original *Irish Republican Army (IRA)*, which was formed in 1917 from the Irish volunteers. This paramilitary group has been fighting against the British to protect its cultural ethnicity and to form the independent Irish republic (McBride, 2011). During a period from the late 1960s to the late 1990s, known as the “Troubles” in Irish history, Irish paramilitaries were involved in organized crimes as a method of terrorist financing (Hourigan et al., 2018). *PIRA* procured its illegal funds through the kidnapping for ransom, smuggling of animal grains, extortion, and film piracy (Horgan and Taylor, 1999) with the further "laundering" through the owned official businesses such as pubs, hackney services, video shops, courier services, a security firm, a haulage company, and guest-houses (Horgan and Taylor, 1997, Clarke and Lee, 2008). Moreover, *PIRA* turned to forming unions with several organized criminal groups. Such "marriages of convenience" expand the possibilities of both parties, criminal and terrorist groups. Links between *PIRA* and Colombian narco-trafficker *Revolutionary Armed Forces of Colombia (FARC)* (i18) were revealed in 2001 after the arrest of several *PIRA* explosive experts in Colombia. The organizations cooperated not only in transactions of narcotics and weapons but also through the clandestine military training provided by *PIRA* to *FARC* (Curtis & Karacan, 2002).

4.2.4. Summary

We expanded on the likelihood of tactical terrorist choices by the investigation of its development over time. We split 46 years of the data into five time periods and explored differences in network properties. We found that the ideological terrorist network has changed over time. It transformed from a sparse net with a few central actors in the 1970s to dense interconnections with powerful focal players in the 1980s and 1990s. The network structure varied with a change in the density. While the number of ties among groups increased, the clustering tendency became low. In the 1990s, the network developed into a centralized organization — a spider with a powerful leading head.

In the 2000s, the ideological terrorist network mutated from a dense network to a fragmented organization with many isolates but stronger grouping bias. A drop in the network connectedness was compensated by an increase in stability of formed links. Clusters, formed in the 2010s, are characterized as the most stable compared to previous records. Thus, in the 2000s and 2010s, reacting to an increased pressure from government efforts to destroy them, the terrorist network gradually transformed into a decentralized starfish while keeping strong spider elements.

5. An Evolution of the Ideological Terrorist Network: From a Spider to a Starfish

Based on the network analysis of the global ideological terrorist network we concluded two main results about the behavior of terrorists when grouped by their ideologies.

Result 1. Almost half (42%) of ideological movements are grouped into four clusters. The similarity analysis of terrorist choices of attack types revealed that 13 ideological movements from the total 31 considered ideologies are connected through 4 clusters (illustrated by the middle graph in Figure 2). While the density of ties is low, there are patterns of compact grouping within certain nodes. An increase in a degree of partial similarity from 0.25 to 0.38 lowers the number of ideologies related in their tactical preferences from 22 to 13 (reported in Table 2), however several ideological dyads and clusters are recognized in both networks (please, see Figure 2).

Result 2. The structure of the ideological terrorist network evolved into a hybrid organization with stable links. NA revealed two patterns in clustering dynamics of the terrorist network over 1970 -2016. First, the growth in ideological connectedness through the deployment of similar tactics was recorded in the 1980s with a further extension in the 1990s (illustrated by Figures 3 and 4). The development of new technologies and historical geopolitical changes in the world may have enhanced cooperation among terrorist organizations. Second, in the 2000s and 2010s the ideological terrorist network modified its structure from centralized hierarchy to decentralized organization (described in details in sections 4.2.1 and 4.2.2). After the terrorist attacks on 9/11, the majority of countries enforced the anti-terrorism policy and developed strong multinational cooperation against the terrorism. Changes in the counterterrorism environment resulted in a recession within interactions among violent groups. The ideological terrorist network transformed into a decentralized net with many isolates. However, the terrorist network contains several dyads and clusters which became more stable over time.

The ideological terrorist network is the perfect example of a starfish. It stands on multiple autonomous lags – ideological groups – which are powerful enough to operate independently. Brafman and Beckstrom (2006) described a starfish organization in five principles applicable to the terrorist network. It resembles circles (1) founded on the norms and not the rules. Norms, such as confidentiality and support, lead to trust between members of the circle. Leaders of terrorist organizations are different from traditional executives. All actions are inspired by the catalysts (2) who develops and share the ideas and leads by example. Shared ideology (3) is a glue which holds the fragmented groups together. Preexisting networks (4), experienced in working together, form the base for cooperation. Every starfish has a champion (5) actively promoting new ideas for implementation.

We found that terrorist organizations, grouped into ideological hubs, form multiple connections among them. Almost half (42%) of the ideologies tend to cluster but do not form a dense network with multiple ties among actors (Result 1). The small number of detected links pictures a fragmented starfish. Yet a tendency to cluster points out emerging structural changes. The nature of links implies the tendency of strong actors, with a large number of ties, to connect with weak groups with a few ties. Furthermore, we identified that several clusters have been stable over decades (Result 2). These findings suggest that terrorist organizations driven by different ideological reasons incline to form unions. Such unions may operate through the one leading center, who makes decisions on the methods of attacks. The central leaders may not be affiliated directly with the terrorist groups and uninvolved in direct terrorist operations. The decisions can be directed through the network for its execution (Sageman, 2011).

There is always a dilemma between a spider and a starfish. A centralized structure enhances the operational efficiency of the terrorist network through the coordination across its divisions. Reduced conflicts, fast execution of decisions, effective use of available resources, and central control with accountability yield the high performance. But, a spider has a critical drawback: a separation of a leader (a spider head) paralyzes the entire network. When the pressure of risks rises, the network mutates. It changes from a spider to a starfish. Such evolution brings the benefits of autonomy and independence into operations of network parts. A decentralized structure raises the level of network preparedness for emergencies such as counterterrorism efforts to destroy it. A starfish's flexibility relieves the burden, empowers lower-level leaders, and eases expansion into new territories. But benefits come with costs – a decrease in network performance.

By analyzing changes of ideological terrorist network over time, we found that its structure transformed from a spider to a starfish and eventually evolved into the combination of two – a hybrid organization (Result 2). Opposed to the prediction "*when attacked, the centralized organization becomes even more centralized*" (the eighth principle of decentralization, Brafman and Beckstrom, 2006, p.138), the terrorist network changed its structure from a spider in the 1980s and 1990s to a starfish in the 2000s and 2010s. After the enhancement of the counterterrorism policy in the 2000s, it became decentralized, which made it less vulnerable to disruption. The evolution of *Hezbollah* and *the Taliban* from consolidation to fragmentation illustrates a change from a spider to a starfish within terrorist organizations (Schmidt, 2010). In our study we found such a shift on the level of ideological terrorist network. Some may argue:

"*it's easy to mistake starfish for spiders*" (the second principle of decentralization, Brafman and Beckstrom, 2006, p. 44) and what happened was a temporary increase in the number of ties between terrorist ideologies. However, the data analysis revealed the spider characters in the network properties for a two decades span, in the 1980s and 1990s.

The actors of decentralized terrorist network are independently sustainable. Instead of expected "*as industries become decentralized, overall profits decrease*" (the sixth principle of decentralization, Brafman and Beckstrom, 2006, p. 53), the number of terrorist attacks did not stop growing after 2000 and even doubled in 2013 – 2016 compared to previous annual estimates. Moreover, *"An open system does not have central intelligence; the intelligence is spread throughout the system… Open systems can easily mutate"* (the third and fourth principles of decentralization, Brafman and Beckstrom, 2006, p. 47-48). Learning and mimicking effective tactics of other players makes terrorist groups capable of combining features of both organizations, a spider and a starfish. This so called "hybrid" structure offers an organizational solution for the collective actions in terms of increased environmental pressure, such as governmental efforts to destroy the network. While keeping its resilience to outside threats (a starfish character), the network is able to spread information and share resources through the formed clusters and dyads (a spider character). The hybrid structure yields the highest long-term performance by mixing the flexibility and autonomy of a starfish with eventual coordination and the operational effectiveness of a spider.

6. Conclusion

In this research, we explored the operational tactics of terrorist groups with the ideological movement as a unit of our analysis. Our main contribution is to provide a holistic analysis of the global terrorist network build on tactical similarities as opposed to studying the operations of specific groups, a more common approach. By focusing of the connections between terrorist ideologies, we used “the starfish and the spider” framework to draw insights along the dimensions of centralization (a spider) versus decentralization (a starfish).

We found that some terrorist groups, with different ideologies, employed similar operational tactics. Almost half of ideological movements have been grouped into clusters, and several clusters have been stable over decades. From a structure of formed clusters, our analysis has identified possible strengths and weaknesses in the terrorist network. The subnetwork with multiple indirect ties is resilient against disruption. However, the chain structure with a singular indirect tie is easiest to collapse by cutting the “key link”. Furthermore, we explored the structural transformation of ideological networks from a starfish to a spider and vice-versa. The decentralized network (starfish) in the 1970s extended into the centralized structure (spider) with powerful focal actors in the 1980s and 1990s. After 2000, the terrorist network adopted the new fragmented organization with many isolates but stable ties. More recently, the ideological terrorist network has evolved into a hybrid structure – a starfish with some spider elements. It combines the benefits of autonomy and independence of a decentralized starfish with the coordination and high-performing activity configurations of a centralized spider. Such ability to mutate makes the terrorist network immune to the old counterterrorism strategies.

Brafman and Beckstrom (2006) regarded the terrorist network as a pure starfish structure and proposed three basic strategies to combat: (1) change the ideology, (2) centralize them, and (3) decentralize yourself. Governments have been employing these three strategies over the last decades but they have been unsuccessful in eliminating terrorism. Thus, in 2010, The U.S. Army effectively adopted the third strategy: they decentralized own capabilities in order to think, act, and operate like the enemy (Dempsey, 2011). Next, in response to the international anti-terrorism enforcement, during the 2000s and 2010s the terrorist network changed the structure by centralizing in parts (the second strategy). In order to change the terrorist ideology (the first strategy), multiple non-profit organizations have acted to impact the perception of the US in places like Pakistan and Kashmir. The shift in the ideology from “Life is hopeless, so I might as well join a terrorist cell,” to “There is hope – I can make my life better” is one of the best weapons against al Qaeda (Brafman and Beckstrom, 2006, p. 145), but the process is difficult. The strategy of positively changing ideology is limited in its capabilities and impossible to implement for terrorists driven by a particular religious beliefs or cultural values. The evolved hybrid structure of the current terrorist network requires governments to find an additional strategy. In order to conquer the enemy, we need the new flexible counterterrorism policy, which can be adjusted to changes in the terrorist network and will remain efficient for a longer period of time.

In our analysis, we observed that the terrorist network morphed its structure over time. It is consistent with a speculation that these modifications are defense responses to environmental changes including government actions (Bier and Gutfraind, 2019)[9]. A salient example is the change in the terrorist network structure from a spider to a starfish after the international counterterrorism enforcement, which followed massive terrorist attacks in 9/11. This suggests that the degree of network decentralization can be influenced. The responsiveness to shifts in the governmental pressure and levels of enforcement is an important behavioral aspect of the

[9] The detailed analysis of factors influencing the terrorist network to change is out of the scope of this article. However, as a future research extension we suggest to explore the impact of various factors (e.g., international cooperation, counterterrorism enforcement, technological advances, cultural and socio-political changes, etc.) on the structure and strategy of violent networks.

terrorist network. This knowledge is the key for the new strategical concept of Terrorism Management aiming to influence the terrorist network structure to change in a certain way.

We discern two courses for Terrorism Management. First, the direction of change in the degree of network decentralization can be anticipated making possible the development of a corresponding combating strategy. "…if a catalyst is killed, the power shifts to the circles, making the organization that much more decentralized" (Brafman and Beckstrom, 2006, p. 142). On the contrary, the shortage of available operational resources dilutes the power of autonomy and leads to the network centralization. When the enemy's reaction to undertaken actions is known, the development of an efficient long term strategy becomes possible. Second, we can force the terrorist network to change towards a specific structure of our choice and use the existing strategy. It is feasible to induce the network transformation by balancing between anti-terrorism enforcement and policy abatement. We are justified to encourage a more centralized network structure to allow a future decapitating strike. It was already done before, but in some cases it happened without a proper realization of final outcomes of undertaken actions. An example is the Colombian conflict between the government and paramilitary terrorist group the Revolutionary Armed Forces of Colombia (FARC). The conflict started in the mid-1960s and lasted for several decades. Counterterrorism strategy against FARC was unsuccessful, and the government was widely criticized for "giving the FARC the upper hand in the military and political balance". Inefficient policy lead to an increase in terrorist operations. In order to improve operational coordination, FARC adopted a centralized structure. The transformation of FARC from a starfish to a spider became a turning point in conflict history. In 2008, the Colombian Armed Forces launched a military operation and killed three members of the FARC Secretariat including their founder. The centralized FARC significantly weakened after the head loss. In 2016, FARC signed a peace deal with the Colombian government. One year later in 2017, FARC disarmed itself and reformed into a legal political party.

By managing the structure of terrorist networks, governments will enhance the effectiveness of current counterterrorism policy for a longer time. The strategy of targeting a spider will remain efficient when the enemy's network is centralized. Similarly, The U.S. Army with decentralized capabilities will achieve better results in a fight with a starfish. The detailed development of counterterrorism actions is beyond the scope of this paper and presents an opportunity for the research extension.

Another contribution of the current research is an approach to blend statistical techniques and network analysis, a first in the analysis of the global ideological terrorist network, and serves as an example of how these techniques can be applied to similar problems in the theoretical research as well as various business practices.

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Chapter 4 Appendix 1.

Description of Terrorist Ideologies

Cell Strategy and Terrorist Groups is a widely spread strategy between terrorist organizations. Cell is an organizational form of terrorist entity which includes between 3-10 individuals. Cells form the hierarchically structured network of units. Typically a cell member does not know the identities of higher-ranking individuals in the network, unless a cell member is the one who communicates with a higher-ranking individual in the organization. Terrorist organizations include: *Irish Republican Army (IRA), Palestine Liberation Organization (PLO), Animal Liberation Front (ALF), Earth Liberation Front (ELF), Abu Nidal Organization (ANO), Zapatista National Liberation Army etc*.

Comparative Religious Terrorist Groups (Christian/ Hindu/ Jewish/ Sikh) are the terrorist organizations that are driven by a particular system of beliefs with corresponding cultural habits and views. They are motivated by religious rather than ethnic or nationalistic beliefs and justify their acts of violence by either a religious motivation, justification, organization, or world view. The common goal of religious terrorist groups is to construct a new society based on the religious and ethno-nationalistic identities. Terrorist organizations include: *Ulster Freedom Fighters (UFF), Popular Resistance Committees, Continuity Irish Republican Army (CIRA), Red Hand Commandos, Terai Army*.

Current Regime Nationalists Terrorist Groups or pro nationalists remain the key nationalism ideology used primarily to sustain state power. Unlike the new regime nationalists and separatists they aim not to pressure the government into concessions but destabilize it and overthrow. Terrorist organizations include: *Armed Islamic Group (GIA), Haqqani Network, Union Guerrera Blanca (UGB), Ranbir Sena, Harkat ul Ansar, Misrata Brigades*.

Deterring Terrorism has motives to control and use federal lands. The terrorist organization which is called *Citizens for Constitutional Freedom* was formed by armed private U.S. militia in the U.S. state of Oregon. They claimed that the United States Constitution allows the ownership of only a limited small size of a land by federal government and the land can be acquired only with a consent of the State. Terrorist organizations include: *Citizens for Constitutional Freedom*.

Diasporas and Terrorism describes activities of groups that were displaced from the lands of the origin but still keep their beliefs and cultural characteristics unity. They include refugees, immigrants, migrant workers, international students, diplomats, documented, and/or undocumented. Terrorist organizations include: *Irish Republican Army (IRA), Palestine Liberation Organization (PLO), Kosovo Liberation Army (KLA), Abu Nidal Organization (ANO), Cambodian Freedom Fighters (CFF).*

Differences between Islamic State (ISIS) and Nusra Front (JN) is detected for such terrorist organizations as *Yarmouk Martyrs Brigade*. For part of its existence it was connected to *Islamic States* but aided to *Nusra Front* later. While the organization proclaimed its strong Islamic beliefs and values it oppose itself to other Islamic rebellions. Terrorist organizations include: *Yarmouk Martyrs Brigade.*

Economic Terrorism and Extortion aims to cause the economic and financial destabilization of the targeted state, group of states or society. They acts internationally and deploy the variety of massive actions of disruption and sophisticated techniques such as a latest information and communication technology. Terrorist organizations include: *Tupac Amaru Revolutionary Movement (MRTA), Ulster Volunteer Force (UVF), Garo National Liberation Army, Irish National Liberation Army (INLA), Free Aceh Movement (GAM).*

Environmental Terrorist Groups exhibit violence in support of biodiversity and bio-centric equality. They believe that human and animal rights are equal and humans dominate the earth illegitimately. The terrorist blames the government and corporations for an unjustified destruction of environment. Terrorist organizations include: *Animal Liberation Front (ALF), Earth Liberation Front (ELF), Animal Rights Militia, Robin Food etc.*

Evolutionary Process of Political Violence to Terrorism as a type of ideology was carried by such organizations as *Ananda Marga*. *Ananda Marga* was founded as a socio-spiritual organization with a stated aim of “liberation of self and service to humanity". Later it was confronted with the Communist Party and the Indian Government.

Extremist Right Wing Terrorist Groups aim to protect traditional values and beliefs, unity and purity of the ethnic group, race, ideology and religion. Their motivation include a variety of beliefs such as anti-communism, neo-fascism and neo-Nazism with a common philosophy to resist to changes in political, economic, social and religious institutions. They fight against globalization and the government, for racial and ethnic supremacy. Terrorist organizations include: *Irish Republican Army (IRA), Jewish Defense League (JDL), Ku Klux Klan, Hizbul Mujahideen (HM), Aryan Republican Army, Ulster Freedom Fighters (UFF) etc.*

Ideological Sources of Radical Islam - Religious (Islamic) groups use violence and the name of Islam oppose the ones who are not like them. They justify their actions through the interpretation of Quran and Hadith with accordance to their own goals and intentions. Terrorist organizations include: *Hezbollah, Armed Islamic Group (GIA), Palestinian Islamic Jihad (PIJ), Muttahida Qami Movement (MQM), Moro National Liberation Front (MNLF), Hizbul Mujahideen (HM) etc*.

Jihadist Terrorist Groups - Religious (Islamic) percept Western societies and policies as actively anti-Islamic. They state themselves as a victim fighting against an aggressor: giving a struggle to defend Islam is a personal obligation and the highest religious priority of all good Muslims. Terrorist organizations include: *al-Qaeda, Hezbollah, Armed Islamic Group (GIA), Hizbul Mujahideen (HM), Moro National Liberation Front (MNLF), Palestinian Islamic Jihad (PIJ), Runda Kumpulan Kecil (RKK), Muttahida Qami Movement (MQM) etc*.

Left Wing Terrorist Groups (Maoist/ Marxist/ Communist/ Socialist) are driven by revolutionary goals to overthrow the existing ruling government or disdain capital, imperial or colonial system and to establish Marxist-Leninist or socialist society. Terrorist organizations include: *Manuel Rodriguez Patriotic Front (FPMR), Armed Islamic Group (GIA), November 17 Revolutionary Organization (N17RO), Red Brigades, Tupac Amaru Revolutionary Movement (MRTA), Simon Bolivar Guerrilla Coordinating Board (CGSB), Action Directe etc.*

Left Wing Terrorist Groups (Anarchist) are revolutionary driven groups which support for the establishment of a decentralized, non-hierarchical sociopolitical system. Terrorist organizations include: *Free Syrian Army, Anarchists, Informal Anarchist Federation, Maximiliano Gomez Revolutionary Brigade, Prima Linea, Revolutionary Struggle, May 19 Communist Order etc*.

Left Wing Terrorist Groups (Marxist) carry the violence in support for communist ideology. They advocate the disruption of existing nation and the rise of proletarian states. It has taken in history the form of state-sponsored terrorism supported by nations such as Soviet Union, China, North Korea, Cambodia. Terrorist organizations include: *Shining Path (SL), Nicaraguan Democratic Force (FDN), Sandinista National Liberation Front (FSLN), First of October Antifascist Resistance Group (GRAPO), United Popular Action Movement, November 17 Revolutionary Organization (N17RO) etc*.

Narcoterrorism refers to two types of terrorism: (1) violence used by the drug dealers with a goal to maximize their profit, and (2) utilization of drug trafficking to fund operations of terrorist organizations. Terrorist organizations include: *Shining Path (SL), Hezbollah, Contras, Kosovo Liberation Army (KLA), Revolutionary United Front (RUF), Bougainville Revolutionary Army (BRA) etc.*

Policy Making within Transnational Terrorist Organizations refers to the idea of terrorists acting as rational policy makers and operating for the good for the society by pursuing of self-perceived justice at some points of the terrorist group operations. *The New Irish Republican Army* has been involved in vigilantism by acting in a law enforcement capacity against alleged drug-dealers and organized crime gangs. The Grey Wolves organization gain 3.6% of Turkish electorate. Terrorist organizations include: *The New Irish Republican Army, Grey Wolves, Ansar Al Sunnah (Palestine), Independent Nasserite Movement*.

Political Responses to Terrorism: Kashmir underline geopolitical disputes primary between India and Pakistan and additionally between Israel and Palestine. The Kashmir crisis is the conflict between groups which support the independence of Kashmir and Indian government. The insurgents in this conflict have strong Islamist roots and supported by Jihadist movements. Terrorist organizations include: *Irish Republican Army (IRA), Moro National Liberation Front (MNLF), Ulster Volunteer Force (UVF), Palestinian Islamic Jihad (PIJ), Palestine Liberation Organization (PLO), Hizbul Mujahideen (HM) etc.*

Quranic Understandings of Violent Jihad - Religious Terrorism (Islamic) legitimizes own terror actions as violent Jihad permitted by Quran. According to Quranic principles of ijtihad, Muslims can interpret and extend their Islamic practice individually as long as their actions are aimed to ensure the will of God in an Islamic community and preserve the Shariat in an Islamic community. The extreme manner in which terrorists interpret the Quran determine the extent of the violence and geopolitical factor. Terrorist organizations include: *Palestine Liberation Organization (PLO), Jammu and Kashmir Liberation Front, Continuity Irish Republican Army (CIRA), Deccan Mujahideen, Iraqi Mujahideen, Palestinian Revolution Forces etc.*

Racist Terrorist Groups include far-right terrorist groups motivated by beliefs in the superiority of one race over another based on their race and ethnicity. Terrorist organizations include: *Janjaweed, Palestine Liberation Organization (PLO), November 17 Revolutionary Organization (N17RO), Pattani United Liberation Organization (PULO) etc.*

Radical Islam and Anti Globalization is the Islamic based ideology, which opposes the military intervention of Western countries (US) against Islamic government and consider it as a new aggression against Muslims. Terrorist organizations include: *Islamic Front, Islamic Movement of Martyrs, Islamic Swords of Justice in the Land of Ribat.*

Religious (all) and Cult Terrorist Groups presents the combination of two venues: strong religious beliefs and centric structure of terrorist organization. Cult terrorism includes such characteristics as a leadership system, conditions of the followers and ideological elements. Terrorist organizations include: *Aum Shinri Kyo, Holy Spirit Movement, Armed Falange, World Church of the Creator, All India Sikh Students Federation (AISSF) etc*.

Separatist / New Regime Nationalist / Ethnic Nationalist aims to gain greater geo-political autonomy from current governing structure. Nationalists seek to form political, economic, social and religious self-determination, which may result in the range from gaining some autonomy to establishing independent and sovereign state. Terrorist organizations example: *Irish Republican Army (IRA), Nicaraguan Democratic Force (FDN), Hezbollah, Baloch Republican Army (BRA), Ulster Volunteer Force (UVF), Nicaraguan Resistance etc.*

State Sponsored Terrorism groups supported by the state against another state or its own people. With the growth of international terrorism the term definition changed to the state support of international terrorism. Terrorist organizations include: *Sandinista National Liberation Front (FSLN), Palestinian Islamic Jihad (PIJ), Free Aceh Movement (GAM), Abu Nidal Organization (ANO) etc*.

Terrorism and Governmental Policy refers to the violence with the aim to shape the policy of the government. The establishment of the new state and new governmental policy is a key ideology for such terrorist formations. Terrorist organizations include: *Shining Path (SL), First of October Antifascist Resistance Group (GRAPO), Palestinian Islamic Jihad (PIJ), November 17 Revolutionary Organization (N17RO) etc.*

Terrorism and the Lone Wolf assumes the violence towards achievement of political or ideological goals executed by the individual or small group of individuals. No membership or cooperation links to other known terrorist groups are found for the lone-wolf terrorists. Terrorist groups include: *Animal Liberation Front (ALF), Earth Liberation Front (ELF), Bavarian Liberation Army, Earth Night Action Group.*

Terrorism and Warlordom considers operations of violent groups, who capture control over ungoverned territories (after the legitimate government lost its control over the territories and the state structure collapsed). This ideology usually takes place in the uncertain political and social environment where the government forces are fighting with armed rebels, insurgents and civil unrest. Terrorist organizations include: *National Patriotic Front of Liberia (NPFL), Mai Mai Simba Militia, Mai Mai Mazembe Militia, Mullah Dadullah Front etc*.

Terrorism International Law arises with a view that legal agreements and treaties between states may restraint the sovereignty of its members. Terrorist organizations include: *Black September*.

Third Party Combatants as a Tool of Terrorism deploys force multipliers such as foreign corps, bodyguards, recruited warriors from abroad, spies, and naïve adventure seeking mercenaries. Terrorist organizations include: *Abu Nidal Organization (ANO), Ninjas, Liberians United for Reconciliation and Democracy (LURD), Panama Defense Force etc*.

Transnational Crime and Terrorism / Organized Crime represents the interaction between terrorism and organized crime. Terrorist organizations include: *Shining Path (SL), Irish*

Republican Army (IRA), Hezbollah, Ulster Volunteer Force (UVF), The New Irish Republican Army etc.
Urban Terrorism select its targets in the urban areas with a high population density with a purpose to maximize the effect of terrorist attacks. Terrorist organizations include: *Tupac Amaru Revolutionary Movement (MRTA), Hezbollah.*

Chapter 4 Appendix 2.

Description of Terrorist Attack Types

Armed Assault is a threat to cause physical harms or death to individuals by using lethal weapons such as a firearm, incendiary or sharp instruments and certain explosive devices (grenades, projectiles and other devices that are thrown).
Assassination is an act of killing of a prominent person such as high-ranking military officers, politicians, government officials, athletes, celebrities etc. The objective of an attack is the specific member of the defined targeted group.
Bombing/Explosion is an attack that is caused by exothermic reaction of an explosive material with a rapid increase in harmful energy release. It causes physical damage to the surrounding territories accompanied with ground- and atmosphere – transmitted shock waves. Bombing/Explosion may include acts with the use of low and high explosives but does not refer to the acts with the use of nuclear bombs.
Facility/Infrastructure Attack is an act with the primary objective to cause the damage to the infrastructure and other facilities or non-human targets such as buildings, railways, pipeline, trains, monuments etc. The harm to humans may be caused incidentally or as a side effect.
Hijacking is an act of illegal seize of a transportation vehicle such as an aircraft, boat, bus etc. with a purpose to change a destination, force to release prisoners or other political objectives.
Hostage Taking (Barricade Incident) is an act of holding hostages with a purpose to achieve political objectives through concession and disruption of normal operations. Barricade incident does not involve moving hostages to a different location and is taken with an intention to keep hostages for a short time.
Hostage Taking (Kidnapping) is an act of holding hostages with a purpose to achieve political objectives through concession and disruption of normal operations. Kidnapping involves taking and moving hostages to a different location for keeping them there for a longer time.
Unarmed Assault is a threat to cause physical harms or death to individuals by using chemical, biological or radiological weapons.
Unknown is an undetermined attack type.

Chapter 4 Appendix 3.

Dictionary Code of Ideologies.

Id	Ideology
i1	Separatist / New Regime Nationalist / Ethnic Nationalist
i2	Left Wing Terrorist Groups (Anarchist)
i3	Racist Terrorist Groups
i4	Cell Strategy and Terrorist Groups
i5	Current Regime Nationalists Terrorist Groups
i6	Narcoterrorism
i7	Third Party Combatants as a Tool of Terrorism
i8	Left Wing Terrorist Groups (Maoist/ Marxist/ Communist/ Socialist)
i9	Left Wing Terrorist Groups (Marxist)
i10	Extremist Right Wing Terrorist Groups
i11	Jihadist Terrorist Groups - Religious (Islamic)
i12	Ideological Sources of Radical Islam - Religious (Islamic)
i13	Religious (all) and Cult Terrorist Groups
i14	Diasporas and Terrorism
i15	Terrorism International Law
i16	Comparative Religious Terrorist Groups (Christian/ Hindu/ Jewish/ Sikh)
i17	Economic Terrorism and Extortion
i18	Transnational Crime and Terrorism / Organized Crime
i19	Political Responses to Terrorism: Kashmir
i20	Radical Islam and Anti Globalization
i21	Environmental Terrorist Groups
i22	State Sponsored Terrorism
i23	Quranic Understandings of Violent Jihad - Religious Terrorism (Islamic)
i24	Terrorism and Warlordom
i25	Terrorism and the Lone Wolf
i26	Policy Making within Transnational Terrorist Organizations
i27	Differences between Islamic State (ISIS) and Nusra Front (JN)
i28	Terrorism and Governmental Policy
i29	Deterring Terrorism
i30	Urban Terrorism
i31	Evolutionary Process of Political Violence to Terrorism

Chapter 4 Appendix 4.

Sample Statistics of Attack Types by Ideology

	Armed Assault	Assassination	Bombing/ Explosion	Facility/Infrastructure Attack	Hijacking	Hostage Taking (Barricade)	Hostage Taking (Kidnapping)	Unarmed Assault
i1	28%	16%	43%	6%	0%	0%	4%	1%
i2	16%	6%	53%	20%	0%	2%	3%	1%
i3	22%	8%	43%	10%	1%	2%	12%	2%
i4	11%	29%	42%	15%	0%	0%	2%	0%
i5	33%	15%	39%	4%	0%	0%	8%	1%
i6	27%	17%	49%	4%	0%	1%	3%	0%
i7	12%	33%	31%	1%	4%	4%	13%	1%
i8	20%	9%	59%	5%	0%	3%	4%	0%
i9	32%	15%	45%	4%	0%	1%	2%	0%
i10	14%	32%	41%	11%	0%	1%	2%	0%
i11	25%	10%	52%	2%	1%	0%	7%	3%
i12	26%	11%	50%	3%	0%	0%	7%	3%
i13	32%	7%	25%	16%	2%	0%	4%	14%
i14	13%	31%	44%	10%	0%	0%	2%	0%
i15	10%	18%	55%	2%	2%	8%	4%	0%
i16	15%	41%	31%	10%	0%	0%	2%	1%
i17	23%	18%	45%	4%	0%	3%	7%	0%
i18	20%	24%	47%	6%	0%	1%	2%	0%
i19	16%	26%	46%	8%	0%	0%	3%	0%
i20	44%	22%	33%	0%	0%	0%	0%	0%
i21	1%	3%	20%	72%	0%	0%	0%	4%
i22	23%	16%	46%	5%	1%	3%	6%	0%
i23	20%	15%	53%	4%	1%	0%	7%	1%
i24	64%	14%	4%	4%	0%	0%	14%	0%
i25	0%	2%	14%	83%	0%	0%	0%	1%
i26	22%	7%	67%	4%	0%	0%	0%	0%
i27	0%	0%	0%	0%	50%	0%	50%	0%
i28	24%	19%	52%	4%	0%	1%	1%	0%
i29	0%	0%	0%	100%	0%	0%	0%	0%
i30	12%	5%	72%	2%	1%	4%	5%	0%
i31	0%	50%	50%	0%	0%	0%	0%	0%

Chapter 4 Appendix 5.

Total Similarity in Terrorist Operations

We used the Discrete Choice Model (DCM) analysis to compare vector distributions of attack types executed by terrorists with different ideologies. DCM allows us to estimate the probability of the individual to make a choice of one option over the set of available alternatives. It is designed to forecast the behavior of the choice maker in a situation with alternative outcomes (Luce, 1959; McFadden, 1980; Hensher & Johnson, 1981). DCMs are often derived from utility theory assuming that each alternative decision from the available set is attached to the certain value representing a measure of satisfaction (Houthakker, 1950). The rational decision-maker will choose the alternative associated with the highest utility.

We applied DCM to derive the choice probabilities for every attack type from the vector of eight attributed to every terrorist ideological movement from the total 31 considered ideologies. Similarly, we estimated the choice probabilities for every attack type attributed to the dyad of ideologies from the total 465 possible pairs. The resulting estimates represent the probability distribution of the choices for the unrestricted model (applied to every ideology separately) and the restricted model (nested on the dyad of ideologies). To compare two models, we applied the maximum log-likelihood function (Manski & McFadden, 1981):

$$\max_{u_1 \ldots u_8} llk = \sum_{i=1}^{31} \sum_{j=1}^{8} (n_i * \log\left(\frac{u_j}{\sum_{j=1}^{8} u_j}\right)) ,$$

where n_i – the number of attacks executed by a singular ideology (i) for the unrestricted model (e.g., a number of acts conducted by separatists) and driven by two ideologies $(i, -i)$ for the restricted model (e.g., a number of acts conducted by groups with separatist and left-wing ideologies); u_j – the likelihood of occurrence of a certain attack type (j) from the set of all alternatives driven by a singular ideology (i) for the unrestricted model (e.g., a probability of conducting bombing/explosion by separatists) and driven by two ideologies $(i, -i)$ for the restricted model (e.g., a probability of conducting bombing/explosion acts by groups with separatist and left-wing ideologies). The estimated log-likelihood values for both restricted and unrestricted models were compared based on the chi-squared test statistics.

We found that the restricted model (p-value < 0.05) is more efficient in explaining the choice distribution than the unrestricted model for nine ideological dyads, including:

1) Jihadist Terrorist Groups - Religious (Islamic) (i11) and Ideological Sources of Radical Islam - Religious (Islamic) (i12),
2) Extremist Right Wing Terrorist Groups (i10) and Diasporas and Terrorism (i14) ,
3) Third Party Combatants as a Tool of Terrorism (i7) and Terrorism International Law (i15),
4) Left Wing Terrorist Groups (Maoist/ Marxist/ Communist/ Socialist) (i8) and Terrorism International Law (i15),
5) Left Wing Terrorist Groups (Maoist/ Marxist/ Communist/ Socialist) (i8) and Policy Making within Transnational Terrorist Organizations (i26),
6) Terrorism International Law (i15) and Economic Terrorism and Extortion (i17),
7) Terrorism International Law (i15) and State Sponsored Terrorism (i22),
8) Economic Terrorism and Extortion (i17) and State Sponsored Terrorism (i22),
9) Policy Making within Transnational Terrorist Organizations (i26) and Terrorism and Governmental Policy (i28).

Islamic ideologies, Jihadist Terrorist Groups - Religious (Islamic) (i11) and Ideological Sources of Radical Islam - Religious (Islamic) (i12), form the first dyad of movements with identical operational tactics. The second dyad reveals unexpected link between Extremist Right Wing Terrorist Groups (i10) and Diasporas and Terrorism (i14). The terrorist organizations fighting against globalization and for racial and ethnic supremacy (*e.g., Irish Republican Army, Jewish Defense League*, *Ku Klux Klan*) made the same choice on the attack types as terrorist groups formed from refugees and immigrants (*e.g., Irish Republican Army, Palestine Liberation Organization, Kosovo Liberation Army*).

Furthermore, terrorist tactics of the Left Wing Groups (i8) driven by revolutionary goals (*e.g., Manuel Rodriguez Patriotic Front (FPMR), Armed Islamic Group (GIA), November 17 Revolutionary Organization (N17RO), Red Brigades*) were similar to Transnational Terrorist Organizations (i26) aiming to change the current policies for the benefits of the society (*e.g. The New Irish Republican Army, Grey Wolves*). Marxist – Leninist political groups (i8) executed the same terrorist activities as Terrorism International Law (i15) - the violent opposition to legal agreements and treaties among countries as restricting for the national sovereignty (*e.g., Black September*). Additionally, Terrorism International Law (i15) and Economic Terrorism and Extortion (i17) (*e.g., Tupac Amaru Revolutionary Movement (MRTA), Ulster Volunteer Force (UVF), Garo National Liberation Army*) used similar sophisticated techniques, such as the latest information and communication technologies for massive actions of disruption. Moreover, both ideologies (i15 and i17) were uniform in their tactical preferences with State Sponsored Terrorism (i22) groups (*e.g., Sandinista National Liberation Front (FSLN), Palestinian Islamic Jihad (PIJ), Free Aceh Movement (GAM)*). Relying on the statement that the GTD does not capture records of state-sponsored terrorism acts, we discontinue the discussion of identified connections with the ideology State Sponsored Terrorism (i22) from further analysis. Finally, violent units driven by the goal to change governmental policy, Policy Making within Transnational Terrorist Organizations (i26), and establish the new state, Terrorism and Governmental Policy (i28) (*e.g., Shining Path (SL), First of October Antifascist Resistance Group (GRAPO), Palestinian Islamic Jihad (PIJ)*), made the same operational choices.

In summary, the analysis of the likelihood of tactical terrorists' choices revealed seven links among ideological terrorist movements. Terrorist organizations driven by discrepant ideological reasoning operated through the same types of attacks. Thus, looking at the distribution of attack types we found that Extremist Right Wing Terrorist (i10) and Diasporas and Terrorism (i14) groups most of the times used bombing and explosions (on average 43%) and assassination (31%). They were rarely involved in hijacking, barricade incidents, and unarmed assaults. The tactical strategy of Jihadist Terrorist Groups - Religious (Islamic) (i11) and Ideological Sources of Radical Islam - Religious (Islamic) (i12) groups relied heavily on the bombing and explosions (51%) and less on armed assaults (26%). The first pair (i10 and i14) chose the facility and infrastructure attacks more frequently (10% of the time) than the dyad of Islamic ideologies (i11 and i12) (3%).

The intriguing point is the "bridging" connection among violent ideological movements. Two ideologies are related indirectly through the unique direct connection with the third ideology. For such extent, Left Wing Terrorist Groups (Maoist/ Marxist/ Communist/ Socialist) (i8) were linked to Third Party Combatants as a Tool of Terrorism (i7) and Economic Terrorism and Extortion (i17) through the direct tie with Terrorism International Law (i15). Thus, the last ideology (i15) played the bonding role in the chain of connections between other root causes (i7, i8, i17). It made possible to spread the information and coordinate their attacks. Simultaneously, the connector makes the chain weak and vulnerable to disruption.

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Chapter 4 Appendix 6.

Membership Structure of Communities

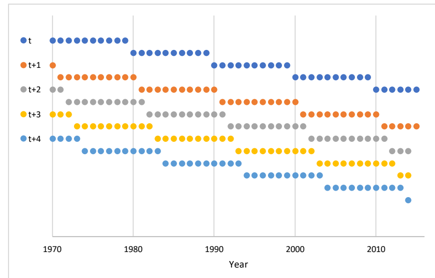
Networks	Communities	Members	Repetitive dyads / clusters	
			Net_2 & Net_3	Net_3 & Net_4
Net_2 (SI ≥ 0.25)	1	i3 i8 i22		
	2	i11 i12 i13 i17		
	3	i4 i7 i10 i14 i16		
	4	i6 i18 i28		
	5	i1 i2 i5 i9 i15 i19 i23	i11 i12	
Net_3 (SI ≥ 0.38)	1	i11 i12	i6 i28	
	2	i4 i10 i14 i16	i17 i22	
	3	i5 i15 i17 i22 i23	i4 i10 i14 i16	
	4	i6 i28	i5 i15 i23	
Net_4 (SI ≥ 0.50)	1	i11 i12		i11 i12
	2	i4 i14		i4 i14

Chapter 4 Appendix 7.

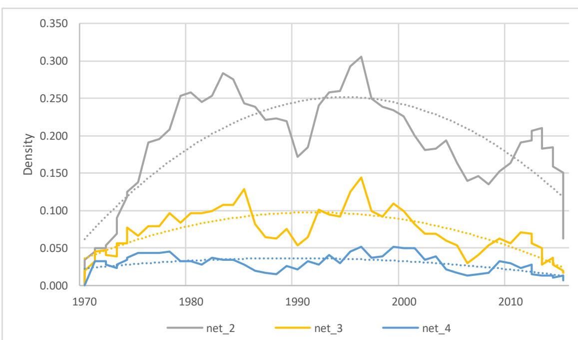
Structural Dynamics of the Ideological Terrorist Networks Over Time

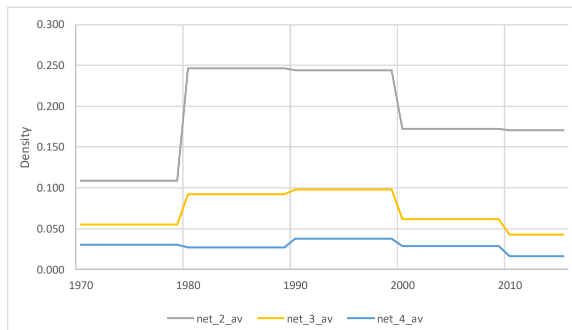
7.1. Networks Matrix Group with Moving Time Frames (1 Year Shift)

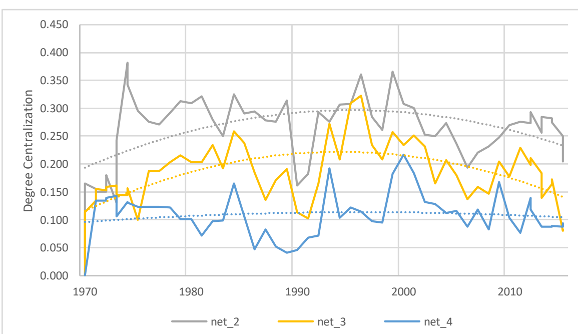
Time Shift	Time Frame 0	1	2	3	4	5
t		(1970 - 1979)	(1980 - 1989)	(1990 - 1999)	(2000 - 2009)	(2010 - 2016)
t+1	(1970)	(1971 - 1980)	(1981- 1990)	(1991 - 2000)	(2001 - 2010)	(2011 - 2016)
t+2	(1970 - 1971)	(1972 - 1981)	(1982 - 1991)	(1992 - 2001)	(2002 - 2011)	(2012 - 2016)
t+3	(1970 - 1972)	(1973 - 1982)	(1983 - 1992)	(1993 - 2002)	(2003 - 2012)	(2013 - 2016)
t+4	(1970 - 1973)	(1974 - 1983)	(1984 - 1993)	(1994 - 2003)	(2004 - 2013)	(2014 - 2016)
t+5	(1970 - 1974)	(1975 - 1984)	(1985 - 1994)	(1995 - 2004)	(2005 - 2014)	(2015-2016)
t+6	(1970 - 1975)	(1976 - 1985)	(1986 - 1995)	(1996 - 2005)	(2006 - 2015)	(2016)
t+7	(1970 - 1976)	(1977 - 1986)	(1987 - 1996)	(1997 - 2006)	(2007 - 2016)	
t+8	(1970 - 1977)	(1978 - 1987)	(1988- 1997)	(1998 - 2007)	(2008 - 2016)	
t+9	(1970 - 1978)	(1979 - 1988)	(1989 - 1998)	(1999 - 2008)	(2009 - 2016)	

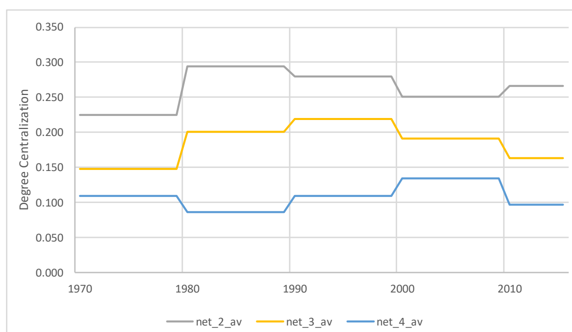


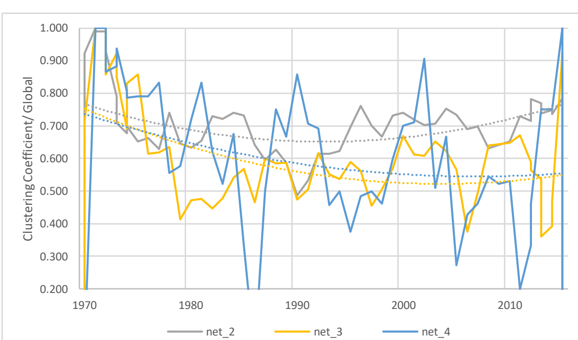
7.2. Networks Cohesion Over Time (Median Point Estimates for Moving Time Frames – on the left, Smooth Mean Estimates for Moving Time Frames – on the right)

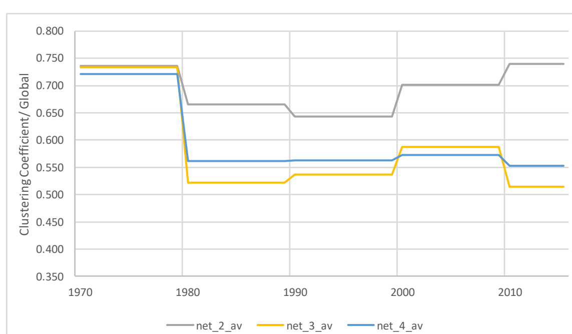


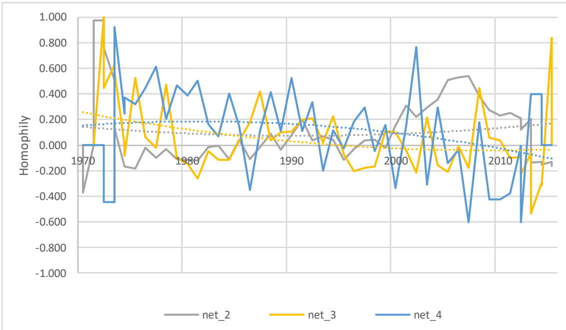


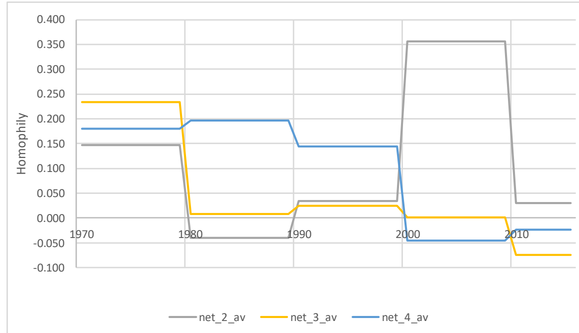












7.3. Comparison of Networks

Network	Time Frame	Number of Edges	Number of Similar Edges	Hamming Distance	Probability of Similar Edges	Probability of Hamming Distance
SI ≥ 0.25	1 (1970 - 1979)	58	35	116	0.60	0.62
	2 (1980 - 1989)	128	73	103	0.60	0.41
	3 (1990 - 1999)	121	56	99	0.62	0.47
	4 (2000 - 2009)	90	42	104	0.47	0.55
	5 (2010 - 2016)	98				
SI ≥ 0.38	1 (1970 - 1979)	36	14	58	0.39	0.67
	2 (1980 - 1989)	50	18	57	0.42	0.61
	3 (1990 - 1999)	43	10	51	0.36	0.72
	4 (2000 - 2009)	28	8	35	0.35	0.69
	5 (2010 - 2016)	23				
SI ≥ 0.50	1 (1970 - 1979)	17	7	19	0.44	0.58
	2 (1980 - 1989)	16	5	20	0.36	0.67
	3 (1990 - 1999)	14	3	18	0.30	0.75
	4 (2000 - 2009)	10	2	12	0.33	0.75
	5 (2010 - 2016)	6				

7.4. Descriptive Statistics of Community Structures

Community Structure Desription	Network	1 (1970 - 1979)	2 (1980 - 1989)	3 (1990 - 1999)	4 (2000 - 2009)	5 (2010 - 2016)
Number of Communities	SI ≥ 0.25	2	3	4	4	3
	SI ≥ 0.38	2	4	4	2	4
	SI ≥ 0.50	2	4	4	3	2
Number of Node in Communities	SI ≥ 0.25	16	22	24	22	21
	SI ≥ 0.38	15	18	18	11	13
	SI ≥ 0.50	12	11	13	10	6
Average Number of Nodes per Community	SI ≥ 0.25	8.0	7.3	6.0	5.5	7.0
	SI ≥ 0.38	7.5	4.5	4.5	5.5	3.3
	SI ≥ 0.50	6.0	2.8	3.3	3.3	3.0
Number of Outsiders	SI ≥ 0.25	15	9	7	9	10
	SI ≥ 0.38	16	13	13	20	18
	SI ≥ 0.50	19	20	18	21	25
Proportion of Nodes Grouped in Communities	SI ≥ 0.25	0.52	0.71	0.77	0.71	0.68
	SI ≥ 0.38	0.48	0.58	0.58	0.35	0.42
	SI ≥ 0.50	0.39	0.35	0.42	0.32	0.19

7.5. Structural Changes in Communities

Comparison Method	Network	SI ≥ 0.25 1 (1970 - 1979)	2 (1980 - 1989)	3 (1990 - 1999)	4 (2000 - 2009)	5 (2010 - 2016)	SI ≥ 0.38 1 (1970 - 1979)	2 (1980 - 1989)	3 (1990 - 1999)	4 (2000 - 2009)	5 (2010 - 2016)	SI ≥ 0.50 1 (1970 - 1979)	2 (1980 - 1989)	3 (1990 - 1999)	4 (2000 - 2009)	5 (2010 - 2016)
Variation of Information (VI)	1 (1970 - 1979)	0.000	1.437	1.468	1.347	1.445	0.000	0.977	1.018	1.200	1.304	0.000	0.755	0.864	0.917	0.828
	2 (1980 - 1989)	1.437	0.000	1.415	1.596	1.660	0.977	0.000	1.027	1.029	1.222	0.755	0.000	0.500	0.766	0.464
	3 (1990 - 1999)	1.468	1.415	0.000	1.410	1.436	1.018	1.027	0.000	1.159	1.140	0.864	0.500	0.000	0.751	0.539
	4 (2000 - 2009)	1.347	1.596	1.410	0.000	1.230	1.200	1.029	1.159	0.000	0.713	0.917	0.766	0.751	0.000	0.302
	5 (2010 - 2016)	1.445	1.660	1.436	1.230	0.000	1.304	1.222	1.140	0.713	0.000	0.828	0.464	0.539	0.302	0.000
Normalized Mutual Information (NMI)	1 (1970 - 1979)	1.000	0.672	0.655	0.701	0.672	1.000	0.804	0.795	0.773	0.758	1.000	0.869	0.847	0.840	0.861
	2 (1980 - 1989)	0.672	1.000	0.639	0.617	0.592	0.804	1.000	0.797	0.808	0.776	0.869	1.000	0.916	0.873	0.925
	3 (1990 - 1999)	0.655	0.639	1.000	0.652	0.636	0.795	0.797	1.000	0.783	0.791	0.847	0.916	1.000	0.873	0.912
	4 (2000 - 2009)	0.701	0.617	0.652	1.000	0.707	0.773	0.808	0.783	1.000	0.876	0.840	0.873	0.873	1.000	0.951
	5 (2010 - 2016)	0.672	0.592	0.636	0.707	1.000	0.758	0.776	0.791	0.876	1.000	0.861	0.925	0.912	0.951	1.000
Split-Join Distance	1 (1970 - 1979)	0	18	23	20	21	0	13	13	16	19	0	12	13	13	12
	2 (1980 - 1989)	18	0	23	25	23	13	0	15	16	19	12	0	9	13	8
	3 (1990 - 1999)	23	23	0	20	17	13	15	0	18	19	13	9	0	12	9
	4 (2000 - 2009)	20	25	20	0	19	16	16	18	0	11	13	13	12	0	5
	5 (2010 - 2016)	21	23	17	19	0	19	19	19	11	0	12	8	9	5	0
Rand index	1 (1970 - 1979)	1.000	0.804	0.772	0.809	0.783	1.000	0.877	0.882	0.858	0.867	1.000	0.935	0.923	0.912	0.925
	2 (1980 - 1989)	0.804	1.000	0.766	0.785	0.763	0.877	1.000	0.901	0.895	0.899	0.935	1.000	0.966	0.942	0.968
	3 (1990 - 1999)	0.772	0.766	1.000	0.787	0.774	0.882	0.901	1.000	0.886	0.903	0.923	0.966	1.000	0.938	0.959
	4 (2000 - 2009)	0.809	0.785	0.787	1.000	0.794	0.858	0.895	0.886	1.000	0.935	0.912	0.942	0.938	1.000	0.974
	5 (2010 - 2016)	0.783	0.763	0.774	0.794	1.000	0.867	0.899	0.903	0.935	1.000	0.925	0.968	0.959	0.974	1.000
Adjusted Rand index	1 (1970 - 1979)	1.000	0.172	0.125	0.155	0.117	1.000	0.279	0.305	0.064	0.011	1.000	0.258	0.212	0.085	0.030
	2 (1980 - 1989)	0.172	1.000	0.158	0.128	0.107	0.279	1.000	0.307	0.142	0.034	0.258	1.000	0.450	0.040	0.195
	3 (1990 - 1999)	0.125	0.158	1.000	0.212	0.212	0.305	0.307	1.000	0.072	0.076	0.212	0.450	1.000	0.139	0.223
	4 (2000 - 2009)	0.155	0.128	0.212	1.000	0.194	0.064	0.142	0.072	1.000	0.218	0.085	0.040	0.139	1.000	0.489
	5 (2010 - 2016)	0.117	0.107	0.212	0.194	1.000	0.011	0.034	0.076	0.218	1.000	0.030	0.195	0.223	0.489	1.000

7.6. Map Dynamics of Community Membership

Network	Time Period	Communities	Members	Repetitive dyads/clusters	
SI ≥ 0.25	1 (1970 - 1979)	1	i11 i12 i15 i2 i22 i28 i3 i8 i9		
		2	i1 i10 i14 i16 i18 i19 i4		
	2 (1980 - 1989)	1	i1 i13 i18 i21 i28 i6 i9	i1 i18	
		2	i10 i14 i19 i22 i4 i5 i7	i10 i14 i19 i4	
		3	i11 i12 i17 i2 i23 i3 i30 i8	i11 i12 i2 i3 i8	
	3 (1990 - 1999)	1	i10 i14 i18 i2 i28 i3 i4 i6 i9		
		2	i17 i30 i8	i17 i30 i8	
		3	i1 i11 i12 i13 i16 i19 i22 i23 i5 i7	i11 i12 i23	
		4	i21 i25	i10 i14 i18 i28 i6 i9	
	4 (2000 - 2009)	1	i17 i22 i3 i5 i8	i17 i8	
		2	i1 i10 i11 i12 i14 i18 i2 i23 i6 i9	i1 i11 i12 i23	
		3	i21 i25 i4	i21 i25	
		4	i16 i19 i28 i30	i16 i19	i1 i10 i18 i9
	5 (2010 - 2016)	1	i1 i10 i17 i18 i28 i3 i8 i9		i21 i25 i4
		2	i21 i25 i4		i11 i12 i2 i6
		3	i11 i12 i16 i19 i2 i22 i26 i30 i5 i6		i16 i19 i30
SI ≥ 0.38	1 (1970 - 1979)	1	i1 i10 i14 i18 i19 i4		
		2	i11 i12 i15 i2 i22 i28 i3 i8 i9		
	2 (1980 - 1989)	1	i1 i28 i9		
		2	i10 i14 i18 i19 i22 i4 i6	i28 i9	
		3	i11 i12 i23 i3	i10 i14 i18 i19 i4	
		4	i17 i2 i30 i8	i11 i12 i3	
	3 (1990 - 1999)	1	i10 i14 i18 i19 i4		
		2	i1 i16 i22 i23 i5	i10 i14 i18 i19 i4	
		3	i11 i12 i17 i28 i6 i9	i11 i12	
		4	i30 i8	i30 i8	i10 i18
	4 (2000 - 2009)	1	i10 i17 i18 i5 i6 i8	i11 i12	
		2	i1 i11 i12 i19 i22	i17 i6	
	5 (2010 - 2016)	1	i1 i2 i8		
		2	i16 i17 i18 i9	i17 i18	
		3	i11 i12 i19	i11 i12 i19	
		4	i28 i5 i6	i5 i6	
SI ≥ 0.50	1 (1970 - 1979)	1	i1 i10 i14 i18 i19 i4		
		2	i2 i22 i28 i3 i8 i9		
	2 (1980 - 1989)	1	i10 i14 i19 i4		
		2	i11 i12		
		3	i23 i3		
		4	i18 i28 i6	i10 i14 i19 i4	
	3 (1990 - 1999)	1	i6 i9		
		2	i10 i14 i19 i4		
		3	i1 i11 i12 i17 i8	i10 i14 i19 i4	
		4	i23 i5	i11 i12	
	4 (2000 - 2009)	1	i5 i8		
		2	i1 i11 i12 i18 i19 i22		
		3	i17 i6	i1 i11 i12	
	5 (2010 - 2016)	1	i18 i6		
		2	i1 i11 i12 i19	i1 i11 i12 i19	

Chapter 4 Appendix 8.

Operational Dynamics of Religious Islamic Ideologies (i11 and i12)

	Religious Islamic Ideologies		1 (1970 - 1979)	2 (1980 - 1989)	3 (1990 - 1999)	4 (2000 - 2009)	5 (2010 - 2016)	Total
i11	Jihadist Terrorist Groups - Religious (Islamic)	Number of Groups	3	18	35	31	23	82
i12	Ideological Sources of Radical Islam - Religious (Islamic)	Number of Groups	1	23	37	30	19	84
		Identical Groups	1	12	30	20	15	55
		% of Identical Groups	33%	41%	71%	49%	56%	50%
i11	Jihadist Terrorist Groups - Religious (Islamic)	Number of Attacks	69	242	716	440	394	1861
i12	Ideological Sources of Radical Islam - Religious (Islamic)	Number of Attacks	58	229	719	454	386	1846
		Attacks by Identicals Groups	58	210	707	388	321	1684
		% of Attacks by Identical Groups	84%	80%	97%	77%	70%	83%