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Essays on Networks and Firm Relations

by

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Professor Bryan S. Graham, Chair
Professor James L. Powell
Professor Demian Pouzo
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Abstract

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This dissertation contains three essays that study relationships among firms. Firms connect to each other via direct and indirect relationships. A network describes these relationships as linkages among firms. This dissertation empirically studies the roles of firms in networks, in particular the incentives firms face when forming linkages with each other.

Chapter 1 studies the structure of supplier-buyer networks of U.S. tech firms from 2003 to 2014. For each year, a supplier-buyer network describes which firms supply to which firms, and equivalently, which firms buy from which firms. I identify four firms - Apple, Dell, IBM, and Microsoft - as the most significant firms in the supplier-buyer networks. Using a community detection method, I find that these four firms each belongs to a different community of firms, indicating that they are closely linked to distinct groups of firms. On the other hand, the four communities, each associated with one of the four firms, are composed of firms in similar industry sectors. These suggest that there exists a certain degree of exclusivity in supplier-buyer relationships of the four firms. Moreover, I rank their significance in the network using measures of centrality and modular centrality, where the latter accounts for the community structure. I find that IBM was by far the most significant firm, both as a supplier and a buyer, until 2010. However, the centrality of Microsoft grew and surpassed IBM in 2014. Furthermore, the growth of Apple's centrality over the years is remarkable.

Chapter 2 describes the relationships among U.S. credit card issuers, hotel chains, and airlines. These firms operate loyalty programs, in which customers may earn points by making purchases. Moreover, they form partnerships with other firms so that the points can be transferred to the loyalty programs of partner firms. Via such *transfer partnerships*, customers may redeem the points for not only the goods and services offered by the firm but also those offered by the partner firms. Thus, the set of partners possessed by a firm is an important marketing tool, and it has an incentive to form partnerships with a select set of firms, as a means of competition. Chapter 2 also describes the data collection procedure, which contains annual observations on transfer partnerships among 3 credit card issuers, 7 hotel chains, and 43 airlines and quarterly observations on their firm-level characteristics from 2014 to 2018.

Chapter 3 utilizes the aforementioned data set to study the formation of transfer partnerships. After describing transfer partnerships among firms as a directed network, I exploit variations in

transfer partnerships and characteristics of firms over time to study how major U.S. credit card issuers choose their airline partners. Partnerships between credit card issuers and hotel chains and partnerships among airlines are taken as given because these partnerships are typically determined by long-term contracts and hence little variation is observed in the data. Recognizing that characteristics of firms, the set of other partners possessed by a credit card issuer (i.e., complementarity of potential partnership to existing set of partners), the set of partners possessed by its partner hotel chains (i.e., indirect partnerships), and the set of partners possessed by other credit card issuers (i.e., partnerships of competitors) may affect the choice of a partner, this chapter uses a sequential network formation model to describe the partnership formation process. A key feature is that the state of the network affects partnership formation. A difficulty is that the order of events - the timeline through which partnerships were formed, rejected, or modified - is not fully observed. I use Markov Chain Monte Carlo to sample the order of events and to estimate model parameters. The result indicates that a credit card issuer tends to favor an airline partner that complements its other airline partners, is a partner of another credit card issuer, and is a partner of its hotel chain partner.

This dissertation is dedicated to my parents and my brother.
Their love gave me the strength to finish the dissertation.

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Contents

Chapter 1

Network Analysis of Supplier-Buyer Relationship: Selected U.S. Tech Firms from 2003 to 2014

1.1 Introduction

Since the pioneering work of Leontief (1951) on input-output linkages among industry sectors, economists have studied how an economic shock to an industry sector may affect other industry sectors, and more generally, the aggregate economy. Recent research on this topic includes Acemoglu et al. (2012), which studies how microeconomic shocks propagate to macroeconomic fluctuations, and Carvalho et al. (2016), which studies the effect of the Great East Japan Earthquake on the aggregate supply chain in Japan.

Input-output linkages among firms are typically described using a network. Such network contains information on which firm supplies to which firms and, if data permit, how much they supply. In other words, the network contains information on supplier-buyer linkages among firms. This framework allows one to study, for example, the relationship among industry sectors or the relationship among regional sectors. Via a chain of linkages, an economic shock to a firm in an industry sector may affect firms in other industry sectors. Similarly, an economic shock to a firm may affect firms across the Pacific Ocean.

This chapter studies the supplier-buyer relationship surrounding U.S. tech firms from 2003 to 2014. For each year, a supplier-buyer network describes such relationship. I identify four tech firms - AAPL, DELL, IBM, and MSFT[1] - as the most significant firms in the network and study changes to their significance over time. Moreover, I use the community detection method of Leicht and Newman (2008) to identify communities in the networks, where a community is a group of firms that are closely linked to each other. For all years, the four firms belong to different communities, indicating that they are closely associated with distinct groups of suppliers

[1]These are ticker symbols for Apple Inc., Dell Technologies Inc., International Business Machines Corporation, and Microsoft Corporation, respectively.

and buyers. On the other hand, these communities possess similar NAICS[2] codes, indicating that the four firms are closely associated with similar industry sectors but with different suppliers and buyers in the industry sectors. This result suggests that the four firms possess a certain degree of exclusivity with their suppliers and buyers.

In addition, I compute measures of centrality to evaluate the significance of AAPL, DELL, IBM, and MSFT in the supplier-buyer network. In particular, I employ five measures of centrality to evaluate their significance in various aspects of network connectivity. For each measure of centrality, I evaluate the firms' influence on the full network and also by utilizing the community structure. The result reveals that until 2010, IBM possessed the largest significance by far. However, the significance of MSFT grew and finally surpassed IBM in 2014. Furthermore, the growth of AAPL's significance over the years is remarkable.

The rest of this chapter is organized as the following. Section 1.2 describes the supplier-buyer network surrounding AAPL, DELL, IBM, and MSFT. Section 1.3 describes communities of firms and the associated NAICS codes. Section 1.4 presents the significance of AAPL, DELL, IBM, and MSFT by computing measures of centrality. Finally, section 1.5 concludes.

1.2 Supplier-Buyer Network

This chapter uses a directed graph to describe supplier-buyer relationships among firms. A (directed) graph consists two components: nodes and (directed) edges. A node represents a firm included in the network, and an edge from a node to another indicates that the source node supplies to the target node. In this chapter, the terms graph and edge are synonymous to network and link, respectively. Formally, a directed graph G is

$$G = (V, E), \tag{1.1}$$

where

$$V = \{1, 2, \ldots, N\} \tag{1.2}$$

is the set of nodes included in the graph. Although I've used an enumeration from 1 to N in this expression, one may use any collection of elements, such ticker symbols of firms, to describe the node set. The edge set

$$E \subseteq \{(i,j) | i,j \in V,\ i \neq j\} \tag{1.3}$$

is such that $(s,t) \in E$ if there exists an edge from the source node s to the target node t. The edge (s,t) is an *out-edge* for node s, as it flows from s, and it is an *in-edge* for t, as it flows into t. Note that unlike an undirected graph, $(s,t) \in E$ does not imply $(t,s) \in E$. Moreover, this specification does not allow self-loops, meaning that a node cannot possess an edge to itself.

A (directed) graph is commonly represented using an adjacency matrix $A \in \{0,1\}^{N \times N}$, where the $(i,j)^{th}$ element

$$A_{ij} = \begin{cases} 1 & \text{if } (i,j) \in E \\ 0 & \text{if otherwise.} \end{cases} \tag{1.4}$$

[2]The North American Industry Classification System (NAICS) assigns codes to firms based on industry sector.

One may extend the adjacency matrix such that $A_{ij} \in \mathbb{R}_+$ for $i \neq j$. In this specification, A_{ij} indicates the strength or weight of the edge from i to j. In this chapter, all elements of the the adjacency matrix is binary; thus it describes whether or not a firm supplies to another, without regards to the amount of transaction. This limitation is due to the lack of data on the amount of transaction between firms. Note that $A_{ii} = 0$ for all i because self-loops are not allowed. In other words, I do not consider transactions within a firm.

The data set[3] contains information on supplier-buyer transactions surrounding large tech firms publicly listed in the U.S. stock market. Using the data set, I construct a supplier-buyer network for each year from 2003 to 2014. The number of firms included in the network, or the size of the node set, ranges from 282 to 400 across the years. An edge indicates that the source node supplies to the target node. For example, an edge from DELL to another firm indicates that DELL sold goods or services to the other firm at least once during the corresponding year. For each year, putting together such transactions generates the supplier-buyer network.

Table 1.1 reports summary statistics of the supplier-buyer networks from 2003 to 2014. The first column ("Year") lists the years. The second column ("#Node") reports the number of firms in the network, and the third column ("#Edge") reports the number supplier-buyer transactions among the firms. The fourth column ("Density") reports the *network density*, defined as

$$\frac{|E|}{|V| \times (|V| - 1)}. \tag{1.5}$$

It is the number of edges divided by the number of possible edges. The reported measures indicate that the networks are not dense, meaning that a large fraction of firms in the network are not directly associated via a supplier-buyer relationship. However, network density does not account for indirect edges, which are indirect relationships such as being a supplier of a supplier. The fifth column ("#Avg Path") reports the average number of connected firms per firm. A node is connected to another node is if there exists a path[4], possibly passing through other nodes, from the former to the latter. For each year, the reported measures indicate that on average, a firm is connected to roughly a fourth of the entire set of firms. In other words, after accounting for indirect supplier-buyer relationship, the firms are more strongly linked to each other than what network density indicates.

The next three columns report information on degrees of nodes. The out-degree of a node is the number of out-edges from the node, and in-degree is the number of in-edges into the node. Note that the sum of out-degrees is equal to the sum of in-degrees, so there is no need to distinguish out- or in-degree when discussing the average degree. The sixth column ("Avg Degree") reports the average degree of a node, which is the sum of degrees divided by the number of nodes. The seventh and eighth columns ("Max In" and "Max Out") report the largest out-degree and the largest in-degree, respectively. Together with average degree, they reveal that

[3] It is the Factset Revere Relationship trial data set. Note that this is a trial data set and may not contain a full description of the supplier-buyer relationships among publicly listed U.S. tech firms. Also, non-publicly listed firms and non-U.S. firms were removed from the data set. All firms with zero observed transactions (i.e., having zero out- or in-edges) were removed from the data set.

[4] A path is a sequence of edges from a node to another. For example, a path from i to j, exists if $(i, j) \in E$ or $(i, k_1), \ldots (k_{L-1}, k_L), (k_L, j) \in E$ for some $\{k_l : 1 \leq l \leq L, L \leq |E| - 2\} \subset V$. Because edges are directed, paths are not reciprocal.

there are a small number of nodes with large out-degree or in-degree, while a large share of the nodes possess only 1 edge[5]. That is, there are a small number of "significant" firms that supply to or buy from a large number of firms, and such feature is observed for all years included in this study.

Table 1.1: Summary Statistics of Supplier-Buyer Networks

Year	#Node	#Edge	Density	Avg #Path	Avg Degree	Max Out	Max In	Out [A, D, I, M]	In [A, D, I, M]
2003	282	453	0.0057	81.1	1.606	86	111	[7, 18, 86, 46]	[19, 57, 111, 54]
2004	290	456	0.0054	78.6	1.572	91	112	[7, 16, 91, 44]	[22, 55, 112, 55]
2005	293	451	0.0053	82.8	1.539	88	123	[5, 18, 88, 49]	[25, 47, 123, 61]
2006	272	415	0.0056	79.6	1.526	77	109	[6, 19, 77, 48]	[26, 40, 109, 53]
2007	267	389	0.0055	66.4	1.457	71	94	[6, 15, 71, 39]	[25, 42, 94, 46]
2008	272	404	0.0055	68.7	1.485	78	89	[5, 23, 78, 43]	[23, 38, 89, 55]
2009	261	388	0.0057	72.8	1.487	73	81	[6, 23, 73, 42]	[22, 37, 81, 54]
2010	286	431	0.0053	72.9	1.507	72	84	[5, 23, 72, 54]	[42, 44, 84, 61]
2011	299	472	0.0053	85.3	1.579	83	84	[6, 21, 83, 67]	[51, 54, 84, 69]
2012	341	504	0.0043	76.7	1.478	79	89	[12, 26, 74, 79]	[66, 63, 89, 68]
2013	370	541	0.0040	88.8	1.462	74	84	[22, 26, 69, 74]	[79, 73, 84, 72]
2014	400	607	0.0038	95.2	1.517	85	90	[32, 26, 69, 85]	[86, 82, 89, 90]

This table reports summary statistics of the supplier-buyer networks from 2003 to 2014. The first column ("Year") lists the years. The second ("#Node") and third ("#Edge") columns report the number of firms and the number of edges between firms, resepctively. The fourth column ("Density") reports network density, which is the number of edges divided by the possible number of edges. The fifth column ("Avg Path") reports the average number of connected firms per firm. A firm is connected to another firm if there exists a sequence of edges from the former to the latter. The sixth column ("#Avg Degree") reports the average number of edges per firm. The next two columns ("Max Out" and "Max In") report the largest outdegree and indegree of a firm, respectively. The last two columns ("Out [A, D, I, M]" and "In [A, D, I, M]") report the out-degrees and in-degrees of [AAPL, DELL, IBM, MSFT], respectively. The entries in each bracket follow the order of firms.

In the supplier-buyer network, I identify AAPL, DELL, IBM, and MSFT as the most "significant" firms. The last two columns ("Out [A, D, I, M]" and "In [A, D, I, M]") respectively report the out-degrees and in-degrees of [AAPL, DELL, IBM, and MSFT]. The entries in each bracket follow the order of firms. The measures indicate that IBM possessed the largest significance overall, in both out-degree and in-degree, until MSFT surpassed it in 2014. It is also notable that the significance of AAPL, especially in in-degree, has been gradually increasing over the years. We can also observe that AAPL and DELL are net receivers, meaning that their in-degrees are much larger than their out-degrees. It indicates that these firms source intermediate goods

[5]By construction of the data set, each node possesses at least one in- or out-edge.

from a large number of suppliers but sell their products to a relatively small number of buyers. Possibly, such characteristic reveals than the business models of AAPL and DELL are different from IBM and MSFT. Moreover, in the event of an economic shock, AAPL and DELL may be affected differently and also may exert a different effect on the supplier-buyer network than IBM and MSFT.

The following sections study the structure of the buyer-supplier network and significance these four firms in the network by dividing the network into communities of firms, characterizing the communities by NAICS codes, and computing measures of centrality. So far, the significance of a firm in the network was characterized only using its out- and in-degree. There are, however, a number of other measures that characterize the significance of a firm. Some of these measures are explained and computed in section 1.4.

1.3 Community of Firms

Recent research in statistical physics and computer science studies how one may detect communities within a network. A community is generally defined as a group of nodes that are more strongly linked to each other than to the rest of the network. Thus, the goal of community detection is to split the node set V into subsets[6], such that nodes belonging to the same subset possess strong linkages among them, while there are relatively weak linkages among the subsets. For the rest of this chapter, an *intra-community* edge (or *intra-edge)* denotes an edge from a node to another within the same community, and an *inter-community* edge (or *inter-edge)* denotes an edge from a node to another node belonging to a different community.

Communities are considered as important building blocks of a network. For the supplier-buyer network, a community of firms may be interpreted as a group of closely associated firms that are likely to be most significantly affected in the event of an economic shock to a community member. However, if the community member is a bridge between communities, a node that is also strongly linked to another community, the shock may also have a significant impact to another community.

1.3.1 Community Detection

I employ the community detection method of Leicht and Newman (2008), which is an extension of Newman (2006) for directed graphs. The fundamental idea is to detect groups of nodes, such that nodes within each group are more densely linked to each other than what is expected under a random network configuration preserving the out-degree and in-degree sequence. Arenas et al. (2007) suggests that for a directed graph, the strength of the linkage from node i to node j, for $i \neq j$, under a random network configuration is

$$\frac{O_i \times I_j}{M}, \tag{1.6}$$

[6]The community detection method used in this chapter partitions V into subsets, meaning that each node belongs to exactly one community.

where O_i and I_j are the out-degree of node i and the in-degree of node j, respectively. $M = |E|$ is the number of edges in the network. Because self-loops are not allowed, the value of equation (1.6) is set to zero whenever $i = j$.

The *modularity* of a network (Girvan and Newman, 2002) is[7]

$$Q = \frac{1}{4M} s' \left(B + B'\right) s. \tag{1.7}$$

B is called the *modularity matrix*, with the $(i, j)^{\text{th}}$ element

$$B_{ij} = A_{ij} - \frac{O_i \times I_j}{M}, \tag{1.8}$$

and $s \in \{-1, 1\}^N$ is the choice variable that partitions the node set into two communities. Essentially, B_{ij} is the difference between the observed strength (as given by the element of the adjacency matrix A_{ij}) and the expected strength of the linkage from i to j. Thus, the larger the value of Q, the greater the strength of linkages within each community is relative to what is expected under a random network configuration with identical out-degree and in-degree sequence. In other words, a larger value of Q indicates that each community contains a larger fraction of edges than what would be expected if edges were placed at random, while preserving the out-degree and in-degree for each node. The optimal choice of s maximizes Q. Because of the binary restriction, it is approximated by choosing a vector in $\{-1, 1\}^N$ that matches the signs of a leading eigenvector[8] of $B + B'$. The result is further fine-tuned using a greedy algorithm, which terminates when Q cannot be improved by altering the community assignment of a node.

The method described above divides the node set of the network into two communities. The node set is divided into more than two communities by iteratively subdividing communities. For a community $C \subset V$, a subdivision, given by $s^{(C)} \in \{-1, 1\}^{\dim(C)}$, occurs only when

$$\Delta Q = \frac{1}{4M} s^{(C)\prime} \left(\tilde{B}^{(C)} + \tilde{B}^{(C)\prime}\right) s^{(C)} \tag{1.9}$$

is positive. $\tilde{B}^{(C)} \in \mathbb{R}^{\dim(C) \times \dim(C)}$ is defined such that the $(i, j)^{\text{th}}$ element

$$\tilde{B}^{(C)}_{ij} = B^{(C)}_{ij} - \frac{1}{2} \delta_{ij} \sum_{k \in C} \left(B^{(C)}_{ik} + B^{(C)}_{ki}\right), \tag{1.10}$$

where $B^{(C)}$ is the submatrix of the modularity matrix B obtained by eliminating the rows and columns corresponding to the nodes that do not belong to C. δ_{ij} takes value 1 if $i = j$ and zero if otherwise.

1.3.2 Communities in Supplier-Buyer Network

Table 1.2 shows a summary of communities in the supplier-buyer networks, from 2003 to 2014. The second column ("#C") reports the number communities; these communities partition the set

[7] This expression uses a symmetrization of $Q = \frac{1}{2M} s' B s$. Since $Q \in \mathbb{R}$, we have $Q = \left(Q + Q'\right)/2$.

[8] A leading eigenvector corresponds to the largest positive eigenvalue.

of firms included in the network. The remaining columns report information about the four largest communities. The entries in each bracket correspond to the $\left[4^{\text{th}}, 3^{\text{rd}}, 2^{\text{nd}}, 1^{\text{st}}\right]$ largest communities.

The third column ("Community Size") reports the community size, which is equal to the number of firms belonging to the community. It reveals that the largest community is significantly larger than other communities. Until 2009, the largest community contained more than 40 percent of the firms in the network; however, its share diminished since 2010 as other communities grew in size. For all years, the size of the smallest community is two.

The fourth column ("#Intra-Edges) reports the number of intra-community edges, and the next two columns ("#Inter-Edges (Out)" and "#Inter-Edges (In)") report the number of inter-community edges to other communities and from other communities, respectively. Comparing the number of intra-community edges to the number of inter-community edges reveals that there remains considerable inter-community linkages after the community division. However, as a fraction of possible edges, the linkages within a community is far stronger than the linkages across communities. Table A.1 in the appendix reports the densities associated with the intra- and inter-community edges, where each density is computed using equation (1.5) with the appropriate number of possible edges as the denominator. Nevertheless, the existence of considerable inter-community edges indicates that if an economic shock occurs to a community member, the shock is unlikely to be contained in its own community. Such feature is further confirmed by the seventh column of the table ("#NC"), which gives the number of firms that are not linked to or linked from other communities. For all years, a large fraction of firms are linked to or linked from other communities, possibly except for one community.

The last column ("Firm") reports the community membership of AAPL, DELL, IBM, and MSFT. For all years, these firms belong to different communities, indicating that they possesses a strong supplier-buyer relationship with different sets of firms. Note that the result does not say that these firms possess completely exclusive set of suppliers or buyers; they may have suppliers or buyers belonging to a community other than its own. The community division also reveals that the community of IBM was the largest community, until the community of MSFT became the largest in 2014. We can also observe that the community of AAPL grew in size over the years, from 17 in 2003 to 77 in 2014. It indicates that over the years, AAPL formed strong supplier-buyer relationships with a larger set firms. Belonging to a larger community, however, does not necessarily indicate that the significance of AAPL in the network grew over the years.

Figure 1.1 graphically illustrates the community divisions. For each year, firms (nodes) are placed on an ellipse, and firms belonging to the same community are placed adjacently. The communities of AAPL, DELL, IBM, and MSFT are color-coded to distinguish them; all other communities are marked in black. Moreover, each of these four firms are placed at the very first, in clockwise orientation, in its community. For example, in sub-figure (a), the magenta-colored nodes covering the left side of the ellipse is the community of IBM, and IBM is placed as the first in clockwise orientation. Each directed line indicates a link from a firm to another. Red-colored lines indicate intra-community edges, and blue-colored lines indicate inter-community edges.

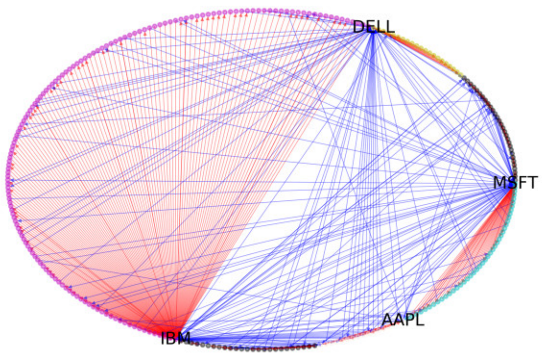
Table 1.2: Community Structure (Largest Four Communities)

Year	#C	Community Size	#Intra-Edges	#Inter-Edges (Out)	#Inter-Edges (In)	#NC	Firm
2003	13	[17, 21, 43, 146]	[18, 21, 49, 158]	[25, 9, 41, 52]	[17, 48, 26, 40]	[3, 18, 29, 93]	[A, D, M, I]
2004	14	[19, 32, 36, 151]	[19, 32, 40, 164]	[28, 18, 28, 53]	[12, 41, 36, 45]	[3, 18, 32, 96]	[A, D, M, I]
2005	13	[26, 30, 53, 142]	[25, 30, 60, 158]	[38, 7, 20, 58]	[15, 44, 43, 26]	[4, 17, 40, 111]	[A, D, M, I]
2006	13	[25, 28, 42, 138]	[25, 27, 48, 152]	[10, 32, 29, 37]	[34, 14, 30, 40]	[18, 4, 37, 96]	[D, A, M, I]
2007	13	[24, 30, 37, 127]	[23, 30, 40, 138]	[20, 22, 23, 33]	[15, 27, 25, 34]	[8, 17, 34, 87]	[A, D, M, I]
2008	14	[23, 31, 44, 124]	[22, 31, 51, 135]	[20, 22, 18, 38]	[10, 31, 34, 38]	[10, 19, 38, 80]	[A, D, M, I]
2009	13	[22, 26, 46, 114]	[21, 26, 51, 125]	[18, 20, 20, 38]	[13, 32, 30, 33]	[9, 15, 41, 73]	[A, D, M, I]
2010	13	[28, 41, 58, 113]	[28, 40, 63, 125]	[15, 32, 23, 39]	[38, 19, 34, 34]	[17, 17, 53, 71]	[D, A, M, I]
2011	13	[37, 44, 61, 123]	[37, 48, 70, 140]	[18, 47, 30, 42]	[29, 28, 40, 45]	[20, 19, 56, 69]	[A, D, M, I]
2012	14	[52, 55, 72, 125]	[54, 55, 81, 129]	[33, 27, 38, 47]	[44, 30, 36, 36]	[24, 34, 66, 76]	[D, A, M, I]
2013	15	[61, 69, 72, 117]	[63, 77, 73, 122]	[27, 37, 39, 55]	[57, 40, 33, 27]	[31, 63, 45, 67]	[D, M, A, I]
2014	18	[61, 66, 77, 137]	[62, 72, 79, 146]	[51, 39, 59, 42]	[45, 55, 27, 66]	[27, 59, 50, 71]	[D, I, A, M]

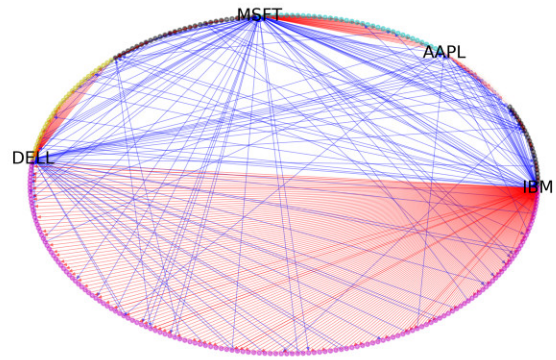
This table describes the result of the community division. The first column ("Year") lists the years. The second column ("#C") reports the number communities; these communities partition the set of firms in the supplier-buyer network. The remaining columns report information about the four largest communities. The entries in each bracket correspond to the $\left[4^{\text{th}}, 3^{\text{rd}}, 2^{\text{nd}}, 1^{\text{st}}\right]$ largest communities. The third column ("Community Size") reports the size of the community, which is equal to the number of firms belonging to the community. The fourth column ("#Intra-Edges") reports the number of intra-community edges. The next two columns ("#Inter-Edges (Out)" and "#Inter-Edges (In)") report the number of inter-community out-edges and in-edges, respectively. The seventh column ("#NC") reports the number of firms that are not linked to or linked from communities other than its own. The last columnm ("Firm") reports the community membership of AAPL, DELL, IBM, and MSFT. For example, [D, A, M, I] indicates that DELL, AAPL, MSFT, and IBM belong to the fouth, third, second, and first largest communities, respectively.

Figure 1.1: Community Division and Out-Edges

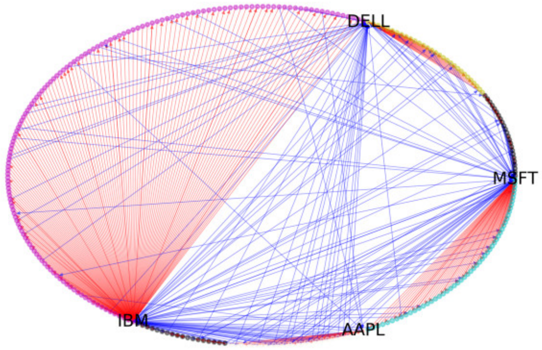
(a) 2003



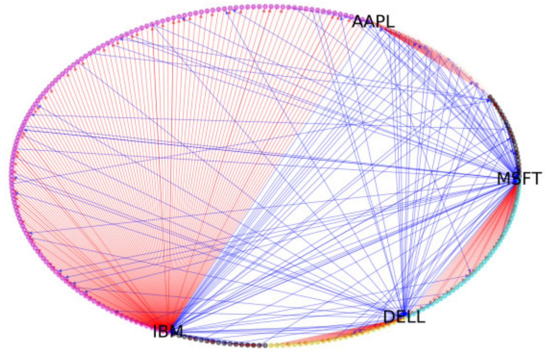
(b) 2004



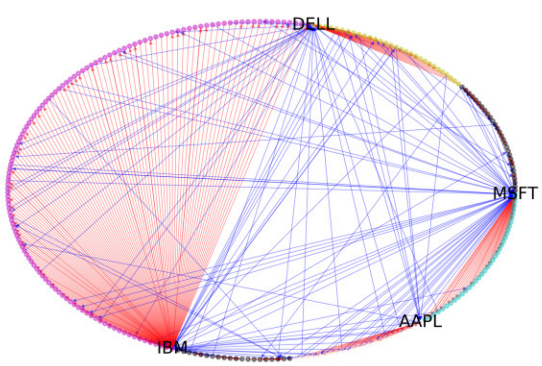
(c) 2005



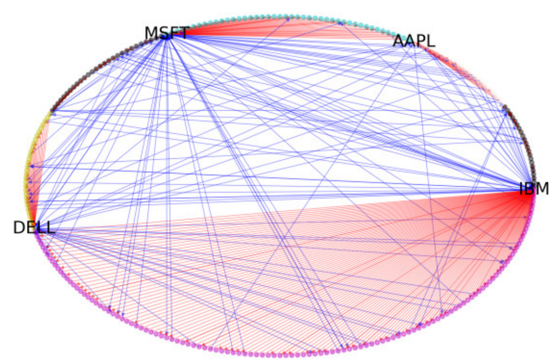
(d) 2006



(e) 2007

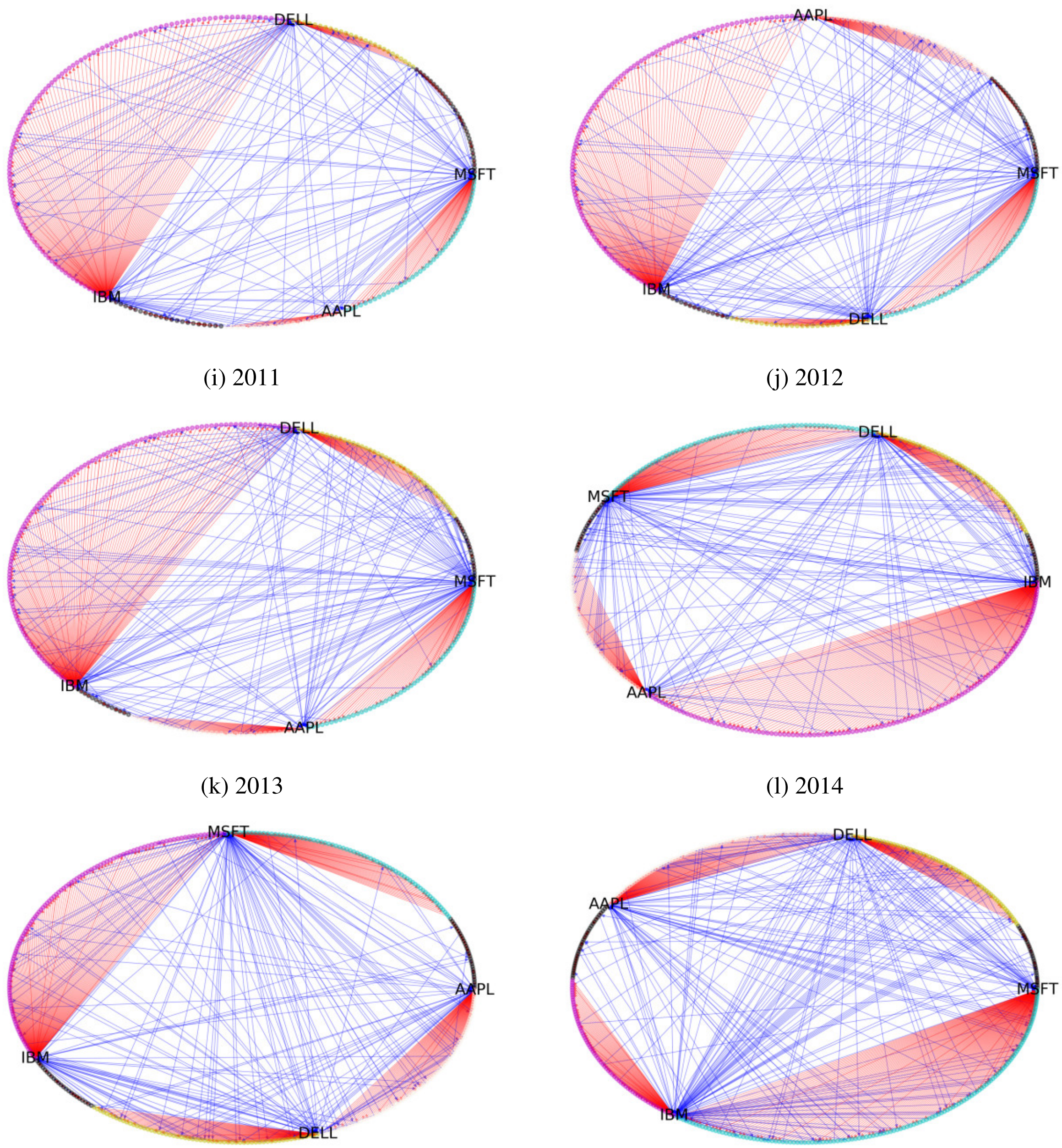


(f) 2008



This figure graphically illustrates the community divisions. For each year, firms (nodes) are placed on an ellipse, and firms belonging to the same community are placed adjacently. The communities of AAPL, DELL, IBM, and MSFT (each belongs to a different community) are color-coded to distinguish them; all other communities are marked in black. (continued on the next page)

Figure 1: Community Division and Out-Edges (Continued)



(g) 2009

(h) 2010

(i) 2011

(j) 2012

(k) 2013

(l) 2014

Moreover, each of the four firms are placed at the very first, in clockwise orientation, in its community. For example, in sub-figure (g), the magenta-colored nodes covering the left side of the ellipse is the community of IBM, and IBM is placed as the first in clockwise orientation. Each directed line indicates a link from a firm to another. The red-colored lines indicate intra-community edges, and the blue-colored lines indicate inter-community edges.

The figure confirms the trend in communities explained earlier. By looking at the share of the ellipse each of the four communities occupies, we can observe that the community of IBM possessed the largest share until 2013, until surpassed by the community of MSFT in 2014. Moreover, the the growth of AAPL's community is remarkable, especially from 2012.

The denseness of the red and blue lines at AAPL, DELL, IBM, and MSFT indicate the strength of intra-community edges (red lines) and inter-community edges (blue lines) of the four firms. First, the strength of intra-community edges at each of AAPL, DELL, IBM, and MSFT is far greater than other firms in the same community, which reveals that each firm is the center of its community. Moreover, until 2013, the strength of intra-community edges was far greater than strength of inter-community edges at IBM, indicating that IBM had far stronger linkages with its community members than with firms in other communities until 2013. For the same period, the strength of intra- and inter-community edges appear to be similar or the former appears to be only slightly stronger at AAPL, DELL, and MSFT. In other words, the supplier-buyer relationship of IBM was more strongly restricted to its own community than the other three firms until 2013. In 2014, however, the strength of intra- and inter-community edges at IBM became similar, while the former became much stronger at MSFT. A possible cause for such shift is that the community of MSFT became the largest in 2014. That is, a number of firms that were strongly associated with IBM in previous years became strongly associated with the other three firms, and the community surrounding IBM became smaller. It reveals that IBM became less significant in the supplier-buyer network in 2014.

Table 1.3 provides details on the number of intra- and inter-community edges of [AAPL, DELL, IBM, MSFT]. The entries in each bracket follow the exact order of firms. The numbers reported in the second and third columns describe the role of the firm as a supplier. The second column ("#Intra-Edges (Out)") reports the number of intra-community edges from the firm, which is equal to the number of firms in the same community the firm supplies to. The third column ("#Inter-Edges (Out)") reports the number of inter-community edges from the firm, which is equal to the number of firms in other communities the firm supplies to. The numbers reported in the next two columns describe the role of the firm as a buyer. The fourth column ("#Intra-Edges (In)") reports the number of intra-community edges to the firm, which is equal to the number of firms in the same community the firm buys from. The last column ("#Inter-Edges (In)") reports the number of inter-community edges to the firm, which is equal to the number of firms in other communities the firm buys from.

The last two columns of table 1.1 indicate that AAPL and DELL are net buyers, meaning that they buy from a much larger number firms than the number of firms they supply to (much more in-edges than out-edges). In table 1.3, comparing the second ("#Intra-Edges (Out)") and the fourth ("#Intra-Edges (In)") columns, and also comparing the third ("#Inter-Edges (Out)") and fifth ("#Inter-Edges (In)") columns, provide information on their roles in their own communities and also with other communities. AAPL buys more from its own community than from other communities. In contrast, DELL buys more from other communities than from its own community. Such information tells us that for AAPL, a demand shock may have a stronger effect on its own community than on other communities. For DELL, a demand shock may have a stronger effect on other communities than on its own community.

Table 1.3: Edges of [AAPL, DELL, IBM, MSFT]

Year	#Intra-Edges (Out)	#Inter-Edges (Out)	#Intra-Edges (In)	#Inter-Edges (In)
2003	[5, 9, 69, 18]	[2, 9, 17, 28]	[13, 12, 89, 31]	[6, 45, 22, 23]
2004	[4, 10, 75, 18]	[3, 6, 16, 26]	[15, 22, 89, 22]	[7, 33, 23, 33]
2005	[5, 16, 57, 31]	[0, 2, 31, 18]	[20, 14, 101, 29]	[5, 33, 22, 32]
2006	[5, 12, 65, 23]	[1, 7, 12, 25]	[22, 13, 87, 25]	[4, 27, 22, 28]
2007	[5, 8, 60, 18]	[1, 7, 11, 21]	[18, 22, 78, 22]	[7, 20, 16, 24]
2008	[4, 14, 65, 26]	[1, 9, 13, 17]	[18, 17, 70, 25]	[5, 21, 19, 30]
2009	[5, 12, 60, 24]	[1, 11, 13, 18]	[16, 14, 65, 27]	[6, 23, 16, 27]
2010	[5, 14, 59, 33]	[0, 9, 13, 21]	[35, 14, 66, 30]	[7, 30, 18, 31]
2011	[6, 10, 75, 39]	[0, 11, 8, 28]	[31, 34, 65, 31]	[20, 20, 19, 38]
2012	[10, 18, 60, 47]	[2, 8, 14, 32]	[45, 36, 69, 34]	[21, 27, 20, 34]
2013	[17, 22, 55, 43]	[5, 4, 14, 31]	[56, 41, 67, 34]	[23, 32, 17, 38]
2014	[16, 14, 38, 79]	[16, 12, 31, 14]	[63, 48, 34, 67]	[22, 23, 53, 21]

This table reports the number of edges associated with [AAPL, DELL, IBM, MSFT]. The entries in each bracket follow the order of firms. The first column ("Year") lists the years. The second column ("#Intra-Edges (Out)") reports the number of intra-community edges from the firm, and the third column ("#Inter-Edges (Out)") reports the number of inter-community edges from the firm. The fourth column ("#Intra-Edges (In)") reports the number of intra-community edges to the firm, and the last column ("#Inter-Edges (In)") reports the number of inter-community edges to the firm.

1.3.3 NAICS Codes of Communities

The North American Industry Classification System (NAICS) assigns codes to firms based on the industry sector they belong to. For example, AAPL, DELL, IBM, and MSFT, respectively, are assigned 33422 ("Radio and Television Broadcasting and Wireless Communications Equipment"), 33411 ("Computer and Peripheral Equipment Manufacturing"), 51913 ("Internet Publishing and Broadcasting and Web Search Portals"), and 51121 ("Software Publishers"). Table A.2 in the appendix provides a dictionary for the NAICS codes that appear in this section.

Table 1.4 describes the NAICS codes associated with the communities of [AAPL, DELL, IBM, MSFT]. The entries in each bracket follow the order of firms. The second column ("NAICS (1^{st})") reports the most frequently observed NAICS code in the community. The third ("NAICS (2^{nd})") and the fourth ("NAICS (3^{rd})") columns report the second-most and the third-most frequently observed NAICS codes in the community, respectively. We can observe that the four communities are associated with similar NAICS codes. In particular, all of them are closely associated with NAICS codes 33441 ("Computer and Peripheral Equipment Manufacturing"), 51121 ("Software Publishers"), 51913 (Internet Publishing and Broadcasting and Web Search Portals), and 42343 ("Computer and Computer Peripheral Equipment and Software Merchant

Wholesalers"). It reveals that an economic shock to any of the four firms will strongly affect these industry sectors. Finally, the last column ("#NAICS") reports the number of unique NAICS codes in the community, which can be interpreted as the diverseness of industries in the community. Over the years, the growth in the diverseness of AAPL's community is remarkable.

Table 1.4: NAICS Codes by Community of [AAPL, DELL, IBM, MSFT]

Year	**NAICS (1st)**	**NAICS (2nd)**	**NAICS (3rd)**	**#NAICS**
2003	[33441, 33441, 33441, 51121]	[51121, 54151, 51121, 51913]	[42343, 32521, 33411, 54151]	[8, 16, 45, 27]
2004	[33441, 33441, 33441, 51121]	[51121, 51913, 51121, 54151]	[42343, 54151, 54151, 56149]	[9, 21, 54, 24]
2005	[33441, 54151, 33441, 51121]	[42343, 51121, 51121, 42343]	[51913, 33441, 33411, 51913]	[11, 20, 53, 32]
2006	[33441, 33441, 33441, 51121]	[42343, 51913, 51121, 33441]	[33411, 51121, 54151, 56149]	[13, 16, 49, 27]
2007	[33441, 33441, 33441, 51121]	[42343, 33411, 51121, 33441]	[53112, 51121, 54151, 33411]	[12, 14, 43, 22]
2008	[33441, 33441, 33441, 51121]	[53112, 33411, 51121, 33411]	[51913, 51913, 54151, 51913]	[10, 18, 46, 28]
2009	[33441, 33441, 33441, 51121]	[42343, 51913, 54151, 51913]	[53112, 51121, 51121, 33411]	[11, 15, 43, 24]
2010	[33441, 51121, 51121, 51121]	[51913, 51913, 33441, 51913]	[42343, 33441, 54151, 54151]	[14, 17, 41, 30]
2011	[33441, 33441, 33441, 51121]	[51913, 33411, 51121, 54151]	[33431, 51913, 54151, 53112]	[18, 14, 43, 34]
2012	[33441, 51121, 33441, 51121]	[51913, 33441, 51121, 51913]	[51121, 54151, 54151, 53112]	[24, 22, 48, 34]
2013	[33441, 33441, 33441, 51913]	[51913, 51121, 51121, 51121]	[51121, 54151, 54151, 54151]	[30, 23, 48, 32]
2014	[33441, 33441, 51121, 51913]	[51913, 51121, 33441, 51121]	[51121, 33411, 54151, 54151]	[34, 21, 34, 44]

This table describes the 5-digit NAICS codes associated with the communities of [AAPL, DELL, IBM, MSFT]. The entries in each bracket follow the order of firms. The first column ("Year") lists the years. The second column ("NAICS (1st)") reports the most frequently observed NAICS code in the community. The third column ("NAICS (2nd)") and the fourth column ("NAICS (3rd)") report the second-most and the third-most frequently observed NAICS codes in the community, respectively. The last column ("#NAICS") reports the number of unique NAICS codes observed in the community.

1.4 Centrality of Firms

This section studies the significance of firms in the supplier-buyer network using measures of centrality. If an economic shock occurs to firm i, the shock will first affect the direct buyers and suppliers of i. Subsequently, the shock will spread out to the buyers and suppliers of these buyers and suppliers, and so on. The centrality of a firm indicates its influence in the supplier-buyer network. A firm with large centrality is significant, meaning that it is highly influential on the supplier-buyer network. This section evaluates the significance of firms using standard measures of centrality and also modular measures of centrality. Modular centrality, a concept proposed by Ghalmane, Hassouni, et al. (2019), distinguishes the influence of a node on its own community and on other communities.

The direction of edges matters in interpreting the centrality of a firm. By construction of the adjacency matrix, $A_{ij} = 1$ if firm i supplies to firm j (j is a buyer of i). Thus, centrality measures computed using the adjacency matrix A are interpreted as the influence of a firm on it buyers, the buyers of these buyers, and so on. This is called the *downstream* channel (stream of goods and services from the firm). Centrality measures using the transpose A' are interpreted as the influence of a firm on its suppliers, the suppliers of these suppliers, and so on. This is called the *upstream* channel (stream of goods and services into the firm).

1.4.1 Measures of Centrality

Researchers of social network, epidemiology, physics, and more generally, graph theory have utilized measures of centrality to evaluate the influence of nodes in the network. I employ the following measures of centrality [see, for example, Newman (2010) for details.]. Note that a centrality measure is always nonnegative, and one should focus on the rankings among nodes a centrality measure assigns, instead of the magnitude. Moreover, comparing magnitudes across different measures of centrality is generally inadequate because they capture different aspects of network connectivity. The notations introduced in section 1.2 are used in the following.

1.4.1.1 (Out-) Degree Centrality

The degree centrality of node i the is fraction of nodes it links to. For a directed graph, it is standard to follow the direction of edges when computing degree centrality. Thus, the out-degree of i, denoted by O_i, is used for computation, and the degree centrality of i is equal to

$$\mathcal{C}_{\mathrm{D}}(i) = \frac{O_i}{N-1} \tag{1.11}$$

For the supplier-buyer network, the degree centrality evaluates the influence of firm i as a supplier. Note that the transpose of the adjacency matrix is used to evaluate the influence of i as a buyer, which is called the in-degree centrality of i. A limitation is that degree centrality only captures the direct influence of a firm.

1.4.1.2 Eigenvector Centrality

Let α denote the largest positive eigenvalue of the adjacency matrix A, with the corresponding normalized eigenvector $\mathcal{C}_{\mathrm{E}} = (\mathcal{C}_{\mathrm{E}}(1), \mathcal{C}_{\mathrm{E}}(2), \ldots, \mathcal{C}_{\mathrm{E}}(N))'$, such that

$$A\mathcal{C}_{\mathrm{E}} = \alpha \mathcal{C}_{\mathrm{E}} \tag{1.12}$$

The eigenvector centrality of node i is equal to $\mathcal{C}_E(i)$, and it can be also written as

$$\mathcal{C}_{\mathrm{E}}(i) = \alpha^{-1} \sum_j A_{ij} \mathcal{C}_{\mathrm{E}}(j). \tag{1.13}$$

Recall that A_{ij} takes value 1 if there exists an edge from i to j and zero if otherwise. Thus, equation (1.13) indicates that the eigenvector centrality of node i is large if it is linked to nodes with large eigenvector centrality. In other words, more significance is assigned to nodes that are linked to significant nodes. Note that this specification evaluates the influence of firms as a suppliers in the downstream channel. The transpose of A is used to compute the influence of firms as a buyers in the upstream channel. I use the following two variations of eigenvector centrality.

Katz Centrality

A potential problem of eigenvector centrality is that in order to possess positive centrality, a node needs to be linked to a node that possesses a positive centrality. In the extreme case with an acyclic[9] digraph, all nodes possess zero eigenvector centrality regardless of the number of links. Thus, eigenvector centrality underestimates the influence of a node that links to a large number of insignificant nodes (i.e., with zero centrality). Katz centrality alleviates this problem by assigning a minimum positive centrality to each node. The Katz centrality of node i is defined as

$$\mathcal{C}_{\mathrm{K}}(i) = a_{\mathrm{K}} \sum_j A_{ij} \mathcal{C}_{\mathrm{K}}(j) + b_{\mathrm{K}}, \tag{1.14}$$

which adds a minimum positive centrality b_{K} to the eigenvector component in equation (1.13). a_{K} assigns a weight to the eigenvector component, and it is bounded away from zero so that we do not have $\mathcal{C}_{\mathrm{K}}(i) = b_{\mathrm{K}}$ for all i. Moreover, it can be shown that $a_{\mathrm{K}} < \alpha^{-1}$ is necessary for convergence of equation (1.14). In this chapter, I use $a_{\mathrm{K}} = 0.9\alpha^{-1}$ and $b_{\mathrm{K}} = 1$. The magnitude of b_{K} is unimportant because we are only interested in ranking the nodes, not the magnitude of the centrality.

PageRank Centrality

A possible weakness of Katz centrality is that it assigns large values of centrality to all nodes that are linked to a node with large centrality. This can be problematic because for example, the significance of a firm that is the sole supplier to a highly significant firm (i.e., with large centrality) should be greater than a firm that is one of many suppliers to a highly significant firm.

[9] A digraph is acyclic if it contains no path from a node to itself.

PageRank centrality alleviates this problem by weighting the eigenvector centrality component of a node by its in-degree. The PageRank centrality of node i is defined as

$$\mathcal{C}_{\mathrm{P}}(i) = a_{\mathrm{P}} \sum_{j=1}^{N} A_{ij} \frac{\mathcal{C}_{\mathrm{P}}(j)}{I_j} + b_{\mathrm{P}}, \tag{1.15}$$

where I_j is the in-degree of node j. For the supplier-buyer network, I_j is large if firm j buys from a large number of suppliers. The suppliers of j gains in centrality by supplying to j, especially if j is a significant firm. The weighting factor $1/I_j$ equally distributes the significance of j to its suppliers. For $I_j = 0$, it is replaced with a constant; the value of the constant is unimportant because in this case, $A_{ij} = 0$ for all i. With such modification, convergence of equation (1.15) requires $a_{\mathrm{P}} < \tilde{\alpha}^{-1}$, where $\tilde{\alpha}$ is the largest positive eigenvalue of AD^{-1}, where $D = \mathrm{diag}\,(I_1, I_2, \ldots, I_N)$. I use $a_{\mathrm{P}} = \min\,(0.85, 0.9\tilde{\alpha}^{-1})$ and as before, $b_{\mathrm{P}} = 1$.

1.4.1.3 Closeness Centrality (Harmonic)

The closeness centrality of node i measures the average distance from i to other nodes in the network. For $i \neq j$, a path from i to j exists (equivalently, i is connected to j) if there exists a sequence of directed edges, possibly passing through other nodes, from i to j. The length of a path is equal to the number of edges in the path, and the distance from i to j is equal to the length of a shortest path. Formally, the distance from i to j is[10]

$$d(i,j) = \begin{cases} \text{Length of shortest path from } i \text{ to } j & \text{if path from } i \text{ to } j \text{ exists} \\ \infty & \text{if no path from } i \text{ to } j \text{ exist} \\ 0 & \text{if } i = j. \end{cases} \tag{1.16}$$

Then the closeness centrality of i is defined as

$$\mathcal{C}_C(i) = \frac{1}{N-1} \sum_{j \neq i} \frac{1}{d(i,j)}, \tag{1.17}$$

which is the inverse harmonic mean of the distances from i to other nodes in the network. It essentially counts the number of nodes i is connected to, discounted by the inverse distance. Thus the closeness centrality of i is large if it is connected to a large number of nodes via short paths.

Closeness centrality assigns high significance to all firms that supply to a highly significant firm (i.e. large closeness centrality), as they can connect to other firms via that firm. Similar to Katz centrality, it can be problematic as closeness centrality may not distinguish the significance between the sole supplier and one of many suppliers to a significant firm. Moreover, it may not account for the existence of multiple shortest paths. For example, consider a case when i is connected to j via a single path $\{(i,k_1),(k_1,j)\}$. Also consider another case when there exists an additional path from i to j, $\{(i,k_2),(k_2,j)\}$, for $k_1 \neq k_2$. In both cases, the distance from i to j is equal to 2, and closeness centrality may not capture the difference in multiplicity.

[10]Note that for a digraph, $d(\cdot,\cdot)$ is not a metric because it does not satisfy the symmetry property.

1.4.1.4 Betweenness Centrality (Shortest Path)

Unlike the previous measures centrality, betweenness centrality captures the significance of a node in maintaining connectivity within the network. Consider a path $\{(i,k),(k,j)\}$, which connects i to j via k. Node k plays an important role because without it, the flow from i to j is disrupted. I use a version of betweenness centrality based on shortest paths. Let $\pi(s,t)$ and $\pi(s,t,;i)$ denote the number of shortest paths from node s to node t and the number of such paths passing through i, respectively. The betweenness centrality of i is defined as

$$\mathcal{C}_B(i) = \sum_s \sum_{t \neq s} \frac{\pi(s,t;i)}{\pi(s,t)}, \tag{1.18}$$

where $\pi(s,t;i)/\pi(s,t)$ is set to zero if $\pi(s,t)$ and $\pi(s,t;i)$ are both zero. For the supplier-buyer network, a firm with large betweenness centrality plays a significant role in maintaining the flow of goods and services in the supply chain. An economic shock to such a firm may disrupt the supply chain.

1.4.2 Modular Centrality

Modular centrality (Ghalmane, Hassouni, et al., 2019) utilizes a community division in computing measures of centrality. Because this chapter distinguishes the significance of a firm in the downstream channel (out-edges) and the upstream channel (in-edges), it is necessary to first establish that the community division discussed in section 1.3.1 does not depend on whether one uses out-edges or in-edges. Recall that computing centrality using the adjacency matrix A corresponds to the downstream channel and using the transpose A' corresponds to the upstream channel. Let O'_i and I'_j denote the out-degree of node i and the in-degree of node j obtained from A'. Using the notation in section 1.3.1,

$$O'_i = I_i,\ I'_j = O_j. \tag{1.19}$$

Thus, the $(i,j)^{\text{th}}$ element of the modularity matrix corresponding to A' is

$$[A']_{ij} - \frac{O'_i \times I'_j}{M} = A_{ji} - \frac{I_i \times O_j}{M} \tag{1.20}$$

$$= [B']_{ij}\,. \tag{1.21}$$

Because the modularity in equation (1.7) uses $B + B'$, the community division method in section 1.3.1 accounts for both the downstream and the upstream channels.

A measure of modular centrality exists for every measure of centrality, and it is defined as a weighted sum of the *local component* and the *global component.* For each measure of centrality, the corresponding local component is computed only using intra-community edges, and the corresponding global component is computed only using inter-community edges. All nodes with zero inter-community edges are excluded when computing the global component, and their global components are set to zero. Thus, the local component of a node is its significance in its own community, and the global component is its significance in communities other than its own.

A different weight is assigned to each community. For community C, the weight of the local component is

$$\mu_C = \frac{\sum_{k\in C} O_k^{\text{intra}}}{\sum_{k\in C} O_k}, \tag{1.22}$$

where O_k^{intra} is the number of out-edges of node k to the members of its community. Thus, μ_C is the fraction of intra-edges of community C. The modular centrality of node i in community C is

$$\mathcal{C}^{\text{M}}(i) = \mu_C \mathcal{C}^{\text{L}}(i) + (1-\mu_C)\,\mathcal{C}^{\text{G}}(i), \tag{1.23}$$

where $\mathcal{C}^L(i)$ and $\mathcal{C}^G(i)$ denote the local component and global component of node i, respectively. Note that the default specification follows the direction of edges, which corresponds to the downstream channel. To compute the modular centrality in the upstream channel, all components are computed using A'.

The weight μ_C assigns a larger importance to the local component for a community with a larger fraction of intra-community edges. Equivalently, the weight assigns a larger importance to the global component for a community with a larger fraction of inter-community edges. Consider a community C in the supplier-buyer network. If μ_C is large, then an economic shock to a member of the community is likely to have stronger effect on the community than the rest of the network, and modular centrality assigns a larger weight to the local significance of firms belonging to the community. If μ_C is small, then an economic shock to a member of the community is likely to have a stronger effect on other communities, and modular centrality assigns a larger weight to the global significance of firms belonging to the community.

1.4.3 Centrality in the Supplier-Buyer Network

Table 1.5 reports a summary of centrality rankings, and table 1.6 reports a summary of modular centrality rankings for AAPL, DELL, IBM, and MSFT. Five measures of centrality - degree, Katz, PageRank, closeness, and betweenness - and the corresponding measures of modular centrality were computed. For each year, firms were ranked based on each measure of centrality. The numbers in each bracket indicate the number of times the firm took the $\left[1^{\text{st}}, 2^{\text{nd}}, 3^{\text{rd}}, 4^{\text{th}}\right]$ rank among the five measures of centrality. For example, $[0, 4, 1, 0]$ indicates that the firm took the second rank four times and the third rank once. Note that each number in the bracket is at most five. For both tables, a column with "(D)" indicates centrality in the downstream channel (significance as a supplier), and "(U)" indicates centrality in the upstream channel (significance as a buyer). Tables A.3, A.4, A.5, and A.6 in the appendix show ticker symbols of the four firms with the largest centrality, for each of the five measures of centrality.

Table 1.5 confirms overwhelming significance of IBM until 2010, in both the downstream and the upstream channels. Until 2010, IBM held the highest rank for each of the five measures of centrality[11]. MSFT, on the other hand, generally held the second highest rank until 2010. Such result coincides with the fact that IBM possessed the largest number of edges and that MSFT possessed the second largest number of edges (see table 1.3). From 2011, however, MSFT

[11] A single exception is the upstream channel in 2008. For this year, IBM held the highest rank for four measures of centrality.

began to catch up with IBM, and the significance of MSFT in the supplier-buyer network finally surpassed IBM in 2014, in both the downstream and upstream channels.

Generally speaking, there is a strong correlation between centrality ranking and the number of edges possessed by the firm, as one would expect from degree centrality. In other words, a firm with a larger number of edges tends to possess a larger significance in the supplier-buyer network. However, in 2013, MSFT possessed more out-edges than IBM (see table 1.3, second and third columns); yet, IBM held the highest rank among three out of the five measures of centrality in the downstream channel. It confirms that different measures of centrality capture different influence of a firm, and careful interpretation is necessary in evaluating the significance of a firm in the supplier-buyer network.

Table 1.5: Frequency of Ranking (Centrality)

Year	**AAPL (D)**	**DELL (D)**	**IBM (D)**	**MSFT (D)**	**AAPL (U)**	**DELL (U)**	**IBM (U)**	**MSFT (U)**
2003	[0, 0, 0, 0]	[0, 1, 3, 0]	[5, 0, 0, 0]	[0, 4, 1, 0]	[0, 0, 0, 2]	[0, 1, 3, 0]	[5, 0, 0, 0]	[0, 4, 1, 0]
2004	[0, 0, 0, 1]	[0, 1, 3, 0]	[5, 0, 0, 0]	[0, 4, 1, 0]	[0, 0, 0, 2]	[0, 0, 4, 0]	[5, 0, 0, 0]	[0, 5, 0, 0]
2005	[0, 0, 0, 1]	[0, 1, 4, 0]	[5, 0, 0, 0]	[0, 5, 0, 0]	[0, 0, 0, 2]	[0, 0, 4, 0]	[5, 0, 0, 0]	[0, 5, 0, 0]
2006	[0, 0, 0, 1]	[0, 0, 4, 0]	[5, 0, 0, 0]	[0, 5, 0, 0]	[0, 0, 0, 2]	[0, 0, 4, 0]	[5, 0, 0, 0]	[0, 5, 0, 0]
2007	[0, 0, 0, 1]	[0, 0, 2, 0]	[5, 0, 0, 0]	[0, 4, 0, 1]	[0, 0, 0, 2]	[0, 0, 3, 0]	[5, 0, 0, 0]	[0, 5, 0, 0]
2008	[0, 0, 0, 1]	[0, 0, 4, 0]	[5, 0, 0, 0]	[0, 5, 0, 0]	[0, 0, 0, 3]	[0, 0, 4, 0]	[4, 1, 0, 0]	[1, 4, 0, 0]
2009	[0, 0, 0, 0]	[0, 0, 4, 0]	[5, 0, 0, 0]	[0, 5, 0, 0]	[0, 0, 0, 2]	[0, 0, 4, 0]	[5, 0, 0, 0]	[0, 5, 0, 0]
2010	[0, 0, 0, 1]	[0, 0, 4, 0]	[5, 0, 0, 0]	[0, 5, 0, 0]	[0, 0, 1, 1]	[0, 0, 3, 1]	[5, 0, 0, 0]	[0, 5, 0, 0]
2011	[0, 0, 0, 2]	[0, 0, 4, 0]	[3, 2, 0, 0]	[2, 3, 0, 0]	[0, 0, 1, 2]	[0, 0, 3, 1]	[3, 2, 0, 0]	[2, 3, 0, 0]
2012	[0, 0, 1, 2]	[0, 0, 3, 1]	[2, 3, 0, 0]	[3, 2, 0, 0]	[0, 0, 2, 0]	[0, 1, 1, 2]	[4, 0, 0, 1]	[1, 4, 0, 0]
2013	[0, 0, 1, 3]	[0, 1, 2, 1]	[3, 1, 1, 0]	[2, 3, 0, 0]	[1, 1, 2, 0]	[0, 1, 2, 1]	[3, 1, 0, 0]	[1, 2, 0, 2]
2014	[0, 1, 3, 0]	[0, 0, 1, 3]	[1, 3, 0, 1]	[4, 1, 0, 0]	[1, 1, 2, 0]	[0, 0, 1, 3]	[1, 2, 1, 0]	[3, 2, 0, 0]

This table reports centrality rankings of AAPL, DELL, IBM, and MSFT, using five measures of centrality: degree, Katz, PageRank, closeness, and betweenness. The entries in each bracket indicate the number of times the firm took the $\left[1^{\text{st}}, 2^{\text{nd}}, 3^{\text{rd}}, 4^{\text{th}}\right]$ rank among the five measures of centrality. For example, [0, 1, 3, 0] indicates that the firm took the 2^{nd} rank for one measure of centrality and 3^{rd} rank for three measures of centrality. A column with "(D)" indicates centrality rankings in the downstream channel (significance as a supplier), and "(U)" indicates centrality rankings in the upstream channel (significance as a buyer).

The result using modular centrality, as reported in table 1.6, is similar but not the same. Recall that modular centrality distinguishes the significance of a firm in its own community (local component) and in other communities (global component). Moreover, it assigns weights to the local and global components depending on the overall intra- and inter-community linkages of the community a firm belongs to. The difference between standard centrality and modular centrality is most apparent if we compare the rankings of IBM and MSFT in the upstream channel in 2012 and 2013. Standard centrality (see table 1.5, eighth and ninth columns) suggests that IBM possessed a larger significance than MSFT in these years; however, modular centrality (see table 1.6, eighth and ninth columns) suggests otherwise. A possible explanation for such difference is that the community of IBM possessed a large fraction of intra-community edges (see table 1.2, fourth, sixth, and eighth columns) and that IBM possessed a stronger significance in other communities than on its own. In other words, in 2012 and 2013, an economic shock to the community of IBM was likely to have a stronger effect on the community members than on others. Because IBM possessed a larger significance on other communities than on its own, the overall significance of IBM under the economic shock was smaller than what standard centrality indicates.

Table 1.6: Frequency of Rankings (Modular Centrality)

Year	**AAPL (D)**	**DELL (D)**	**IBM (D)**	**MSFT (D)**	**AAPL (U)**	**DELL (U)**	**IBM (U)**	**MSFT (U)**
2003	[0, 0, 0, 0]	[0, 0, 2, 1]	[5, 0, 0, 0]	[0, 5, 0, 0]	[0, 0, 0, 2]	[2, 2, 1, 0]	[3, 2, 0, 0]	[0, 1, 4, 0]
2004	[0, 0, 0, 0]	[0, 0, 4, 0]	[5, 0, 0, 0]	[0, 4, 0, 0]	[0, 0, 0, 2]	[0, 2, 2, 0]	[4, 1, 0, 0]	[1, 2, 2, 0]
2005	[0, 0, 0, 0]	[0, 0, 2, 1]	[5, 0, 0, 0]	[0, 3, 0, 0]	[0, 0, 0, 2]	[0, 2, 2, 0]	[4, 1, 0, 0]	[1, 2, 2, 0]
2006	[0, 0, 0, 0]	[0, 0, 3, 0]	[5, 0, 0, 0]	[0, 5, 0, 0]	[0, 0, 0, 2]	[0, 2, 2, 0]	[5, 0, 0, 0]	[0, 3, 2, 0]
2007	[0, 0, 0, 1]	[0, 1, 3, 0]	[5, 0, 0, 0]	[0, 3, 1, 0]	[0, 0, 0, 2]	[0, 0, 4, 0]	[5, 0, 0, 0]	[0, 4, 0, 0]
2008	[0, 0, 0, 0]	[0, 1, 3, 0]	[5, 0, 0, 0]	[0, 3, 1, 0]	[0, 0, 0, 2]	[0, 0, 4, 0]	[5, 0, 0, 0]	[0, 5, 0, 0]
2009	[0, 0, 0, 0]	[1, 1, 2, 0]	[4, 1, 0, 0]	[0, 2, 2, 0]	[0, 0, 0, 2]	[1, 0, 4, 0]	[4, 0, 1, 0]	[0, 5, 0, 0]
2010	[0, 0, 0, 0]	[0, 0, 4, 0]	[4, 1, 0, 0]	[1, 3, 0, 0]	[0, 0, 0, 2]	[1, 1, 3, 0]	[4, 0, 1, 0]	[0, 4, 1, 0]
2011	[0, 0, 0, 0]	[1, 0, 3, 0]	[3, 2, 0, 0]	[1, 3, 1, 0]	[0, 0, 0, 2]	[0, 0, 3, 0]	[4, 1, 0, 0]	[1, 4, 0, 0]
2012	[0, 0, 1, 2]	[0, 1, 3, 0]	[1, 4, 0, 0]	[4, 0, 0, 1]	[0, 0, 1, 1]	[0, 1, 1, 1]	[2, 3, 0, 1]	[3, 1, 1, 0]
2013	[1, 0, 0, 3]	[0, 0, 4, 0]	[0, 5, 0, 0]	[4, 3, 0, 1]	[0, 1, 0, 0]	[1, 0, 2, 0]	[1, 4, 0, 0]	[3, 0, 1, 1]
2014	[1, 0, 2, 1]	[0, 1, 1, 2]	[1, 2, 2, 1]	[3, 1, 0, 1]	[0, 2, 0, 2]	[0, 1, 1, 1]	[3, 1, 0, 0]	[2, 1, 2, 0]

This table reports modular centrality rankings of AAPL, DELL, IBM, and MSFT, using five measures of centrality: degree, Katz, PageRank, closeness, and betweenness. The numbers in each bracket indicate the number of times the firm took the $\left[1^{\text{st}}, 2^{\text{nd}}, 3^{\text{rd}}, 4^{\text{th}}\right]$ rank among the five measures of centrality. For example, [0, 0, 2, 1] indicates that the firm took the 3^{rd} rank for two measures of centrality and 4^{th} rank for one measure of centrality. A column with "(D)" indicates centrality rankings in the downstream channel (significance as a supplier), and "(U)" indicates centrality rankings in the upstream channel (significance as a buyer).

1.5 Concluding Remarks

This chapter studied communities of firms, identified significant firms, and ranked significant firms in the supplier-buyer network surrounding U.S. tech firms from 2003 to 2014. A limitation of the study is that I employed an incomplete data set[12], and the resulting analysis of the supplier-buyer network may be incorrect. Moreover, the analysis does not account for the strength of

[12]It is a trial version of the Factset Revere Relationship data set.

relationship between firms, which can be captured by the dollar amount of transactions between firms. The strength of relationship was omitted because the data set contains only partial observations on the amount of supplier-buyer transactions. With a comprehensive data set, one could model the supplier-buyer network as a weighted directed graph and conduct a more extensive analysis.

Moreover, the community detection method employed in this chapter does not allow overlapping communities, in which a firm may belong to more than one community. Such firm may play a crucial role in the network, for example, as a bridge connecting different communities. Palla et al. (2005), Lancichinetti et al. (2009), and Ghalmane, Cherifi, et al. (2019) are examples of recent research on detecting overlapping communities and evaluating significance of nodes utilizing overlapping communities.

Finally, this chapter described potential effects of an economic shock taking the supplier-buyer network as given. However, the network, both the node set and edges, may change as a result of an economic shock. In other words, a firm may disappear from the network, possibly due to financial hardship, or linkages among firms may change as a result of an economic shock. To allow such changes to the network, it is necessary to employ a network formation model, which models the incentives of firms in forming linkages.

Chapter 2

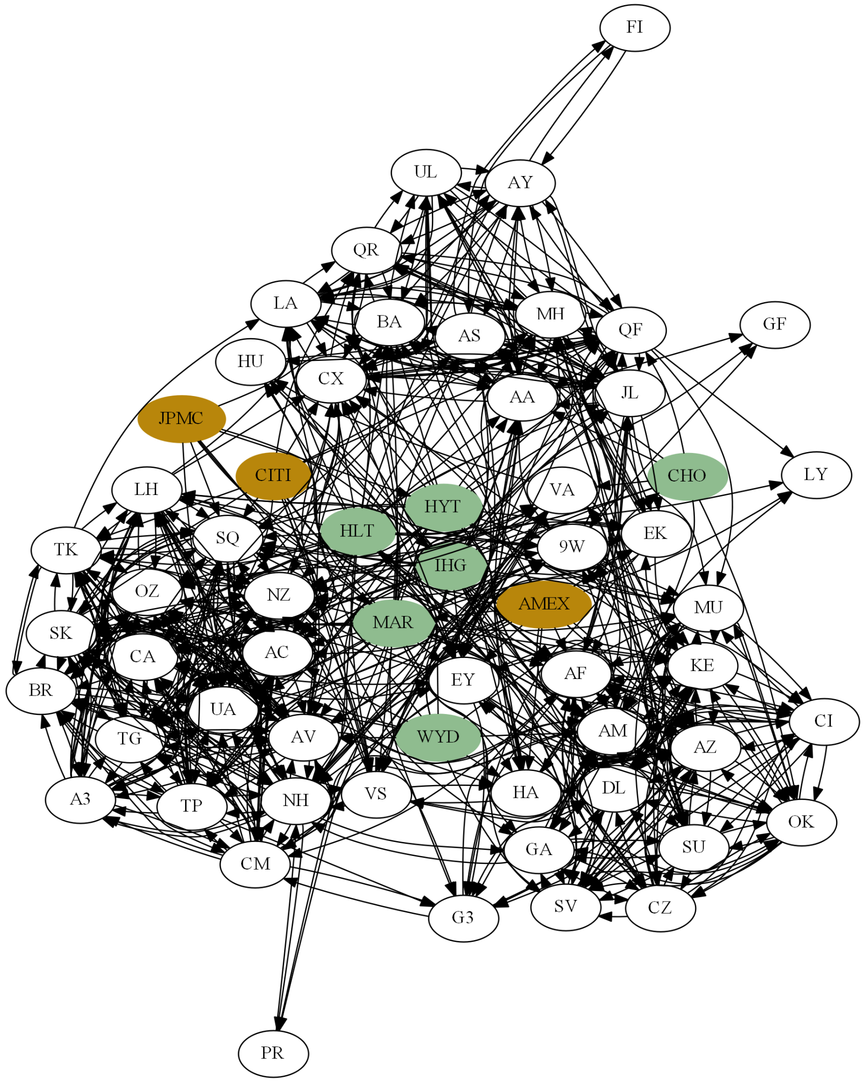
Description of U.S. Credit Card Issuers, Hotel Chains, and Airlines

2.1 Introduction

Researchers of strategic business management have studied incentives in partnership formation between firms. Several recent developments include the following. Gulati (1995) analyzes how the network of firms affects the formation of alliances using a panel data of partnerships between firms . Chung et al. (2000) studies how complementarity, status similarity, and the network of firms affect alliance formation among investment banks in the U.S. Rothaermel and Boeker (2008) studies the roles of complementarity and status similarity in the formation of alliances, using a network of pharmaceutical firms. Lin et al. (2009) studies the motives in alliance formation based on how complementarity, status, and the network of firms affect the performance of firms. Similar to the supplier-buyer network in chapter 1, researchers describe partnerships between firms using a network. The difference is that instead of studying the structure of a network, researchers focus on why the network was formed as observed.

This chapter describes incentives in partnership formation and the data collection procedure preceding the empirical study on partnership formation between credit card issuers and airlines in chapter 3, which also involves partnership formation between hotel chains and airlines. Each of these firms operates a loyalty program to attract new customers and retain existing customers. In essence, customers earn points in a firm's loyalty program by purchasing goods or services offered by the firm, and the points may be redeemed for goods or services offered by the firm. In addition, firms form partnerships with other firms, where a partnership allows the transfer of points from a firm's loyalty program to the partner's loyalty program. I denote such partnership as *transfer partnership*. A transfer partnership allows customers to redeem loyalty points for goods and services offered by the partner firm, making the loyalty program more attractive to customers. Thus, the set of partners possessed by a firm is an important marketing tool, and it has an incentive to form partnerships with a select set of firms to enhance its loyalty program, as a means of competition. Moreover, characteristics of the partners possessed by a firm are crucial in differentiating its loyalty program, as goods and services offered by different firms are not the same.

Figure 2.1: Network Map (Nov. 2018)



This figure illustrates the network of loyalty programs observed in November 2018. The golden, teal, and white nodes are the loyalty programs of credit card issuers, hotel chains, and airlines, respectively. See table B.5 in the appendix for a dictionary of node names. A directed link from a node to another indicates that points may be transferred from the source node to the target node. Nodes are positioned close to each other if they are strongly connected via direct and indirect links. The cluster of airlines on the bottom-left is Star Alliance, the cluster on the bottom-right is SkyTeam, and the cluster on the top is Oneworld. AMEX is positioned close to SkyTeam. On the other hand, JPMC and CITI are positioned close to Star Alliance and Oneworld.

In order to study the formation of transfer partnerships, I have collected two sets of data containing observations from 2014 to 2018. The first data set contains annual observations on transfer partnerships among 3 credit card issuers, 7 hotel chain, and 47 airlines. Using a network map, figure 2.1 illustrates transfer partnerships among these firms observed in November 2018. Each node represents a firm's loyalty program. In particular, the golden, green, and white nodes are the loyalty programs of credit card issuers, hotel chains, and airlines, respectively. A directed line from a node to another indicates that loyalty points in the source node may be transferred to the target node. Table B.1 in the appendix provides a brief history of changes to transfer partnerships possessed by the three credit card issuers. The second data set contains quarterly observations on firm-level characteristics. In chapter 3, I utilize variations in transfer partnerships and in firm-level characteristics to study the formation of transfer partnerships.

The rest of this chapter is organized as the following. Section 2.2 explains incentives in partnership formation, which guided the data collection procedure. Section 2.3 describes the data collection procedure. Section 2.4 concludes.

2.2 Incentives in Partnership Formation

Major credit card issuers in the U.S. operate loyalty programs to reward customers. For example, American Express Company (AMEX), Citibank (CITI), and J.P. Morgan Chase (JPMC), operate Membership Rewards, ThankYou Rewards, and Ultimate Rewards, respectively. These programs are associated with their flagship credit card products, and customers may earn points by signing up for or making purchases using the products.

The loyalty program of a credit card issuer is an important marketing tool. Wirtz et al. (2007) finds that the attractiveness of a credit card issuer's loyalty program has a positive effect on the consumer's share of wallet[1], above and beyond the consumer's psychological attachment to the firm. Sharply rising expenditures by credit card issuers confirm the importance of loyalty programs. In the fourth quarter of 2016, JPMC spent up to \$300 mil. on the Ultimate Rewards program to reward the customers of a new credit card product launched in August 2016[2]. The expenditures of AMEX on the Membership Rewards program increased from \$6.8 bil. in 2016 to \$7.6 bil in 2017, and then to \$9.7 bil. in 2018. For 2017 and 2018, the expenditures accounted for a third of AMEX's total expenses. At the end of 2018, AMEX's liability for unclaimed points in the Membership Rewards program was \$8.4 bil. (American Express Company, 2014-2018).

Credit card issuers possess partners from a diverse pool of industries. Via the partners, they can offer a variety of redemption options for loyalty points beyond cash, such as gift cards, merchandises, and travel rewards. Credit card issuers possess different sets of partners, and who they are partnered with is a significant source of product differentiation. In particular, the differentiation emanates primarily from partners in the travel industry because all redemption options for loyalty points, except for travel rewards, are similar to redeeming for cash. First, there

[1]The share of wallet for a credit card issuer is the share of purchases made using the firm's credit card products.

[2]Jennifer Surane and Hugh Son. (2016). "Dimon Says New Sapphire Card Cuts Profit by Up to \$300 Million in Quarter." *Bloomberg.* December 6. https://www.bloomberg.com/news/articles/2016-12-06/dimon-says-new-card-cuts-profit-by-up-to-300-million-in-quarter.

is hardly any difference in the assortment of non-travel rewards offered by the loyalty programs of credit card issuers. Moreover, the redemption rates for non-travel rewards are completely determined by cents-per point rates. Because the cents-per-point rates of each loyalty program are tightly linked to its redemption rate for cash, redeeming for non-travel rewards is essentially the same redeeming for cash, possibly with a small discount. For example, customers of AMEX, CITI, and JPMC may use loyalty points to redeem for merchandises sold at Amazon.com[3], with redemption rates of 0.7, 0.8, and 0.8 cents per point, respectively[4]. That is, for non-travel rewards, the loyalty programs are differentiated only by the redemption rates set by the credit card issuers.

In contrast, a redemption for travel rewards is typically done by transferring points to a partner's loyalty program[5], and the redemption value of loyalty points depends on how the customer perceives the portfolio of transfer partners possessed by the credit card issuer. That is, the conversion ratios of points to the loyalty programs of partners, the redemption options offered by the loyalty programs of partners, and the consumer's preferences for the partner firms affect the attractiveness of travel rewards offered by a credit card issuer. The portfolio of partners in the travel industry differentiates one loyalty program to another, appealing to heterogeneous preferences of consumers for the partner firms and their loyalty programs. Figure B.3 shows an example of a portfolio of partners possessed by a credit card issuer and how it is used in marketing. The fact that more credit card issuers are launching loyalty programs with points transferable to partners in the travel industry confirms the significance of travel rewards and that the portfolio of transfer partners is a significant source of product differentiation. In particular, Barclays US[6] and Capital One[7] launched such loyalty programs in 2018, each with a different portfolio of airline partners.

The partnership between a credit card issuer and a travel firm (i.e., hotel chain or airline) is a form of *brand alliance*. This term was coined by Rao and Ruekert (1994) to describe the joint-branding of firms, where the integration of products and services may also occur. A canonical example of brand alliance is issuing co-branded credit cards. For example, AMEX issues credit card products under the brand name of Delta Air Lines (DL). Joint with DL, AMEX can offer complementary services to customers of DL, including airport lounge access, free checked baggage, and the ability to earn points in DL's loyalty program. On the other hand, DL gains from discounts on payment processing fees and by selling its loyalty points to AMEX[8]. Such co-brand relationship is mutually beneficial for both firms. AMEX gains by appealing to customers of DL, expanding its customer base. In fact, AMEX reports its co-branded credit card portfolio with DL

[3]One may also view this as redeeming for gift cards at Amazon.com.

[4]For AMEX, CITI, and JPMC, the redemption rates for cash are 0.6, 0.5, and 1 cent per point, respectively

[5]The credit card issuer purchases points from the travel firm to facilitate the transfer of points. In 2014-2015, American Airlines earned 1.3-1.6 cents per point sold to non-airline partners (American Airlines, 2014-2015).

[6]Barclays US. (2018). "Barclays Launches Premier Global Travel Card that Rewards Cardmember Loyalty: Barclays Arrival Premier World Elite Mastercard." April 4. https://cards.barclaycardus.com/banking/about-us/newsroom/barclays-launches-arrival-premier-world-elite-mastercard/ .

[7]Brian Kelly. (2018). "Capital One Venture Card Adds Airline Transfer Partners, Offers Limited Time 75,000-Mile Bonus." *Forbes*. November 13. https://www.forbes.com/sites/thepointsguy/2018/11/13/capital-one-venture-card-lto/#70e949b1383d.

[8]Customers of the co-branded credit cards receive points in DL's loyalty program as rewards. AMEX pays DL for the points.

accounted for 8 percent of its total billed business[9] and 21 percent of its total outstanding card-member loans in 2018 (American Express Company, 2014-2018). DL also gained by $3.4 bil. in 2018, and it expects the annual benefit to grow to $7 bil. by 2023[10]. A co-brand partnership usually lasts for ten or more years and is typically exclusive to the credit card issuer[11].

A transfer partnership is similar to a co-brand partnership but with weaker integration, shorter duration, and without exclusivity. The portfolio of transfer partners is updated in as little as three months, and no apparent exclusivity is observed, as credit card issuers often share common transfer partners. Integration occurs through the loyalty programs, as customers of the credit card issuer gain access to the redemption options offered by the partner's loyalty program by transferring points. A transfer partnership is a brand alliance between loyalty programs. The credit card issuer gains by enhancing the attractiveness of its loyalty program, especially for frequent customers of the partner firm. On the other hand, the partner firm not only increases its revenue by selling points to the credit card issuer but also gains from better brand awareness, especially by customers of the credit card issuer.

The pursuit of resources and reputation possessed by partners can explain how a credit card issuer chooses its transfer partners. This chapter defines resources as tangible assets and reputation as intangible assets possessed by a firm. The resource-based view (Penrose, 1959; Barney, 1991) suggests that the incentive in forming a partnership is to gain access to strategic resources possessed by the partner firm. For the loyalty program of a credit card issuer, the resources possessed by an airline is the redemption options for flights, via the airline's loyalty program. Each airline's loyalty program offers different accessibility and different redemption rates of loyalty points to various geographic zones, accounting for differences in flight routes and cost advantages possessed by airlines. Thus, according to the resource-based view, a credit card issuer would favor a transfer partner that enhances the redemption options of its loyalty program. Reputation characterizes the institutional aspects of a firm, such as market share and brand familiarity; it is essentially how consumers perceive a firm. By forming a transfer partnership with a firm, a credit card issuer can appeal to the partner's frequent customers, expanding its customer base. This view is compatible with brand spillover effects, as suggested by Simonin and Ruth (1998) and Newmeyer et al. (2013). According to this view, a credit card issuer would favor transfer partners with a stronger market presence.

The pursuit of resources and reputation would suggest that a credit card issuer should choose a large portfolio of transfer partners to enhance the redemption options of its loyalty programs and to broaden its customer base. However, the credit card issuer has other incentives. First, enhancing the redemption options of its loyalty program lowers the revenue of its co-brand partners, as fewer customers sign up for or make purchases using the co-branded credit card products. For major U.S. airlines, the revenue earned from selling loyalty points accounts for a significant

[9]Total billed business is the total amount of card purchases.

[10]Delta Air Lines. (2019). "American Express and Delta Renew Industry-Leading Partnership, Lay Foundation to Continue Innovating Customer Benefits." April 2. https://news.delta.com/american-express-and-delta-renew-industry-leading-partnership-lay-foundation-continue-innovating.

[11]There are a few exceptions. For example, American Airlines has co-brand partnerships with both Citibank and Barclays US.

share of their operating revenue[12]. Second, the cost of operating a loyalty program is realized when customers redeem points; thus, more valuable redemption options induces more redemption of loyalty points, increasing costs for the credit card issuer. With such incentives, it is unclear what characteristics a credit card issuer seeks in its partners, and an empirical revealed-preference analysis would enhance our understanding of partnership formation between credit card issuers and firms in the travel industry. Moreover, one could utilize such understanding to make predictions on what may happen to the partnerships in the event of an exogenous shock.

Note that this section focused on the incentives in partnership formations between credit card issuers and airlines because it is the focus of chapter 3[13]. The incentives in partnership formation between hotel chains and airlines are similar in the sense that a partnership allows the hotel chain to utilize the resources and reputation possessed by the partner airline. The incentives in partnership formation among airlines, such as an airline alliance, is beyond the scope of this chapter and chapter 3.

2.3 Data Collection

2.3.1 Initial Screening of Firms

The data collection started in January 2017 by recording the transfer partners of four credit card issuers: American Express Company (AMEX), J.P. Morgan Chase (JPMC), Citibank (CITI), and Diner's Club. Initially, all of their transfer partners and the transfer partners of these partners were included in the study. Except for a few[14], all transfer partners were hotel chains or airlines.

I have defined the market scope as credit card issuers that serve U.S. consumers and hotel chains and airlines with significant market presence. Here is the list of firms that were excluded because they did not satisfy the criteria. Diner's Club International was removed because it did not offer credit card products to U.S. consumers. AccorHotels was excluded because it had small presence in the U.S., with about 40 hotel properties. La Quinta Inns and Suites[15] was excluded because it had small presence in the worldwide market. Low-cost and ultra low-cost airline carriers such as JetBlue Airways (B6), Southwest Airlines (WN), Virgin America (VX), Frontier Airlines (F9), and Spirit Airlines (NK) were excluded. Small U.S.-domestic regional airlines, such as Penair (7H), and Great Lakes Airlines (ZK), and small foreign regional airlines such as

[12]For example, United Airlines (a co-brand partner of JPMC) earned approximately $1.2 bil. revenue from selling loyalty points in 2017. It accounted for about 3.2 percent of the airline's total operating revenue (United Airlines, 2014-2018). In the same year, American Airlines (a co-brand partner of CITI) earned $2.2 bil. revenue from selling loyalty points. It accounted for about 5.2 percent of the airline's total operating revenue (American Airlines, 2014-2018). These are the amounts sold to non-airline third-party partners. The amounts only include recognized revenues, excluding deferred revenues.

[13]In chapter 3, I focus on partnership formation between credit card issuers and airlines, while taking partnerships between credit card issuers and hotel chains, and partnerships between airlines as exogenous. Partnership formation between hotel chains and airlines is modeled but is not the focus.

[14]Plenti is an example. Users of Plenti received points by making purchases at selected retailers. It is was subsidiary of AMEX and dissolved in 2018.

[15]La Quinta Inns and Suites was acquired by Wyndham Hotels and Resorts in May 2018.

Flybe (BE), were excluded. Airlines with small market presence, such as Air Mauritius (MK), Interjet (4O), Air Balic (BT), Oman Air (WY) were also excluded.

Airlines with no observed transfer partnerships with any of the credit card issuers or the hotel chains were removed. They were Aerolineas Argentinas (AR), Air India (AI), Azul Brazilian Airlines (AD), Ethiopian Airlines (ET), EgyptAir (MS), Middle East Airlines (ME), Royal Air Maroc (AT), Royal Jordanian Airlines (RJ), S7 Airlines (S7), Ukraine Airlines (PS), Vietnam Airlines (VN), Westjet (WS), and Xiamen Airlines (MF). In addition, Fiji Airways was excluded because enrolling in its loyalty program requires an annual fee. All subsidiary brands of airlines were removed.

Some airlines were removed because they used loyalty programs of other airlines. Air Europa (UX), Kenya Airways (KQ), and TAROM (RO) were removed because they used the loyalty program of Air France[16] (AF). LOT Polish Airlines (LO), Austrian Airlines (OS), Brussels Airlines (SN), Eurowings (EW), and Swiss International Air Lines (LX) were removed because they used the loyalty program of Lufthansa (LH). Iberia (IB) and Aer Lingus (EI) were removed because they used the same loyalty points (Avios) as British Airways[17]. Air Serbia (JU) was removed because it used the loyalty program of Etihad Airways (EY). Note that points in the associated loyalty programs could be used to redeem for flight services offered by these airlines. For example, points in the loyalty program of Air France could be used to redeem for flights offered by Kenya airways. To account for such integration, the geographical hub regions of these airlines were added to the parent airline of the associated loyalty program. Thus, AF, LH, and EY were assigned more than one hub region. Table B.2 in the appendix reports the firms remaining after the initial screening.

2.3.2 Data Source and Availability

I collected two set of data from 2014 to 2018. The first data set contains annual observations on transfer partnerships among firms. The second data set contains quarterly observations on firm-level characteristics. Some firms were further excluded from the study because data were not available.

The first data set contains snapshots of transfer partnerships among the firms for November 2014, 2015, 2016, 2017, and 2018. Each snapshot corresponds to the network of loyalty programs observed in the fourth quarter of the year. For November 2017 and 2018, I obtained the relevant information directly from the official websites of firms. I also collected a snapshot for February 2017. I constructed the snapshot of transfer partnerships for November 2016 by updating the snapshot for February 2017 after scrutinizing official announcements of firms. I constructed the snapshots for November 2014 and 2015 similarly, by updating the snapshot for November 2016. The snapshots also include transfer ratios of points between loyalty programs.

The second data set contains quarterly observations on firm-level characteristics, using the U.S. standard calendar quarters. The first quarter (Q1) is from January 1 to March 31, the second quarter (Q2) is from April 1 to June 30, the third quarter (Q3) is from July 1 to September 30, and the fourth quarter (Q4) is from October 1 to December 31. Some documents reported data

[16] Air France (AF) and KLM (KL) are treated as a single entity.

[17] Aer Lingus, British Airways, and Iberia belong to the same parent firm, International Airlines Group.

under different formats; I converted them to this quarterly format. For example, monthly data were aggregated to construct quarterly data, and data reported under a different calendar quarters were corrected so that all data entries follow the same format.

For publicly-listed firms in the U.S., I collected firm-level data from their quarterly and annual SEC filings (U.S. Securities and Exchange Commission forms 10Q and 10K). The publicly-listed firms include all three credit card issuers[18], five hotel chains[19], and five airlines[20]. For other firms, firm-level data were collected from their quarterly, bi-annual, or annual financial reports, investor presentations, and reports on operating statistics. Geographic locations of airline hubs were also collected from the official websites of airlines.

For hotel chains and airlines, information on the redemption rates of loyalty points were collected from their official websites and images of the official redemption charts found using search engines. For those without a redemption chart, I constructed comparable redemption rates by trying out a number of bookings using loyalty points on their official websites. The bookings were not tried out for the quarters before Q1 of 2017, which are before I started the data collection. Instead, the redemption rates for 2017 were used because there were no observed changes to the redemption rates for those firms. For hotel chains, I recorded the redemption rates for standard rooms. For airlines, I recorded the redemption rates for economy-class seats. Note that for credit card issuers, I did not collect the redemption rates of loyalty points. It was because the portfolio of transfer partners possessed by the credit card issuer determine the value of its loyalty points, as the redemption rates for non-travel rewards are generally inferior to travel rewards.

I was unable to obtain firm-level data for certain firms. For hotel chains, the data for Best Western were not available because it is a private firm. Radisson Hotels publishes quarterly financial reports; however, they do not include data on the firm's operations in the U.S. These two were excluded from the study. For airlines, I was unable to obtain firm-level data for Alitalia (AZ), Gulf Air (GF), Hainan Airlines (HU), Malaysia Airlines (MH), Czech Airlines (OK), Philippine Airlines (PR), Qatar Airlines (QR), Saudia (SV), and TAP Portugal (TP). While data are available for El Al Israel (LY), it was also excluded because its loyalty program had limited redemption options. Note that I still included transfer partnerships associated with these airlines in the first data set.

The data contain annual observations on transfer partnerships among 3 credit card issuers, 7 hotel chains, and 43 airlines and quarterly observations on their firm-level characteristics, from 2014 to 2018. Table 2.1 lists these firms, and table B.5 in the appendix provides full names of firms and geographic hub zones for airlines. The network map in figure 2.1 illustrates transfer partnerships among these firms and the 10 airlines (without firm-level data) in November 2018. Note that a few firms disappear in the later part of the data due to mergers and financial hardships. For example, SPG, AB, and SA are not present in the network map of 2018.

[18] They are AMEX, JPMC, and CITI.

[19] They are Hilton Hotels and Resorts, Hyatt Hotels, Marriott Hotels and Resorts, Starwood Hotels and Resorts, and Wyndham Hotels and Resorts.

[20] They are AA, AS, DL, HA, and UA.

Table 2.1: List of Firms

Industry	Firm
Credit Card Issuer	American Express Company (AMEX), J.P. Morgan Chase (JPMC), Citibank (CITI)
Hotel Chain	Choice Hotels (CHO), Hilton Hotels and Resorts (HLT), Hyatt Hotels (HYT), International Hotels Group (IHG), Marriott Hotels and Resorts (MAR), Starwood Hotels and Resorts (SPG), Wyndham Hotels and Resorts (WYD)
Airlines (IATA Code)	9W, A3, AA, AB, AC, AF, AM, AS, AV, AY, BA, BR, CA, CI, CM, CX, CZ, DL, EK, EY, FI, G3, GA, HA, JL, KE, LA, LH, MU, NH, NZ, OZ, QF, SA, SK, SQ, SU, TG, TK, UA, UL, VA, VS

This table reports the list of firms included in the data. Some firms were excluded after defining the market. Small regional airlines and airlines that use loyalty programs of other airlines were excluded. All private firms were excluded. Certain firms were excluded because data were not available. The first column ("Industry") lists the three industry types, and the second column ("Firm") reports the firms in each industry type.

2.3.3 Data Collection Procedure

This section provides details on how the data entries were recorded. I begin by describing how the snapshots of transfer partnerships were recorded. Each snapshot was recorded using an adjacency matrix with real entries. A transfer partnership indicates that loyalty points can be transferred from the source firm's loyalty program to the target firm's loyalty program. Moreover, the associated transfer ratio indicates the number of points in the target loyalty program that can be obtained per 1 points in the source loyalty program. For a pair of firms (order of the pair matters), the corresponding entry in the adjacency matrix is equal to the transfer ratio if there is a transfer partnership from the source to the target and zero if otherwise. For example, 1 point of AMEX (source) could be transferred to obtain 1.5 points of HLT (target), and I recorded this 1.5, from AMEX to HLT. A single exception is partnerships between airlines. A partnership between two airlines does not explicitly allow the transfer of loyalty points; instead, it allows customers to use points in the source firm's loyalty programs to redeem for flight services offered by the target firm. For partnerships between airlines, I used entered 1 if such redemption of points was possible and zero if otherwise. Note that such relationship is different from a codeshare agreement between airlines. A codeshare agreement allows an airline to market seats on a flight (at least partially) operated by the codeshare partner. Such flight is offered by the airline, not by its codeshare partner.

Next, I describe how I recorded the redemption rates of airline loyalty points, which are often called "miles". Recording the redemption rates was straightforward for airlines that provide zone-based redemption charts, similar to figure B.2 in the appendix. I began with 17 geographic zones (see table B.3 in the appendix) to accommodate various zone definitions of airlines. Using continental U.S[21]. as the departure location, I recorded the required number of points to redeem for a economy-class flight during off-peak seasons to each of the 17 zones. For flights within

[21]Here, continental U.S. also includes Alaska and Canada. I used this term for brevity of expression.

the continental U.S., I recorded the required number of points for flights between the west coast and the east coast. For each zone, the redemption rates of airline loyalty points is equal to the amount of loyalty points required for a round-trip divided by 2. For each airline, I marked non-accessible zones with zero; a zone is non-accessible if loyalty points of the airline cannot be redeemed for a flight from the continental U.S. to the zone. Due to differences in flight routes and cost over the flight routes, airlines possess different accessibility and redemption rates for the zones. Afterwards, I consolidated the 17 zones into 12 zones (see "Flight Redemption Zones" in table B.4 in the appendix) by combining nearby zones. I recorded the average of the redemption rates over the consolidated zones; any zones marked with zero was excluded when computing the average.

For airlines that provide distance-based charts (for example, see figure B.1 in the appendix), I determined accessibility and flight distances to the 17 zones by assessing each airline's own flight routes and flight routes accessible via its partners, where the partnership information is given by the snapshots of the network. Whenever available, I used flight distance calculators on the official websites of airlines in order to accurately assess flight distances to the zones. For airlines that did not provide such tools, I used the flight distance calculator of a partner airline. I find it reasonable because all airlines that did not provide such tools belonged to an airline alliance, and alliance members typically share flight routes with other members. In order to account for the flight distance within the continental U.S., I selected two U.S. international airports - LAX and JFK - as departure locations and selected an international airport as destination (see table B.3 in the appendix) for each of the 17 zones except for the continental U.S.. For flights within the continental U.S., I selected JFK and ORD as the departure locations and LAX and the destination. For each zone, I obtained two required number of points, one for each departure location, and then recorded the average as the redemption rate. For all airlines, I marked non-accessible zones with zero; any zones marked with zero was excluded when computing the average.

I used a similar procedure for collecting the redemption rates of loyalty points for hotel chains. Except for CHO, hotel chains provided redemption charts that specify the required number of points to redeem for a standard room (for 1 night) in various tiers of hotel properties. Each hotel chain assigns tiers to its properties based on their prestige, and the number of tiers varied from 1[22] to 11. For each hotel chain and for each tier, I selected up to 10 hotel properties and assessed their room rates in dollar amounts. Then I reclassified all hotel tiers into 7 categories based on the room rates so that the categories are comparable across different hotel chains. Finally, I recorded the redemption rates[23] of loyalty points for each of the 7 categories for each hotel chain. For some hotel chains, I consolidated multiple tiers into a single category by averaging the required number of points over relevant properties. For some, I expanded a tier into multiple categories. For example, WYD assigned a single tier to all of its hotel properties until Q2 of 2015. Thus, the required number of points was the same for all hotel properties of WYD until Q2 of 2015, and I recorded the same redemption rates for the 7 categories for WYD. For CHO, I tried out bookings for a variety of hotel properties to assess room rates and points redemption rates. Then I assigned

[22]From May 2015 to Apr 2019, one could use 15,000 points to redeem for a standard room in any WYD properties. They had a redemption chart with multiple categories before May 2015.

[23]For HLT, I recorded the redemption rates for off-peak seasons. Other hotel chains did not distinguish off-peak season until September 2019.

categories to its hotel properties so that the room rates for those properties are similar to properties of other hotel chains in the same category. For each category, I recorded the redemption rate for CHO by averaging the required numbers of points over its properties in the category. Note that I assumed the redemption rates for CHO before Q1 of 2017 (before the data collection started) to be the same as 2017, because I could not find an evidence that any changes were made to the required number of points.

Next, I describe how I collected key performance indicators (KPIs) of firms. Note that I converted all monetary units to million U.S. dollars using the spot exchange rates on the last day of the corresponding quarter. I converted all distance units to million kilometers.

I collected four KPIs for credit card issuers: Credit Card Purchase, Outstanding Loans, Delinquency Rate, and Writeoff Rate. Note that for each firm, I recorded only the data for its credit card divisions that serve U.S. consumers and small businesses to be consistent with the market scope, which limits credit card issuers to those that serve U.S. consumers. For AMEX, I recorded the data for its U.S. Consumer Services (USCS) division [24]. For CITI, I recorded the data for its credit card division of North America GCB (Global Consumer Banking). For JMPC, I recorded the data for its credit card division excluding commercial (corporate) cards[25]. Credit Card Purchase is the total amount of purchases made using the firm's credit card products, which is a measure of demand for the firm's credit card products. For AMEX, I aggregated the amounts for credit card products and charge card products; to my knowledge, the other credit card issuers did not offer charge card products to U.S. consumers. Outstanding Loans is the total amount of loans outstanding at the end of the quarter, excluding the loans held for sale. AMEX reported Outstanding Loans separately for its credit card business (reported as "Loans") and charge card business (reported as "Accounts Receivable"); I recorded the aggregated amount. Delinquency Rate is the percentage of Outstanding Loans that were past due for 30 or more days, and Writeoff Rate is the percentage of net write-off[26] in Outstanding Loans, in percentage terms. They measure the quality of credit possessed by the credit card issuer's customers. For AMEX, Delinquency Rate and Writeoff Rate were averaged over its credit card business and charge card business, weighted by the business's share of Outstanding Loans.

I collected five KPIs for hotel chains: Revenue, Operating Income, Number of Hotels, RevPar (Revenue per Available Room), and Occupancy Rate. Revenue is equal to the total operating revenue of the hotel chain, including revenue from both owned and leased properties. Operating Income is equal to EBIT (earnings before interest and taxes), which is Revenue subtracted by operating expenses, including depreciation and amortization. Note that I recorded Revenue and Operating Income as reported at the end of the financial period; that is, any amendments reported in later periods were ignored. I recorded all other variables as reported in the hotel chain's financial reports. Number of Hotels is the total number of hotel properties marketed under the hotel chain's brands, including properties owned and leased by the hotel chain. RevPar is computed by dividing the room revenue of each hotel property by its number of rooms and then aggregating over the properties owned and leased by the hotel chain. It is a measure of the consumer's willingness to pay for lodging services offered by the hotel chain. Occupancy rate is computed by

[24] From Q2 2018, it was reorganized as the U.S. category of Global Consumer Services Group (GCSG).

[25] From 2015, commercial card business was reported separately under Corporate and Investment Bank segment.

[26] Net write-off is debt written-off less of recovery.

dividing the number of sold room by the number of rooms for each hotel property and then aggregating over the properties owned and leased by the hotel chain. It is the percentage of the hotel chain's capacity that were actually consumed. the Only bi-annual observations were available for IHG, and I divided them in half to construct quarterly observations.

Following the guideline of Belobaba and Swelbar (2019), I collected five KPIs for airlines: Revenue, Operating Income, Passenger Revenue, Revenue Passenger Kilometers (RPK), and Available Seat Kilometers (ASK). Revenue is equal to the total operating revenue of the firm, including revenue from chartered flights, cargo, and other transportation-related operations. Operating Income is equal to EBIT (earnings before interest and taxes), which is Revenue subtracted by operating expenses, including depreciation and amortization. I excluded all exceptional items, such as expenses for acquiring aircraft and mergers, from Operating Income. Note that I recorded Revenue and Operating Income as reported at the end of the financial period; that is, any amendments reported in later periods were ignored. Passenger Revenue is the airline's revenue from scheduled passenger flights and chartered flights, which is a measure of the airline's overall size in passenger transportation services. It is slightly different from the guideline of Belobaba and Swelbar (2019), as their definition of passenger revenue excludes revenue from chartered flights. I chose to include both because a number of airlines did not report the revenues separately. RPK is the total flight distance of sold seats, which is equal to the sum of flight distances of all paid passengers. It is a measure of quantity demanded for flight services offered by the airline. ASK is the total flight distance of all seats, and it is a measure of the supply or capacity of flight services produced by the airline. Note that some other KPIs, as discussed in Belobaba and Swelbar (2019), can be constructed using these three. For example, PRASK (passenger revenue per available seat kilometer) can be constructed by dividing Passenger Revenue by ASK. PRASK is a measure of the consumer's willingness to pay for the airline's flight services. For some airlines, I aggregated monthly measures to construct quarterly RPK and ASK. A few airlines only reported bi-annual or annual data; I split them equally to construct quarterly observations.

I left the definitions and interpretations of some variables unexplained in this section. They will be discussed in section 3.6.1 of chapter 3.

2.4 Concluding Remarks

This chapter explained the incentives of credit card issuers, hotel chains, and airlines in forming transfer partnerships. It also described the market scope and how I collected relevant data for 3 credit card issuers, 7 hotel chains, and 43 airlines. The next chapter utilizes the data to analyze the network of loyalty programs, studying why firms formed transfer partnerships as observed. Unfortunately, certain firms were excluded because data were not available. However, those firms possessed small market share and also weak presence in the network of loyalty programs. Excluding those firms is unlikely to have a significant impact on the empirical analysis.

Chapter 3

Network of Loyalty Programs: A Sequential Formation

3.1 Introduction

In 2015, 55 percent of U.S. consumers chose rewards as the most attractive credit card feature, and this rate rose steadily to 79 percent in 2018[1] (Total Systems Services, 2016-2018)[2]. Sharply rising expenditures by credit card issuers confirm the importance of customer rewards. In the fourth quarter of 2016, J.P. Morgan Chase (JPMC) spent up to $300 mil. on customer rewards[3] for a new credit card product. The expenditures of American Express Company (AMEX) on customer rewards increased from $6.8 bil. in 2016 to $7.6 bil in 2017, and then to $9.7 bil. in 2018. For 2017 and 2018, the expenditures accounted for a third of AMEX's total expenses. At the end of 2018, AMEX's liability for unclaimed customer rewards was $8.4 bil. (American Express Company, 2016-2018).

Major credit card issuers in the U.S. operate loyalty programs to reward customers. Customers may earn points in these programs by signing up for credit card products or making purchases using them. An example is the Membership Rewards program of AMEX, and the firm states

> "...through our Membership Rewards program we have partnered with businesses in many industries, including the airline industry, to offer benefits to Card Member participants."
>
> American Express Company (2014-2018)

Through its partners, a credit card issuer can offer a variety of points redemption options beyond cash, such as gift cards, merchandises, and travel rewards, for its loyalty program.

[1] In 2018, interest rate was ranked second at 67 percent, and card brand was ranked third at 55 percent.

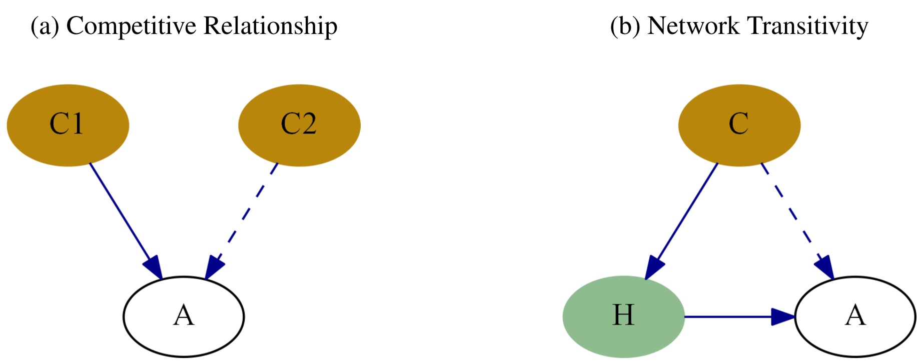
[2] Total Systems Services (NASDAQ: TSS) is a U.S.-based payment processing provider with more than $4 billion revenue in 2018.

[3] Jennifer Surane and Hugh Son. (2016). "Dimon Says New Sapphire Card Cuts Profit by Up to $300 Million in Quarter." *Bloomberg*. December 6. https://www.bloomberg.com/news/articles/2016-12-06/dimon-says-new-card-cuts-profit-by-up-to-300-million-in-quarter.

The partners possessed by a credit card issuer is a significant source of product differentiation; in particular, the differentiation emanates primarily from partners in the travel industry. It is because all points redemption options, except for travel rewards, are similar to redeeming for cash. First, there is hardly any difference in the assortment of non-travel rewards offered by the loyalty programs. Moreover, the redemption rates of loyalty points for non-travel rewards are completely determined by cents-per point rates for the face value of the rewards. Because the cents-per-point rates of each loyalty program are tightly linked to its redemption rate for cash, redeeming for non-travel rewards are essentially redeeming for cash, possibly with a small discount. That is, for non-travel rewards, the loyalty programs are differentiated only by the redemption rates set by the credit card issuers.

In contrast, a redemption for travel rewards is typically done by transferring points to a partner's loyalty program, and the redemption value of a credit card issuer's loyalty program depends on how the customer perceives the portfolio of transfer partners possessed by the credit card issuer. That is, the conversion ratios of points to the loyalty programs of partners, the redemption options offered by the loyalty programs of partners, and the consumer's preferences for the partner firms affect the attractiveness of travel rewards offered by a credit card issuer. The portfolio of travel partners differentiates one loyalty program to another, appealing to heterogeneous preferences of consumers for the partner firms and their loyalty programs. The fact that more credit card issuers are launching loyalty programs with points transferable to partners in the travel industry confirms the significance of travel rewards and that the portfolio of travel partners is a significant source of product differentiation.

Figure 3.1: Network Effects



This figure illustrates the network effects. Sub-figure (a) illustrates competitive relationship. C1 and C2 are two credit card issuers, and A is an airline. A is a transfer partner of C1, and a positive competitive relationship would suggest C2 is more likely to form a transfer partnership with A than otherwise. Sub-figure (b) illustrates network transitivity. C, H, and A are a credit card issuer, a hotel chain, and an airline, respectively. H is a transfer partner of C, and A is a transfer partner of H; a positive network transitivity would suggest C is more likely to form a transfer partnership with A than otherwise.

This chapter studies how a credit card issuer chooses its portfolio of transfer partners in the travel industry, in particular, the airline partners. The focus is on how resource complementarity and the network of firms affect partner choice. For a credit card issuer, the resources possessed by an airline is the redemption options for flights, via the airline's loyalty program. Each airline's loyalty program offers different accessibility and points redemption rates for various geographic zones, which account for the differences in flight routes and cost advantages possessed by the airlines. The resource complementarity of an airline is how forming a transfer partnership with the airline adds to redemption options offered by the credit card issuer's loyalty program. Thus resource complementarity not only depends on the resources possessed by the airline but also the set of other airline partners possessed by the credit card issuer. Moreover, this chapter studies two network effects: *Competitive Relationship* and *Network Transitivity*. I define Competitive Relationship as whether or not a credit card issuer is more likely to form a transfer partnership with an airline that is a partner of another credit card issuer. I define Network Transitivity as whether or not a credit card issuer is more likely to form a transfer partnership with an airline that is a transfer partner of a partner hotel chain. Figure 3.1 graphically illustrates these network effects.

The choice of a transfer partner not only depends on the resources possessed by the potential partner but also on how the resources complement the resources possessed by other airline partners. Moreover, the choice of partners by competing credit card issuers and the partnership structure within the travel industry may affect the choice, and vice versa. In other words, the behavior of firms affects the environment, and the environment also affects the behavior of firms. Zeggelink (1996) describes this phenomenon as "The transformation from micro to macro, therefore, is not a simple sum of individual actions." Such externality makes it difficult to use typical regression models to describe partner choices, because the choices are not independent of each other. For friendship networks, researchers often utilize sequential network formation processes to accommodate such externality, where agents are treated as nodes, and the opportunity to modify a linkage between two agents occurs along some sequence. Linkages are sequentially determined according to the optimizing behavior of agents based on the current state of the network, and the state of the network is updated reflecting their actions. Research utilizing such sequential network formation process includes Christakis et al. (2010) and Snijders et al. (2010), to name a few. The model of this chapter follows a similar process but accounts for asymmetry in the roles and objectives of firms.

This chapter uses a directed network to describe transfer partnerships among loyalty programs. The loyalty programs of credit card issuers, hotel chains, and airlines constitute the node set. A link from a node to another indicates that loyalty points in the source node can be transferred to the target node, and the associated link weight indicates the transfer ratio. In other words, a link indicates a transfer partnership, and the link weight indicates the transfer ratio associated with the transfer partnership. In order to facilitate the transfer of points, the source node purchases points from the target node. Thus, unlike a friendship network, nodes play asymmetric roles as buyers and sellers. Moreover, nodes belonging to different industry sectors - credit card issuers, hotel chains, and airlines - may have different incentives in forming transfer partnerships. I accommodate such features by splitting the network into subnetworks, and linkages are determined by interactions among nodes within a subnetwork, while taking account of the states of other subnetworks. In each subnetwork, I assign distinct roles to nodes either as choosers or bidders. Bidders are potential transfer partners of choosers, and links are always directed from the choosers to the bidders. Thus, subnetworks are uni-directional bipartite. Moreover, I use a sequential authority mechanism to describe the interactions between choosers and bidders. First, bidders submit take-it or leave-it bids to choosers based on pairwise characteristics of bidders and choosers. Second, choosers either accept or reject bids, one at a time. A bid represents how favorable the terms of contract offered by the bidder is to the chooser. I endow all nodes with full information on the entire network but assume that they are myopic.

After receiving bids, choosers sequentially meet bidders to add, remove, or maintain linkages, and the outcomes of the meetings determine the network formation process for a given period. A period denotes the time frame for the transition of the network from an initial state to an ending state, and the the network formation process describes such transition. In each period, (chooser, bidder) pairs meet according to an unknown sequence of bilateral meetings, and in each meeting, the chooser is given the opportunity to modify the linkage to the bidder. The model accommodates transitions of the network over multiple periods by specifying a different sequence of meetings for each period, possibly with a different node set. The sequence of meetings specifies the ordering of meetings (chooser, bidder) pairs across all subnetworks, and I assume that each (chooser, bidder) pair meets exactly once.

The sequence of meetings is a crucial part of the network formation process because the current state of the network at a meeting depends on the outcomes of past meetings. In each meeting, the chooser makes the choice to add, remove, or maintain linkage to the bidder such that the resulting portfolio of partners optimizes the chooser's objective function under the current state of the network. The specification of the chooser's objective function may be different across subnetworks, as choosers belonging to different industry sectors may have different incentives in forming linkages. Note that I model interactions between credit card issuers and airlines and between hotel chains and airlines, while taking linkages from credit card issuers to hotel chains and linkages among airlines as exogenous. Although the focus of this chapter is on how credit card issuers choose their airline partners (linkages from credit card issuers to airlines), modeling the choice of hotel chains (linkages from hotel chains to airlines) is necessary because their choices affect the current state of the network at a meeting between a credit card issuer and an airline.

The primary estimands are the parameters of the chooser's objective function, with credit card issuers as the choosers. The chapter also estimates the parameters of the hotel chain's objective function, but it only briefly discussed. The estimation procedure involves two steps. The first step constructs the bids of airlines to both credit card issuers and to hotel chains. Because bids are observed only for linked pairs (i.e., pairs with transfer partnership), I fitted a hedonic regression model to predict the bids for non-linked pairs. The second step utilizes the method of Christakis et al. (2010) to estimate the parameters of the objective functions, using the predicted bids from the first step. The method involves Markov Chain Monte Carlo iterations and a convergence criterion suggested by Gelman and Rubin (1992).

This chapter conducts a revealed-preference analysis using observations on 3 credit card issuers, 7 hotel chains, and 43 airlines from 2014 to 2018. Chapter 2 contains details on the data collection procedure. The estimation result indicates the following. Other things equal,

1. A credit card issuer is more likely to form a transfer partnership with an airline that the complements the redemption options of its loyalty program.

2. A credit card issuer is more likely to form a transfer partnership with an airline that is a transfer partner of another credit card issuer. That is, there is statistical evidence for positive Competitive Relationship.

3. A credit card issuer is more likely to form a transfer partnership with an airline that is a transfer partner of its hotel partner. That is, there is statistical evidence for positive Network Transitivity.

In particular, result 1 suggests that a credit card issuer tends to pursue resource complementarity when choosing its airline partners, rather than their individual resources.

The rest of the chapter is organized as the following. Section 3.2 discusses related research. Section 3.3 describes the transfer partnerships as a network of loyalty programs. Section 3.4 describes the model, and section 3.5 discusses the estimation method. Section 3.5 briefly discusses the data and presents the estimation result. Finally, 3.7 concludes.

3.2 Related Research

Researchers typically model strategic network formation as a collection of pairwise interactions, where the formation of linkage between a pair of agents depends on their characteristics and possibly the characteristics of other agents. Researchers often regard the observed state of the network as an equilibrium outcome, using the pairwise stability of Jackson and Wolinsky (1996) as the equilibrium condition. The pairwise stability extends Nash equilibrium to accommodate pairwise interactions, such that for each pair, neither one of the agents can be made better off by modifying the linkage between the pair. Research that employs the pairwise stability views strategic network formation as a simultaneous-move game.

The simultaneity and possible existence of multiple equilibria complicate estimation. Tamer (2003) explains that naively using regression models may result in biased estimation in the presence of multiple equilibria. Sheng (2018) provides a discussion on multiple equilibria in networks and the problem in parameter identification for network formation models. de Paula et al. (2015) and Sheng (2018) each presents a partial identification method for network formation models based on subnetworks. Jia (2008) utilizes the lattice theory of Tarski (1955) and Topkis (1955) to restrict the set of Nash equilibria in a simultaneous-move game, where Walmart and K-Mart strategically choose their store locations. Nishida (2015) extends the method of Jia (2008) to study strategic location choices of the convenience-store industry in Japan. Miyauchi (2016) extends the method of Jia (2008) and presents an identification method for analyzing the formation of pairwise stable networks. Lee and Fong (2013) develops a two-stage model of strategic network formation, where the first stage determines potential partners and the second stage models linkage formations as bilateral Nash bargaining games.

Christakis et al. (2010) and Snijders et al. (2010) each presents a model of sequential network formation, in which the network transitions from a state to the next state via some unknown sequence of meetings between myopic agents. By construction, their specifications do not allow the existence of multiple equilibria as how the network transitions depends on the ordering of events laid out by the sequence of meetings. However, the model parameters cannot be feasibly estimated because the sequence of meetings is unknown. They employ Bayesian methods to sample the sequence of meetings and estimate the model parameters using Markov Chain Monte Carlo. This chapter is built upon their framework but with focus on strategic formation of portfolios of partners, with asymmetric roles of agents in the network.

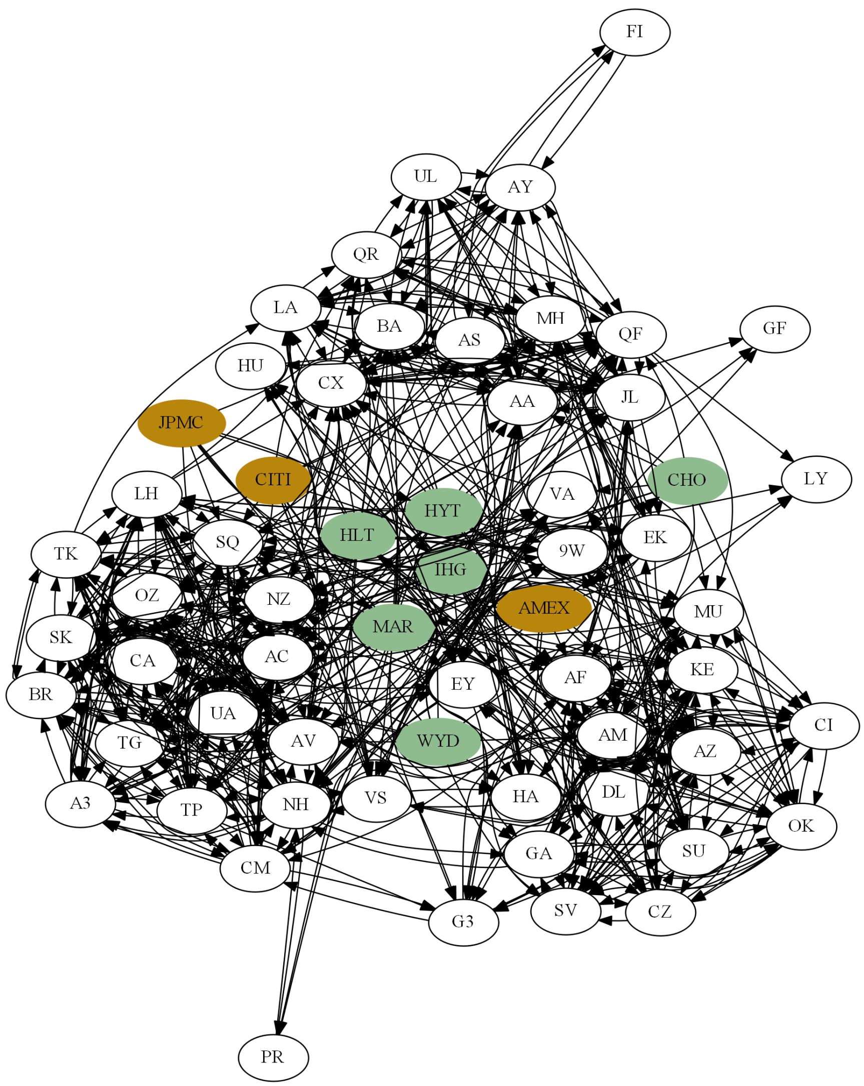
3.3 Network of Loyalty Programs

The network of loyalty programs is composed of transfer partnerships among of 3 credit card issuers, 7 hotel chains, and 43 airlines. Figure 3.2 is a snapshot of this network observed in November 2018. A node represents the loyalty program of a firm. In particular, the golden, teal, and white nodes are the loyalty programs of credit card issuers, hotel chains, and airlines, respectively. A directed link indicates a transfer partnership. That is, a directed link from a node to another indicates that loyalty points can be transferred from the source node to the target node. Each link is assigned a weight, which indicates the associated the transfer ratio. A transfer ratio is the number of points in the target node that can be obtained per 1 point in the source node. An exception is the links between airline nodes. A link from an airline node to another indicates that loyalty points in the source node can be used to redeem for flights offered[4] by the target node. The formation of links among airlines is complex, with strategic motives over flight routes. Moreover, a large share of the links are partnerships formed via airline alliances, for which no observed changes are observed since 2014. I take the links among airlines as exogenous, and they are assigned a weight of 1.

In figure 3.2, nodes are positioned close to each other if they are strongly connected via direct and indirect links. The cluster of airlines on the lower-left is Star Alliance, the cluster on the lower-right is SkyTeam, and the cluster on the top is Oneworld. We can observe that AMEX (American Express Company) is positioned close to SkyTeam, while JPMC (J.P. Morgan Chase Bank) and CITI (Citibank) are positioned close to Star Alliance and Oneworld. The focus of this chapter is to study why the linkages between the credit card issuers and the airlines were formed as observed. In particular, the aim is to explain how characteristics of firms and network linkages affected the formation of linkage between a credit card issuer and an airline.

[4]This is not the same as a flight operated by the partner airline. For example, a codeshare flight is sold by an airline but can be operated by a partner airline. Having a codeshare agreement does not imply being able to use points to redeem for flights offered by the partner airline.

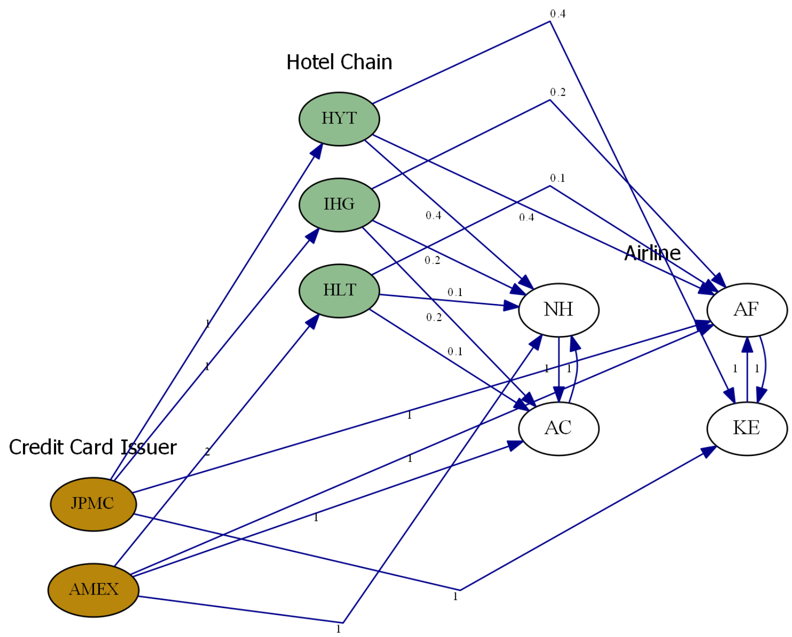
Figure 3.2: Network Map (Nov. 2018)



This figure illustrates the network of loyalty programs observed in November 2018. The golden, teal, and white nodes are the loyalty programs of credit card issuers, hotel chains, and airlines, respectively. See table B.5 in the appendix for a dictionary of node names. A directed link from a node to another indicates that points may be transferred from the source node to the target node. Nodes are positioned close to each other if they are strongly connected via direct and indirect links. The cluster of airlines on the bottom-left is Star Alliance, the cluster on the bottom-right is SkyTeam, and the cluster on the top is Oneworld. AMEX is positioned close to SkyTeam. On the other hand, JPMC and CITI are positioned close to Star Alliance and Oneworld.

Figure 3.3 visualizes the network of loyalty programs using a subset of the nodes. I remark three critical features. First, except for airlines, there are no links between nodes within the same industry sector[5]. This reveals a non-cooperative relationship among credit card issuers and among hotel chains. Second, there are no linked pointing to credit card issuers. Third, there are no links from airlines to hotel chains[6]. Such features, along with classification of nodes by industry sector, allow splitting the network into four subnetworks.

Figure 3.3: Network of Loyalty Programs (Abridged, Nov. 2018)



This figure is an abridged version of figure 3.2, with only a subset of the nodes. The golden, teal, and white nodes are the loyalty programs of credit card issuers, hotel chains, and airlines, respectively. A directed link from a node to another indicates that points may be transferred from the source node to the target node. Except for the links between airlines, each link weights indicates the transfer ratio per 1 point in the source node. A link between airlines indicate that points in the source node can be used to redeem for flights offered by the target node. All links between airline nodes are assigned a weight of 1.

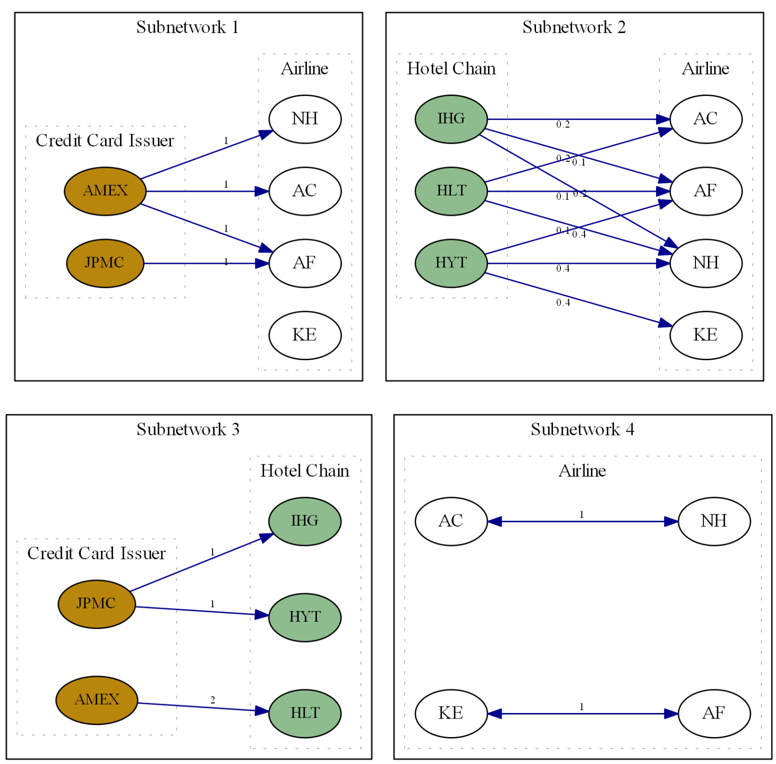
[5]A special exception is a merger between hotel chains. For example, the merger of Marriott International and Starwood Hotels and Resorts enabled transfers between their loyalty programs. The loyalty programs were completely integrated shortly after.

[6]There are a few exceptions. For example, loyalty points of a few airlines can be transferred to Hilton Hotels & Resorts.

Figure 3.4 illustrates the splitting. Subnetwork 1 describes linkages from credit card issuers to airlines, and subnetwork 2 describes linkages from hotel chains to airlines. Subnetwork 3 describes linkages from credit card issuers to hotel chains, and subnetwork 4 describes linkages among airlines. In particular, subnetworks 1,2, and 3 describe linkages involving two different industry sectors. These subnetworks are uni-directional bipartite because all links are directed from one industry sector to another, and there are no links within the same industry.

I model only the formation of subnetworks 1 and 2. Although the focus is on the formation of subnetwork 1, modeling subnetwork 2 is necessary because the formation of the subnetworks may depend on each other. This is further explained in section 3.4.5. As discussed in section 2.2, transfer partnerships between credit card issuers and hotel chains are determined by co-brand partnerships, and thus the formation of subnetwork 3 is taken as exogenous. Subnetwork 4, which describes partnerships among airlines, is also taken as exogenous, as explained earlier in this section.

Figure 3.4: Splitting into Subnetworks



The network in figure 3.3 is split into four subnetworks. Subnetwork 1 (upper left) describes linkages from credit card issuers to airlines. Subnetwork 2 (upper right) describes linkages from hotel chains to airlines. Subnetwork 3 (lower left) describes linkages from credit card issuers to hotel chains. Subnetwork 4 (lower right) describes linkages between airlines.

In the following sections, $\boldsymbol{D}$ represents the full network, and $\boldsymbol{D}_1, \boldsymbol{D}_2, \boldsymbol{D}_3, \boldsymbol{D}_4$ represent subnetworks 1,2,3,4, respectively. They are adjacency matrices corresponding to the network and the subnetworks. For example, the $(s,t)^{\text{th}}$ element of $\boldsymbol{D}$ is equal to 1 if there exists a link from node s to node t and zero if otherwise. The information on link weights (i.e., transfer ratios) is kept separately from the adjacency matrix. In the following, firms, loyalty programs of firms, and nodes are synonymous unless I explicitly distinguish them. For example, I often use "credit card issuer" to denote the "loyalty program of the credit card issuer" or the corresponding node in the network. However, I explicitly distinguish the characteristics of firms (e.g., key performance indicators) and the characteristics of loyalty programs (e.g., redemption rates of loyalty points).

3.4 The Model

The model assumes that at least two states of the network are observed. The observed states of the network are viewed as snapshots of a discrete-time stochastic process. This specification reflects that contracts (transfer partnerships) between firms are revised at some time interval and the process continues indefinitely. The model describes the transition of the network from an initial state $\boldsymbol{D}^t$ to the next observed state $\boldsymbol{D}^{t+1}$, which I also denote as the ending state.

The sequential network formation model of Christakis et al. (2010) is particularly well-suited to describe the transition of network as a discrete-time process. However, their model assumes that the initial state of the network is the null state (i.e., no links between agents) and can accommodate only one transition. This chapter's model is built upon their work but allows agents to possess links in the initial state and accommodates transitions over multiple periods. From here on, the term *period* t indicates the time frame for the transition from $\boldsymbol{D}^t$ to $\boldsymbol{D}^{t+1}$. The model accommodates transitions of the network over multiple periods by assuming that the model parameters are invariant over time. Section 3.5.2 provides a more detailed explanation on the specification.

I allow asymmetric roles of agents in the network formation process, by utilizing the unidirectional bipartite structure of the subnetworks 1 and 2. The model simplifies the asymmetric roles of firms as *bidders* and *choosers*, and linkages are determined according to interactions between them via a sequential authority mechanism. First, bidders submit bids to choosers, where a bid represents the terms of contract proposed by the bidder to the chooser. After receiving the bids, choosers choose whether or not to accept the bids. A link from a chooser to a bidder is added or maintained if the bidder's bid is accepted by the chooser, and an existing link is removed or no linkage is maintained if the bidder's bid is not accepted by the chooser. In subnetwork 1, airlines are the bidders, and credit card issuers are the choosers. In subnetwork 2, airlines are the bidders and hotel chains are the choosers.

For the rest of the chapter, the letters i, j, and k indicate an arbitrary credit card issuer, hotel chain, and airline, respectively. $\mathbb{I}^t, \mathbb{H}^t$, and $\mathbb{K}^t$ respectively denote the set credit card issuers, hotel chains, and airlines for period *t.* Note that the superscript t indicates that the node sets may vary over the periods. Table 3.1 provides a reference for notations used throughout this chapter.

Table 3.1: Table of Notations

Notation	Description
Subnetwork 1	Chooser: credit card issuers, Bidder: airlines
Subnetwork 2	Chooser: hotel chains, Bidder: airlines
Subnetwork 3	Between credit card issuers and hotel chains (exogenous)
Subnetwork 4	Between airlines (exogenous)
C_i^t	Key performance indicators (KPIs) of credit card issuer i for period t
H_j^t	Key performance indicators of hotel chain j for period t
A_k^t	Key performance indicators of airline k for period t
$\mathbb{K}^t$	Set of airlines for period t; $\mathbb{I}^t$, $\mathbb{J}^t$ are similar
$\boldsymbol{A}^t$	Collection of A_k^t for $k \in \mathbb{K}^t$; $\boldsymbol{C}^t, \boldsymbol{H}^t$ are similar
$\boldsymbol{A}_{-k}^t$	$\boldsymbol{A}^t$ except A_k^t; $\boldsymbol{C}_{-i}^t, \boldsymbol{H}_{-j}^t$ are similar
v_i^t	Value of node i's point for period t; v_j^t, v_k^t are similar
$\boldsymbol{v}^t$	Collection of v_i^t,v_j^t, v_k^t for all $i \in \mathbb{I}^t$, $j \in \mathbb{J}^t$, $k \in \mathbb{K}^t$
w_{ik}^t	Transfer ratio from i to k for period t; w_{jk}^t is similar
b_{ik}^t	Bid i receives from k for period t; b_{jk}^t is similar
w_i^t	Collection w_{ik}^t for $k \in \mathbb{K}^t$; b_i^t is similar
$\boldsymbol{w}^t$	Collection of w_i^t for $i \in \mathbb{I}^t$; $\boldsymbol{b}^t$ is similar
ϵ_{ki}^t	Idiosyncratic factor of k specific to i for period t; $\epsilon_{ik}^t, \epsilon_{jk}^t$ are similar
S^t	Sequence of meetings for period t
M^t	Length of S^t
m	Position of meeting in S^t
$(i^{t,m}, k^{t,m})$	m^{th} meeting in period t if occurs in subnetwork 1
$(j^{t,m}, k^{t,m})$	m^{th} meeting in period t if occurs in subnetwork 2
$P_i^{t,m}$	i's portfolio of partners at beginning of m^{th} meeting in period t; $P_j^{t,m}$ is similar
$\boldsymbol{D}^t$	Adjacency matrix of the network at beginning of period t
$\boldsymbol{D}^{t,m}$	Adjacency matrix of the network at the beginning of m^{th} meeting in period t
$\boldsymbol{D}_{-i}^{t,m}$	$\boldsymbol{D}^{t,m}$ excluding node i; $\boldsymbol{D}_{-j}^{t,m}$ is similar
$\boldsymbol{D}_1^{t,m}$	Adjacency matrix of subnetwork 1 at beginning of m^{th} meeting in period t
$\boldsymbol{D}_2^{t,m}$	Adjacency matrix of subnetwork 2 at beginning of m^{th} meeting in period t
$\boldsymbol{D}_3^t$	Adjacency matrix of subnetwork 3 for period t (exogenous)
$\boldsymbol{D}_4^t$	Adjacency matrix of subnetwork 4 for period t (exogenous), also includes information on redemption rates of airline loyalty points
$\boldsymbol{D}_{1,-i}^{t,m}$	$\boldsymbol{D}_1^{t,m}$ excluding node i; $\boldsymbol{D}_{2,-j}^{t,m}$ is similar

3.4.1 Model Outline

This section describes the timeline of the model and the information set available to the nodes (loyalty programs of firms). For each period,

1. The initial state of the network is equal to the state at the end of the previous period. All nodes possess full information over the full network.

2. Nature draws a sequence of meetings. It is unknown to all nodes.

3. All bidders simultaneously submit bids to all choosers. Each chooser observes only the bids submitted to itself.

4. Bilateral meetings between choosers and bidders occur along the sequence of meetings. The sequence of meetings encompasses all (bidder, chooser) pairs for subnetworks 1 and 2. There are three possible outcomes for each meeting. In a meeting, the chooser

   (a) Adds a new link with the bidder.

   (b) Removes an exiting link with the bidder.

   (c) Maintains status quo.

5. The outcome of a meeting is immediately revealed to all nodes. The next meeting occurs.

For the rest of the chapter, a credit card issuer (i) serves as the chooser and an airline (k) serves as the bidder. The case with a hotel chain (j) as the chooser and an airline (k) as the bidder is discussed briefly.

3.4.2 Bidders

To facilitate the transfer of loyalty points, credit card issuers make cash payments to airlines, based on negotiated cents-per-point prices. The bid submitted by airline k to credit card issuer i is a one-dimensional object describing the price and other factors specified in the terms of contract proposed by k. I assume that the transfer ratio from i to k, after accounting for the relative values of loyalty points of i and k, captures the terms of contract. Let b_{ik}^t denote the bid submitted by k to i for period t. It is given by

$$b_{ik}^t = \frac{w_{ik}^t}{v_i^t/v_k^t}, \tag{3.1}$$

where w_{ik}^t is the transfer ratio from i to k. v_i^t and v_k^t are the values of loyalty points of nodes i and k, respectively. A larger (smaller) w_{ik}^t indicates 1 point in node i can be transferred to obtain a larger (smaller) amount of points in node k. Equation (3.1) states that a large transfer ratio is observed either because i's points are more valuable than k's (large v_i^t/v_k^t) or because i received favorable terms of contract from k (a large b_{ik}^t). This specification is somewhat restrictive because it is possible that a credit card issuer smooths its transfer ratios across its partners. An extreme case would be setting a single transfer ratio for all transfer partners, regardless of the heterogeneity in cost associated with facilitating the transfers of loyalty points.

v_i^t and v_k^t denote the points redemption values of nodes i and k. For the airline k, v_k^t accounts for all redemption options for flights accessible via its loyalty program, including its own flights and the flights of its partners. Thus v_k^t depends the redemption options of loyalty points offered by k and redemption options granted by its partners. For credit card issuer i, v_i^t only accounts for its own points redemption options, excluding the redemption options accessible via the transfer partners. The procedure for constructing the node values is explained in section C.2.1. Table C.1 and figure C.1 in the appendix report details on values of nodes for airlines and hotel chains, respectively.

The values serve a tool for comparing loyalty points within the same industry and across different industries, so that the normalized transfer ratios $\frac{w_{ik}^t}{v_i^t/v_k^t}$ are comparable for all (i, k) pairs. For example, the transfer ratio from AMEX to AM is 1.6, while the transfer ratios for most other airlines are 1. The discrepancy exists because the loyalty points of AM are in kilometer units, while the loyalty points of most other airlines are in mile units. These transfer ratios are not comparable unless the difference in units is accounted for.

b_{ik}^t is observed (constructed from observed variables) only when there exists a link from i to k because otherwise w_{ik}^t is not observed. I construct the missing bids using a hedonic regression model

$$b_{ik}^t = \beta_c' C_i^t + \gamma_c' A_k^t + \epsilon_{ki}^t \tag{3.2}$$

where C_i^t and A_k^t are key performance indicators (KPIs) of the credit card issuer i and the airline k, respectively, in period t (in the empirical analysis, I applied logarithmic transformations to the KPIs except for those in percentage units). The subscript c for coefficients β_c and γ_c indicate that the coefficients are specific to the bids for credit card issuers. Moreover, I assume that the coefficients are invariant over the periods. ϵ_{ki}^t denotes the unobserved idiosyncratic factor of k specific to i. I also impose the following assumption.

Assumption 1. *For all t and for all $i \in \mathbb{I}^t, k \in \mathbb{K}^t$*

$$\epsilon_{ki}^t \big| C_i^t, A_k^t \sim \textit{i.i.d.} \tag{3.3}$$

$\boldsymbol{C}_{-i}^t$ denotes the collection of KPIs of all credit card issuers in $\mathbb{I}^t$ excluding i, and $\boldsymbol{A}_{-k}^t$ denotes the collection of KPIs of all airlines in $\mathbb{K}^t$ excluding k. This assumption implies that bidders are non-strategic agents and that bids are determined only at pairwise level. The same specification applies with i replaced by j (a hotel chain) and C_i^t replaced with H_j^t (KPIs of j in period t), in which case the coefficients β_h and γ_h carry the subscript h to indicate that the coefficients are specific to the bids for hotel chains.

Table 3.2: OLS Estimation of Hedonic Regression Model

Variable	Credit Card Issuer	Hotel Chain
log(Credit Card Purchase)	0.0504**	-
	(0.020)	
Delinquency Rate	-0.0167	-
	(0.106)	
Writeoff Rate	-0.0365	-
	(0.062)	
log(Hotel Revenue)	-	0.0074
		(0.005)
log(Number of Hotels)	-	0.0031
		(0.004)
log(RevPAR)	-	-0.0056
		(0.025)
Occupancy Rate	-	-0.0005
		(0.002)
log(Passenger Revenue)	-0.0136	-0.0206*
	(0.038)	(0.011)
log(RPK)	-0.0069	0.0854
	(0.227)	(0.052)
log(ASK)	0.0496	-0.0447
	(0.228)	(0.054)
Adj. R-squared	0.988	0.944
No. observations	79	458

This table reports OLS estimates of the hedonic regression models for bids. The first column lists the covariates included in the hedonic regression models (see section 3.6.1 for definitions). The second column reports parameter estimates associated with the bids for credit card issuers, submitted by airlines. The third column reports parameter estimates associated with the bids for hotel chains, submitted by airlines. Standard errors are reported in parentheses. ** indicates statistical significance at 0.05 level. * indicates statistical significance at 0.1 level.

Table 3.2 reports the OLS fit of the hedonic regression model (see appendix C.2.2 for the estimation procedure; see section 2.3.3 in chapter 2 for details on the variables). The estimation result suggests that a credit card issuer with a larger amount Credit Card Purchase (total amount of credit card purchases processed) tends to receive larger bids from airlines (more favorable to the credit card issuer), other things equal. They also suggest that an airline with a larger Passenger Revenue (revenue from passenger flights) tend to submit smaller bids to hotel chains (less favorable to hotel chains), other things equal. In both estimation of bids (bids for credit card issuers and bids for hotel chains), the reported R^2 is close to 1, indicating that the included KPIs well explain the variations in the bids.

Table 3.3 reports summary statistics for the observed and the fitted bids. The OLS estimation smooths outliers with extremely small or large bids; however, overall, the distribution of the fitted bids is similar to the observed bids. The similarity is partially is due to the assumption that bidders are non-strategic, and thus whether or not the bidder has links (transfer partnerships) with a certain group of choosers does not affect its bids. I further used the fitted bids and equation (3.1) to construct the potential transfer ratios for all (chooser, bidder) pairs.

Table 3.3: Summary Statistics of Bids

Chooser	N	Mean	SD	10th	25th	Med	75th	90th
Credit Card Issuers	79	0.933	0.113	0.752	0.900	0.963	1.012	1.045
Credit Card Issuers (Fitted)	381	0.915	0.055	0.844	0.881	0.917	0.958	0.990
Hotel Chains	458	0.262	0.066	0.182	0.217	0.259	0.304	0.345
Hotel Chains (Fitted)	848	0.257	0.021	0.232	0.241	0.256	0.274	0.286

This table compares fitted bids with observed bids (constructed from observed variables). The OLS estimation smooths outliers with extremely low and extremely large bids. However, the distribution of the fitted bids are overall comparable with the observed bids for both credit card issuers and hotel chains.

3.4.3 Choosers

After receiving bids, the chooser strategically chooses a portfolio of transfer partners such that the portfolio maximizes its objective function. The objective function of credit card issuer i has the form

$$\begin{aligned} U_c\left(P_i^t; b_i^t, w_i^t, \boldsymbol{A}^t, \boldsymbol{D}_{1,-i}^t \boldsymbol{D}_2^t, \boldsymbol{D}_3^t, \boldsymbol{D}_4^t, \epsilon_i^t, \theta_c\right) &= g_c\left(P_i^t, b_i^t, w_i^t, \boldsymbol{A}^t, \boldsymbol{D}_{1,-i}^t, \boldsymbol{D}_2^t, \boldsymbol{D}_3^t, \boldsymbol{D}_4^t, \theta_c\right) \\ &\quad + \sum_{k \in P_i^t} \epsilon_{ik}^t \end{aligned} \tag{3.4}$$

$P_i^t \subseteq \mathbb{K}^t$ denotes the current portfolio of airline partners possessed by i, and $b_i^t = \{b_{ik}\}_{k \in \mathbb{K}^t}$ is the collection of bids i receives in period t. $\{w_i^t\}_{k \in \mathbb{K}^t}$ is the collection of potential transfer ratios for i, and $\boldsymbol{A}^t$ is the collection of A_k^t for all $k \in \mathbb{K}^t$. $\boldsymbol{D}_{1,-i}^t$ is the adjacency matrix indicating the current state of the subnetwork 1, excluding the part associated with i. $\boldsymbol{D}_2^t, \boldsymbol{D}_3^t,$ and $\boldsymbol{D}_4^t$ are adjacency matrices indicating current states of subnetworks 2,3, and 4, respectively. These four matrices contain the information of $\boldsymbol{D}_{-i}^t$, which the adjacency matrix for the network, excluding the part associated with i. $\epsilon_i^t = \{\epsilon_{ik}^t\}_{k \in \mathbb{K}^t}$ is the collection of unobserved idiosyncratic factors of i specific to k. The vector of model parameters θ_c is specific to credit card issuers and is invariant across periods. A restriction is that ϵ_{ik}^t enters the objective function additively. I also assume the following.

Assumption 2. *For all t and for all $i \in \mathbb{I}^t, k \in \mathbb{K}^t$*

$$\epsilon_{ik}^t \big| b_i^t, w_i^t, \boldsymbol{A}^t, \boldsymbol{D}^t \sim i.i.d. \tag{3.5}$$

Equation (3.5) states that the idiosyncratic factors are independent and identically distributed, conditional on the bids received by the credit card issuer, its potential transfer ratios, the KPIs of airlines, and the current state of the network. For the empirical analysis, I endowed the idiosyncratic factors with the following distribution:

$$\epsilon_{ik}^t \big| b_i^t, w_i^t, \boldsymbol{A}^t, \boldsymbol{D}^t \overset{\text{i.i.d.}}{\sim} Logistic(0,1). \tag{3.6}$$

$g_c(\cdot)$ has the following linear form (replacing the notations $\boldsymbol{D}_{1,-i}^t, \boldsymbol{D}_2^t, \boldsymbol{D}_3^t, \boldsymbol{D}_4^t$ with $\boldsymbol{D}_{-i}^t$).

$$\begin{aligned} g_c\left(P_i^t, b_i^t, w_i^t, \boldsymbol{A}^t, \boldsymbol{D}_{-i}^t, \theta_c\right) = \theta_{0c} & \\ & + \theta_{1c}\left|P_i^t\right| + \theta_{2c}' Performance\left(P_i^t, b_i^t, \boldsymbol{A}^t\right) + \theta_{3c} GeoHub\left(P_i^t\right) \\ & + \theta_{4c} Mileage\left(P_i^t, w_i^t, \boldsymbol{D}_4^t\right) + \theta_{5c} Routes\left(P_i^t, \boldsymbol{D}_4^t\right) \\ & + \theta_{6c} Competitor\left(P_i^t, \boldsymbol{D}_{1,-i}^t\right) + \theta_{7c} Transitivity\left(P_i^t, \boldsymbol{D}_2^t, \boldsymbol{D}_3^t\right), \end{aligned} \tag{3.7}$$

where $\theta_c = (\theta_{0c}, \theta_{1c}', \theta_{2c}, \theta_{3c}, \theta_{4c}, \theta_{5c}, \theta_{6c}, \theta_{7c})'$. θ_{0c} is the constant term.

The first three components serve as controls. $|P_i^t|$ is the number of airline transfer partners possessed by i, which controls for the cost and benefit associated with the size of the portfolio. *Performance* is a measure of market performance of the airlines in the portfolio. It is equal to

$$\sum_{k \in P_i^t} \frac{b_{ik}^t}{\sum_{k \in P_i^t} b_{ik}^t} A_k^t, \tag{3.8}$$

which is a weighted average of the KPIs of the airlines in the portfolio, with more importance given to airlines that submitted larger bids. This component serves as a proxy for the overall institutional characteristics of the partner airlines. *GeoHub* is the number of distinct airline hub locations, which is a measure of geographic diverseness possessed by the portfolio (see table B.5 for details). The underlying view is that credit card issuers target U.S. consumers with diverse geographic affinity and seek to enhance the attractiveness of their loyalty programs by partnering with airlines with strong presence in various geographic regions.

The fourth component is a measure of redemption options of loyalty points for flights granted by the portfolio (see appendix C.2.3 for details). Other things equal, a lower value of *Mileage* indicates that the redemption options granted by the portfolio of transfer partners is more cost-effective, in terms of i's loyalty points, in redeeming for flights to various geographic regions. In other words, a lower value of *Mileage* indicates that the resources of airline partners included in the portfolio well complement each other and that the portfolio of transfer partners grants better redemption options for i's loyalty program. The fifth component, *Routes,* is the total number reward flight routes granted by the portfolio, which is a measure of diverseness in redemption for reward flights granted by the portfolio of airline partners. *Routes* counts all routes of reward flights, with multiplicity for the same flight route granted by different airline partners. Note that for brevity of notation, I specify that $\boldsymbol{D}_4^t$ also contains information on the redemption options of airline loyalty points for period t.

The last two components capture the effect of network linkages, which are transfer partnerships of other firms, in partner choice. *Competitor* is the number of i's airline partners that are also partners of other credit card issuers. Specifically, it is equal to

$$\left|\left\{k \in P_i^t : \left[\boldsymbol{D}_{1,-i}^t\right]_{\tilde{i}k} = 1,\ \forall \tilde{i} \neq i\right\}\right|, \tag{3.9}$$

where $[\boldsymbol{D}]_{ik}$ denotes the $(i,k)^{\text{th}}$ element of the matrix $\boldsymbol{D}$. *Transitivity* is the number of i's airline partners that are also partners of i's hotel partners, which is equal to

$$\left|\left\{k \in P_i^t : \left[\boldsymbol{D}_2^t\right]_{jk} = 1,\ \forall j \text{ s.t. } \left[\boldsymbol{D}_3^t\right]_{ij} = 1\right\}\right|. \tag{3.10}$$

With hotel chain j as the chooser, the objective function

$$\begin{aligned} U_h\left(P_j^t; b_j^t, w_j^t, \boldsymbol{A}^t, \boldsymbol{D}_1^t, \boldsymbol{D}_{2,-j}^t, \boldsymbol{D}_3^t, \boldsymbol{D}_4^t, \epsilon_j^t, \theta_h\right) &= g_h\left(P_j^t, b_j^t, w_j^t, \boldsymbol{A}^t, \boldsymbol{D}_1^t, \boldsymbol{D}_{2,-j}^t, \boldsymbol{D}_3^t, \boldsymbol{D}_4^t, \theta_h\right) \\ &\quad + \sum_{k \in P_j^t} \epsilon_{jk}^t \end{aligned} \tag{3.11}$$

is specified similarly with a different vector of model parameters θ_h. The subscript *h* indicates it is associated with hotel chains.

As the portfolio is updated sequentially (explained in the next subsection), by adding, removing, or maintaining links with airlines, the components of θ capture the marginal contributions of variables to the objective function.

3.4.4 Sequence of Meetings

In each period, bilateral meetings between bidders and choosers occur according to a sequence of meetings. In each meeting, the chooser, after observing all of its bids, decides to accept or reject the bidder's bid. Similar to Christakis et al. (2010), I specify that all (chooser, bidder) pairs meet exactly once in each period. Moreover, I specify that the sequence of meetings is unknown to all nodes in the network. Note that the node set and the sequence of meetings may be different over the periods.

Let

$$S_1^t = \left[\left(i^{t,1}, k_1^{t,1}\right), \left(i^{t,2}, k_1^{t,2}\right), \ldots, \left(i^{t,M_1^t}, k_1^{t,M_1^t}\right)\right] \tag{3.12}$$

$$S_2^t = \left[\left(j^{t,1}, k_2^{t,1}\right), \left(j^{t,2}, k_2^{t,2}\right), \ldots, \left(j^{t,M_2^t}, k_2^{t,M_2^t}\right)\right]. \tag{3.13}$$

S_1^t and S_2^t denote the sequence of meetings between nodes within subnetwork 1 and within subnetwork 2, respectively, in period *t*. Each element of S_1^t and S_2^t is a unique (chooser, bidder) pair, and the superscripts *t, m* indicate the *m*$^{\text{th}}$ meeting in period *t*. M_1^t and M_2^t denote the lengths of the two sequences. S^t denotes the complete sequence of meetings in period *t*, and it is a mixture of S_1^t and S_2^t with length equal to $M^t = M_1^t + M_2^t$. Thus the *m*th meeting in S^t is be either $(i^{t,m}, k^{t,m})$ or $(j^{t,m}, k^{t,m})$. Because each pair meets exactly once in a period, a (chooser,bidder) pair can appear only once in S^t.

Without loss of generality, let $(i^{t,m}, k^{t,m})$ be the *m*th meeting in period *t* (i.e., the *m*th is meeting is between a credit card issuer and an airline). I assume that the chooser is myopic so that it maximizes the objective function given the current state of the network, without forming expectations for future states of the network. Formally, let $P_{i^{t,m}}^{t,m}$ and $P_{i^{t,m}}^{t,m+1}$ denote the portfolio of airline partners possessed by $i^{t,m}$ at the beginning and immediately after the m^{th} meeting, respectively. $\boldsymbol{D}_{-i^{t,m}}^{t,m}$ denotes the state of network, excluding the part associated with $i^{t,m}$, at the beginning of the *m*th meeting. Note that $P_{i^{t,m}}^{t,m}$ is determined by the outcomes of previous meetings involving $i^{t,m}$, and $\boldsymbol{D}_{-i^{t,m}}^{t,m}$ is determined by the outcomes of previous meetings not involving $i^{t,m}$. The outcome of the *m*th meeting satisfies

$$U_c\left(P_{i^{t,m}}^{t,m+1}; b_{i^{t,m}}^t, w_{i^{t,m}}^t, \boldsymbol{A}^t, \boldsymbol{D}_{-i^{t,m}}^{t,m}, \epsilon_{i^{t,m}}^t, \theta_c\right) \geq U_c\left(P_{i^{t,m}}^{t,m} \cup \{k^{t,m}\}; b_{i^{t,m}}^t, w_{i^{t,m}}^t, \boldsymbol{A}^t, \boldsymbol{D}_{-i^{t,m}}^{t,m}, \epsilon_{i^{t,m}}^t, \theta_c\right) \quad (3.14)$$

$$U_c\left(P_{i^{t,m}}^{t,m+1}; b_{i^{t,m}}^t, w_{i^{t,m}}^t, \boldsymbol{A}^t, \boldsymbol{D}_{-i^{t,m}}^{t,m}, \epsilon_{i^{t,m}}^t, \theta_c\right) \geq U_c\left(P_{i^{t,m}}^{t,m} \backslash \{k^{t,m}\}; b_{i^{t,m}}^t, w_{i^{t,m}}^t, \boldsymbol{A}^t, \boldsymbol{D}_{-i^{t,m}}^{t,m}, \epsilon_{i^{t,m}}^t, \theta_c\right). \quad (3.15)$$

3.14 states that $i^{t,m}$ cannot be made better off by adding $k^{t,m}$ to its portfolio (if $k^{t,m}$ is not in the portfolio) or removing $k^{t,m}$ from its portfolio (if $k^{t,m}$ is in the portfolio) immediately after the *m*th meeting, other things equal. In other words, $i^{t,m}$ cannot be made better off by altering its choice in the *m*th meeting under the current state of the network. This specification reflects the view that the network evolves constantly, and one can only observe snapshots of the network. There are infinitely may meetings laid out in the future as the number of periods grows, and the chooser cannot predict future states of the network. Instead, the chooser chooses what is optimal under the current state of the network.

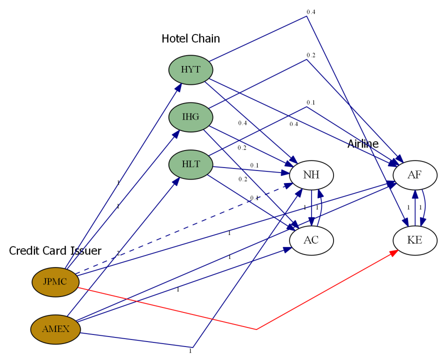
3.4.5 Dependency on Sequence of Meetings

For each period, the sequence of meetings lays out the ordering of events that constitute the transition of the network. Thus, for a given (chooser, bidder) pair, the current state of the network may be different under a different sequence of meetings. A problem arises because we do not observe the sequence of meetings.

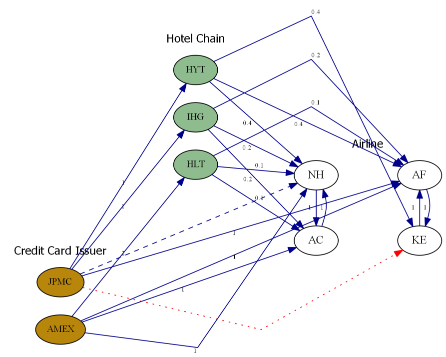
Figure 3.5 visualizes such differences in the current state of the network. KE was removed from JPMC's portfolio of transfer partners in 2018; however, we do not know if the meetings between JPMC and other airlines occurred before or after the removal of KE. We also do not know if the meetings between other credit card issuers and KE occurred before or after the removal.

Figure 3.5: Dependence on Sequence of Meetings

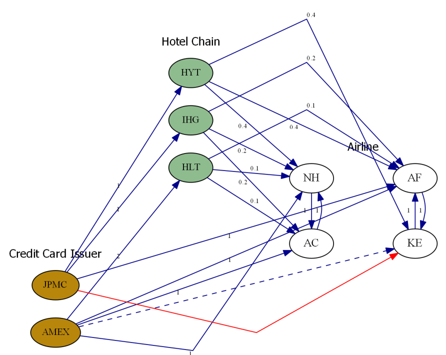
(a) (JPMC, NH) occurs before (JPMC, KE)



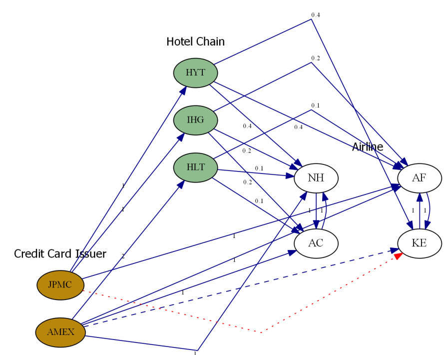
(b) (JPMC, NH) occurs after (JPMC, KE)



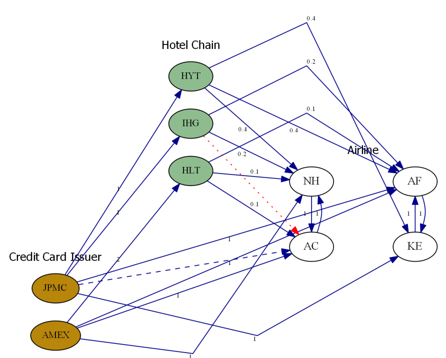
(c) (AMEX, KE) occurs before (JPMC, KE)



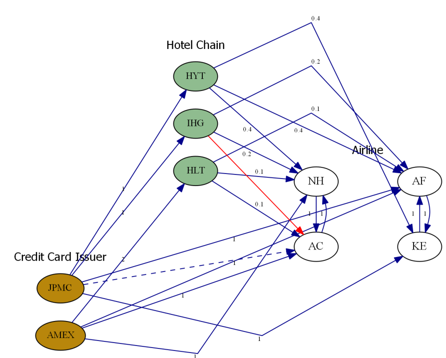
(d) (AMEX, KE) occurs after (JPMC, KE)



(e) (JPMC, AC) occurs before (IHG, AC)



(f) (JPMC, AC) occurs after (IHG, AC)



Sub-figures (a) and (b) illustrate how the order of a credit card issuer's own meetings may affect the current state of the network it faces. In (a), JPMC meets NH before the link from JPMC to KE was removed. In (b), JPMC meets NH after the link from JPMC to KE was removed. (c) and (d) illustrate how the order of another credit card issuer's meetings may affect the current state of the network. In (c), AMEX meets KE before the link from JPMC to KE was removed. In (d), AMEX meets KE after the link from JPMC to KE was removed. (e) and (f) illustrate how the order of a hotel chain's meetings may affect the current state of the network. In (e), JPMC meets AC before the link from IHG to AC was added. In (f), JPMC meets AC after the link from IHG to AC was added.

Sub-figures (a) and (b) illustrate the current state of the network at the beginning of the meeting between JPMC and an airline, occurring before and after the removal, respectively. In sub-figure (a), JPMC has a link to KE when it meets NH, and in sub-figure (b), JPMC does not have a link to KE when it meets NH. For these cases, the current state of the network at the meeting between JPMC and NH vary depending on the ordering of meetings associated with JPMC.

Sub-figures (c) and (d) illustrate the current state of the network at the beginning of the meeting between AMEX and KE, occurring before and after the removal, respectively. In sub-figure (c), JPMC has a link to KE when AMEX meets KE, and in sub-figure (d), JPMC does not have a link to KE when AMEX meets KE. For these cases, the current state of the network at the meeting between AMEX and KE vary depending on the ordering of meetings associated with another credit card issuer, JPMC.

IHG has been a hotel transfer partner of JPMC at least from 2014 to 2018, and IHG added AC to its portfolio of airline transfer partners in 2016. Here, we do not if the meeting between JPMC and AC occurred before or after the addition. Sub-figures (e) and (f) illustrate the current state of the network at the beginning of the meeting between JPMC and AC, occurring before and after the addition, respectively. In sub-figure (e), IHG does not have a link to AC when JPMC meets AC, and in sub-figure (f), IHG has a link to AC when JPMC meets AC. For these cases, the current state of the network at the meeting between JPMC and AC vary depending on the ordering of meetings associated with a partner hotel chain of JPMC.

3.4.6 Meeting Outcomes

Because each (chooser, bidder) pair meets exactly once in each period, the linkage between a pair is completely determined by the outcome of the meeting between them. Conversely, the initial state and the ending state of the network completely determines the meeting outcomes. Recall that $\boldsymbol{D}^t$ and $\boldsymbol{D}^{t+1}$ denote the initial and the ending states of the network for period t. There are four possible cases:

1. $\left[\boldsymbol{D}^t\right]_{i^{t,m}k^{t,m}} = 0$ and $\left[\boldsymbol{D}^{t+1}\right]_{i^{t,m}k^{t,m}} = 0$
   - $i^{t,m}$ does not add $k^{t,m}$ its portfolio at the end of m^{th} meeting (no changes).
   - $i^{t,m}$ is better of with $P^{t,m}_{i^{t,m}}$ than $P^{t,m}_{i^{t,m}} \cup \{k^{t,m}\}$.
2. $\left[\boldsymbol{D}^t\right]_{i^{t,m}k^{t,m}} = 0$ and $\left[\boldsymbol{D}^{t+1}\right]_{i^{t,m}k^{t,m}} = 1$
   - $i^{t,m}$ adds $k^{t,m}$ to its portfolio at the end of m^{th} meeting.
   - $i^{t,m}$ is better of with $P^{t,m}_{i^{t,m}} \cup \{k^{t,m}\}$ than $P^{t,m}_{i^{t,m}}$.
3. $\left[\boldsymbol{D}^t\right]_{i^{t,m}k^{t,m}} = 1$ and $\left[\boldsymbol{D}^{t+1}\right]_{i^{t,m}k^{t,m}} = 0$
   - $i^{t,m}$ removes $k^{t,m}$ from its portfolio at the end of m^{th} meeting.
   - $i^{t,m}$ is better of with $P^{t,m}_{i^{t,m}} \setminus \{k^{t,m}\}$ than $P^{t,m}_{i^{t,m}}$.
4. $\left[\boldsymbol{D}^t\right]_{i^{t,m}k^{t,m}} = 1$ and $\left[\boldsymbol{D}^{t+1}\right]_{i^{t,m}k^{t,m}} = 1$

- $i^{t,m}$ does not remove $k^{t,m}$ from its portfolio at the end of m^{th} meeting (no changes).
- $i^{t,m}$ is better of with $P^{t,m}_{i^{t,m}}$ than $P^{t,m}_{i^{t,m}} \backslash \{k^{t,m}\}$.

3.5 Estimation Method

Given the fitted bids and potential transfer ratios constructed in section 3.4.2 (they are treated as observed variables), the model specification yields a likelihood function describing the transition of the network, conditional on the sequence of meetings. Following the estimation method suggested by Christakis et al. (2010), I use two iterations of the Metropolis-Hastings algorithm (Metropolis et al., 1953), one for θ and the other for the sequence of meetings. There is a feedback loop between the iterations, such that θ is updated given a sequence of meetings, and the sequence of meetings is updated given a value of θ. $\theta = (\theta_c', \theta_h')'$ denotes the full vector of model parameters including the parameters of the credit card issuer's and the hotel chain's objective function.

3.5.1 Conditional Likelihood Function

Given the sequence of meetings, the conditional probability of the transition from $\boldsymbol{D}^t$ to $\boldsymbol{D}^{t+1}$ is constructed by assigning probabilities to the 4 cases in section 3.4.6. Consider $(i^{t,m}, k^{t,m})$ as the m^{th} meeting in S^t. Define

$$\begin{aligned}\Delta U^{t,m}_{c+} \equiv U_c &\left(P^{t,m}_{i^{t,m}} \cup \left\{k^{t,m}\right\}; b^t_{i^{t,m}}, w^t_{i^{t,m}}, \boldsymbol{A}^t, \boldsymbol{D}^{t,m}_{-i^{t,m}}, \epsilon^t_{i^{t,m}}, \theta_c\right) \\ &- U_c\left(P^{t,m}_{i^{t,m}}; b^t_{i^{t,m}}, w^t_{i^{t,m}}, \boldsymbol{A}^t, \boldsymbol{D}^{t,m}_{-i^{t,m}}, \epsilon^t_{i^{t,m}}, \theta_c\right) \quad (3.16)\end{aligned}$$

$$\begin{aligned}\Delta U^{t,m}_{c-} \equiv U_c &\left(P^{t,m}_{i^{t,m}} \backslash \left\{k^{t,m}\right\}; b^t_{i^{t,m}}, w^t_{i^{t,m}} \boldsymbol{A}^t, \boldsymbol{D}^{t,m}_{-i^{t,m}}, \epsilon^t_{i^{t,m}}, \theta_c\right) \\ &- U_c\left(P^{t,m}_{i^{t,m}}; b^t_{i^{t,m}}, w^t_{i^{t,m}} \boldsymbol{A}^t, \boldsymbol{D}^{t,m}_{-i^{t,m}}, \epsilon^t_{i^{t,m}}, \theta_c\right) \quad (3.17)\end{aligned}$$

and similarly

$$\begin{aligned}\Delta g^{t,m}_{c+} \equiv g_c &\left(P^{t,m}_{i^{t,m}} \cup \left\{k^{t,m}\right\}; b^t_{i^{t,m}}, w^t_{i^{t,m}}, \boldsymbol{A}^t, \boldsymbol{D}^{t,m}_{-i^{t,m}}, \theta_c\right) \\ &- g_c\left(P^{t,m}_{i^{t,m}}; b^t_{i^{t,m}}, w^t_{i^{t,m}}, \boldsymbol{A}^t, \boldsymbol{D}^{t,m}_{-i^{t,m}}, \theta_c\right) \quad (3.18)\end{aligned}$$

$$\begin{aligned}\Delta g^{t,m}_{c-} \equiv g_c &\left(P^{t,m}_{i^{t,m}} \backslash \left\{k^{t,m}\right\}; b^t_{i^{t,m}}, w^t_{i^{t,m}}, \boldsymbol{A}^t, \boldsymbol{D}^{t,m}_{-i^{t,m}}, \theta_c\right) \\ &- g_c\left(P^{t,m}_{i^{t,m}}; b^t_{i^{t,m}}, w^t_{i^{t,m}}, \boldsymbol{A}^t, \boldsymbol{D}^{t,m}_{-i^{t,m}}, \theta_c\right). \quad (3.19)\end{aligned}$$

Equations (3.16) and (3.17) correspond to changes to the objective function of $i^{t,m}$ induced by adding $k^{t,m}$ to and removing $k^{t,m}$ from its portfolio, respectively, during the m^{th} meeting. Equation (3.4) yields

$$\Delta U_{c+}^{t,m} = \Delta g_{c+}^{t,m} + \epsilon_{i^{t,m}k^{t,m}}^{t} \tag{3.20}$$

$$\Delta U_{c-}^{t,m} = \Delta g_{c-}^{t,m} - \epsilon_{i^{t,m}k^{t,m}}^{t}. \tag{3.21}$$

Thus the probability assigned to the 4 cases in section 3.4.6 are, respectively

$$\mathbb{P}\left(\Delta U_{c+}^{t,m} \leq 0\right) = \mathbb{P}\left(\epsilon_{i^{t,m}k^{t,m}}^{t} \leq -\Delta g_{c+}^{t,m}\right) \tag{3.22}$$

$$\mathbb{P}\left(\Delta U_{c+}^{t,m} > 0\right) = \mathbb{P}\left(\epsilon_{i^{t,m}k^{t,m}}^{t} > -\Delta g_{c+}^{t,m}\right) \tag{3.23}$$

$$\mathbb{P}\left(\Delta U_{c-}^{t,m} \leq 0\right) = \mathbb{P}\left(\epsilon_{i^{t,m}k^{t,m}}^{t} \geq \Delta g_{c-}^{t,m}\right) \tag{3.24}$$

$$\mathbb{P}\left(\Delta U_{c+}^{t,m} > 0\right) = \mathbb{P}\left(\epsilon_{i^{t,m}k^{t,m}}^{t} < \Delta g_{c-}^{t,m}\right) \tag{3.25}$$

The same result holds for hotel chains as choosers, with ΔU_c and Δg_c replaced by ΔU_h and Δg_h, respectively.

Let $S^{t,m}$ denote the m^{th} meeting in S^t. Define $\theta = (\theta_c', \theta_h')'$. Under the assumption given by equation (3.5) , the probability of the transition from $\boldsymbol{D}^t$ to $\boldsymbol{D}^{t+1}$ conditional on S^t (the conditional likelihood of θ) is given by the following.

$$\begin{aligned}
&\mathbb{P}\left(\boldsymbol{D}^{t+1}|\boldsymbol{D}^t, \boldsymbol{b}^t, \boldsymbol{A}^t, \boldsymbol{w}^t, S^t; \theta\right) = \\
&\quad \prod_{m=1}^{M^t+1} \mathbb{1}\left\{S^{t,m} = \left(i^{t,m}, k^{t,m}\right)\right\} \mathbb{P}\left(\epsilon_{i^{t,m}k^{t,m}}^{t} \leq -\Delta g_{c+}^{t,m}\right)^{\mathbb{1}\left\{\left[\boldsymbol{D}^{t,m}\right]_{i^{t,m}k^{t,m}}=0, \left[\boldsymbol{D}^{t+1}\right]_{i^{t,m}k^{t,m}}=0\right\}} \\
&\quad \times \mathbb{1}\left\{S^{t,m} = \left(j^{t,m}, k^{t,m}\right)\right\} \mathbb{P}\left(\epsilon_{j^{t,m}k^{t,m}}^{t} \leq -\Delta g_{h+}^{t,m}\right)^{\mathbb{1}\left\{\left[\boldsymbol{D}^{t,m}\right]_{j^{t,m}k^{t,m}}=0, \left[\boldsymbol{D}^{t+1}\right]_{j^{t,m}k^{t,m}}=0\right\}} \\
&\quad \times \mathbb{1}\left\{S^{t,m} = \left(i^{t,m}, k^{t,m}\right)\right\} \mathbb{P}\left(\epsilon_{i^{t,m}k^{t,m}}^{t} > -\Delta g_{c+}^{t,m}\right)^{\mathbb{1}\}\left\{\left[\boldsymbol{D}^{t,m}\right]_{i^{t,m}k^{t,m}}=0, \left[\boldsymbol{D}^{t+1}\right]_{i^{t,m}k^{t,m}}=1\right\}} \\
&\quad \times \mathbb{1}\left\{S^{t,m} = \left(j^{t,m}, k^{t,m}\right)\right\} \mathbb{P}\left(\epsilon_{j^{t,m}k^{t,m}}^{t} > -\Delta g_{h+}^{t,m}\right)^{\mathbb{1}\}\left\{\left[\boldsymbol{D}^{t,m}\right]_{j^{t.m}k^{t,m}}=0, \left[\boldsymbol{D}^{t+1}\right]_{j^{t,m}k^{t,m}}=1\right\}} \\
&\quad \times \mathbb{1}\left\{S^{t,m} = \left(i^{t,m}, k^{t,m}\right)\right\} \mathbb{P}\left(\epsilon_{i^{t,m}k^{t,m}}^{t} \geq \Delta g_{c-}^{t,m}\right)^{\mathbb{1}\left\{\left[\boldsymbol{D}^{t,m}\right]_{i^{t,m}k^{t,m}}=1, \left[\boldsymbol{D}^{t+1}\right]_{i^{t,m}k^{t,m}}=0\right\}} \\
&\quad \times \mathbb{1}\left\{S^{t,m} = \left(j^{t,m}, k^{t,m}\right)\right\} \mathbb{P}\left(\epsilon_{j^{t,m}k^{t,m}}^{t} \geq \Delta g_{h-}^{t,m}\right)^{\mathbb{1}\left\{\left[\boldsymbol{D}^{t,m}\right]_{j^{t,m}k^{t,m}}=1, \left[\boldsymbol{D}^{t+1}\right]_{j^{t,m}k^{t,m}}=0\right\}} \\
&\quad \times \mathbb{1}\left\{S^{t,m} = \left(i^{t,m}, k^{t,m}\right)\right\} \mathbb{P}\left(\epsilon_{i^{t,m}k^{t,m}}^{t} < \Delta g_{c-}^{t,m}\right)^{\mathbb{1}\left\{\left[\boldsymbol{D}^{t,m}\right]_{i^{t,m}k^{t,m}}=1, \left[\boldsymbol{D}^{t+1}\right]_{i^{t,m}k^{t,m}}=1\right\}} \\
&\quad \times \mathbb{1}\left\{S^{t,m} = \left(j^{t,m}, k^{t,m}\right)\right\} \mathbb{P}\left(\epsilon_{j^{t,m}k^{t,m}}^{t} < \Delta g_{h-}^{t,m}\right)^{\mathbb{1}\left\{\left[\boldsymbol{D}^{t,m}\right]_{j^{t,m}k^{t,m}}=1, \left[\boldsymbol{D}^{t+1}\right]_{j^{t,m}k^{t,m}}=1\right\}}
\end{aligned} \tag{3.26}$$

where $\boldsymbol{b}^t = \left\{b_i^t, b_j^t\right\}_{i \in \mathbb{I}^t, j \in \mathbb{J}^t}$ and $\boldsymbol{w}^t = \left\{w_i^t, w_j^t\right\}_{i \in \mathbb{I}^t, j \in \mathbb{J}^t}$ denote the collection of bids and potential transfer ratios, respectively, encompassing both credit card issuers and hotel chains.

3.5.2 Two-Period Conditional Likelihood

This subsection extends the previous subsection to construct a two-period conditional likelihood of θ. It is not difficult to further extend it to accommodate transitions of the network over than two periods. I impose the following assumptions.

Assumption 3. *For all t,*

$$\begin{aligned}\mathbb{P}\left(\boldsymbol{D}^{t+2}\middle|\boldsymbol{D}^{t},\boldsymbol{D}^{t+1},\boldsymbol{b}^{t},\boldsymbol{b}^{t+1},\boldsymbol{w}^{t},\boldsymbol{w}^{t+1},\boldsymbol{A}^{t},\boldsymbol{A}^{t+1},S^{t},S^{t+1};\theta\right)\\ =\mathbb{P}\left(\boldsymbol{D}^{t+2}\middle|\boldsymbol{D}^{t+1},\boldsymbol{b}^{t+1},\boldsymbol{w}^{t+1},\boldsymbol{A}^{t+1},S^{t+1};\theta\right)\end{aligned} \tag{3.27}$$

$$\mathbb{P}\left(\boldsymbol{D}^{t};\theta\right)=\mathbb{P}\left(\boldsymbol{D}^{t}\right) \tag{3.28}$$

$$\mathbb{P}\left(\boldsymbol{C}^{t},\boldsymbol{A}^{t},\boldsymbol{v}^{t};\theta\right)=\mathbb{P}\left(\boldsymbol{C}^{t},\boldsymbol{A}^{t},\boldsymbol{v}^{t}\right), \tag{3.29}$$

where $\boldsymbol{C}^t=\{C_i^t\}_{i\in\mathbb{I}^t}$ is the collection of KPIs of all credit card issuers, and $\boldsymbol{v}^t=\left\{v_i^t,v_j^t,v_k^t\right\}_{i\in\mathbb{I}^t,j\in\mathbb{J}^t,k\in\mathbb{K}^t}$ is the collection of all values of nodes (redemption values of loyalty points).

Equation (3.27) states that conditional on the state of the network and other observed variables in the previous period, earlier history does not help to explain the transition of the network during the current period. Equation (3.28) states that unconditional on the previous state of the network and other observed variables, θ cannot explain the probability of observing the current state of the network. Equation (3.29) states that corporate management and performance does not depend on θ. In particular, it specifies that KPIs of firms and values of nodes are independent of how credit card issuers choose airline transfer partners. Note that this does not state that KPIs of firms of values of nodes are independent of transfer partnerships. I also assume that the sequence of meetings S^t is a random variable independent of θ.

For brevity of notation, let $\boldsymbol{X}^t=\left(\boldsymbol{b}^t,\boldsymbol{w}^t,\boldsymbol{A}^t\right)$, which is the collection of all observed variables except the states of the network $\boldsymbol{D}^t$. Conditional on S^{t_0} and S^{t_0+1}, the transition from $\boldsymbol{D}^{t_0}$ to $\boldsymbol{D}^{t_0+1}$ and then from $\boldsymbol{D}^{t_0+1}$ to $\boldsymbol{D}^{t_0+2}$ has probability

$$\begin{aligned}&\mathbb{P}\left(\boldsymbol{D}^{t_0+1},\boldsymbol{D}^{t_0+2}\middle|\boldsymbol{D}^{t_0},\boldsymbol{X}^{t_0},\boldsymbol{X}^{t_0+1},S^{t_0},S^{t_0+1};\theta\right)=\\ &\qquad\mathbb{P}\left(\boldsymbol{D}^{t_0+1}\middle|\boldsymbol{D}^{t_0},\boldsymbol{X}^{t_0},S^{t_0};\theta\right)\mathbb{P}\left(\boldsymbol{D}^{t_0+2}\middle|\boldsymbol{D}^{t_0+1},\boldsymbol{X}^{t_0+1},S^{t_0+1};\theta\right).\end{aligned} \tag{3.30}$$

The posterior of θ is equal to

$$\begin{aligned}&\mathbb{P}\left(\theta\middle|\boldsymbol{D}^{t_0},\boldsymbol{D}^{t_0+1},\boldsymbol{D}^{t_0+2},\boldsymbol{X}^{t_0},\boldsymbol{X}^{t_0+1},S^{t_0},S^{t_0+1}\right)=\\ &\qquad\frac{\mathbb{P}\left(\boldsymbol{D}^{t_0+1}\middle|\boldsymbol{D}^{t_0},\boldsymbol{X}^{t_0},S^{t_0};\theta\right)\mathbb{P}\left(\boldsymbol{D}^{t_0+2}\middle|\boldsymbol{D}^{t_0+1},\boldsymbol{X}^{t_0+1},S^{t_0+1};\theta\right)\pi_\theta(\theta)}{\mathbb{P}\left(\boldsymbol{D}^{t_0+1},\boldsymbol{D}^{t_0+2}\middle|\boldsymbol{D}^{t_0},\boldsymbol{X}^{t_0},\boldsymbol{X}^{t_0+1},S^{t_0},S^{t_0+1}\right)},\end{aligned} \tag{3.31}$$

where $\pi_\theta(\cdot)$ is the prior of θ.

3.5.3 Markov Chain Monte Carlo

Similar to Christakis et al. (2010), I endow S^t with the discrete uniform distribution over its support $\mathbb{S}^t$. The support is all arrangements of the sequence of (chooser, bidder) pairs in period *t*. In other words, I assume no prior knowledge on the sequence of meetings, and each sequence of meetings is equally likely. Moreover, S^t is independent of $S^{t'}$ for all $t\neq t'$ and of all other variables. The chained two-period sequence (S^t,S^{t+1}) also has the discrete uniform distribution over the support $\mathbb{S}^t \times \mathbb{S}^{t+1}$. For the two-period setting, the unconditional likelihood of θ (integrated over all sequences of meetings) is equal to

$$\begin{aligned}&\mathbb{P}\left(\boldsymbol{D}^{t_0+1}, \boldsymbol{D}^{t_0+2} \middle| \boldsymbol{D}^{t_0}, \boldsymbol{X}^{t_0}, \boldsymbol{X}^{t_0+1}; \theta\right) = \\ &\qquad \frac{1}{|\mathbb{S}^{t_0}| \times |\mathbb{S}^{t_0+1}|} \sum_{S^{t_0} \in \mathbb{S}^{t_0}} \sum_{S^{t_0+1} \in \mathbb{S}^{t_0+1}} \mathbb{P}\left(\boldsymbol{D}^{t_0+1} \middle| \boldsymbol{D}^{t_0}, \boldsymbol{X}^{t_0}, S^{t_0}; \theta\right) \\ &\qquad\qquad \times \mathbb{P}\left(\boldsymbol{D}^{t_0+2} \middle| \boldsymbol{D}^{t_0+1}, \boldsymbol{X}^{t_0+1}, S^{t_0+1}; \theta\right). \end{aligned} \tag{3.32}$$

Computing the maximum likelihood estimator using equation 3.32 is infeasible because $|\mathbb{S}^{t_0}|$ and $|\mathbb{S}^{t_0+1}|$ are large. The network of loyalty programs is relatively small with 3 credit card issuers, 7 hotel chains, and 43 airline. Nevertheless, the network contains 430 (chooser, bidder) pairs, and the chained two-period sequence of meetings has a support with cardinality $(430!)^2$.

The estimation of θ utilizes two iterations of the Metropolis-Hastings algorithm: one for sampling θ given a draw of (S^{t_0}, S^{t_0+1}) , the other for sampling (S^{t_0}, S^{t_0+1}) given a draw of θ. With randomly drawn initial values $\theta^{(0)}$ and $S^{(0)}$, the $(l+1)^{th}$ iteration $\theta^{(l+1)}$ is updated given $(S^{t_0}, S^{t_0+1})^{(l)}$, and $(S^{t_0}, S^{t_0+1})^{(l+1)}$ is updated given $\theta^{(l+1)}$, for $l = 0, 1, 2, \ldots$. The goal is to estimate the posterior distribution of θ, unconditional on (S^{t_0}, S^{t_0+1}).

3.5.3.1 Iterations of $\theta^{(l)}$

Given $\theta^{(l)}$ and $(S^{t_0}, S^{t_0+1})^{(l)}$, let $\tilde{\theta}$ be the candidate for $\theta^{(l+1)}$ drawn from the proposal distribution

$$q_\theta\left(\theta|\theta^{(l)}, \boldsymbol{D}^{t_0}, \boldsymbol{D}^{t_0+1}, \boldsymbol{D}^{t_0+2}, \boldsymbol{X}^{t_0}, \boldsymbol{X}^{t_0+1}, \left(S^{t_0}, S^{t_0+1}\right)^{(l)}\right). \tag{3.33}$$

For brevity of notation, define $S_2 \equiv (S^{t_0}, S^{t_0+1})$ and suppress the observed variables $\boldsymbol{D}^{t_0}, \boldsymbol{D}^{t_0+1}, \boldsymbol{D}^{t_0+2}, \boldsymbol{X}^{t_0}, \boldsymbol{X}^{t_0+1}$. Thus, $q_\theta\left(\theta \middle| \theta^{(l)}, S_2^{(l)}\right)$ is equivalent to equation (3.33), and similarly, $\mathbb{P}\left(\theta \middle| S_2\right)$ is equivalent to equation (3.31). The Metropolis-Hastings ratio for updating $\theta^{(l+1)}$ is given by

$$r_\theta\left(\tilde{\theta}, \theta^{(l)}|S_2^{(l)}\right) = \min\left\{1, \frac{\mathbb{P}\left(\tilde{\theta}|S_2^{(l)}\right) q_\theta\left(\theta^{(l)}|\tilde{\theta}, S_2^{(l)}\right)}{\mathbb{P}\left(\theta^{(l)}|S_2^{(l)}\right) q_\theta\left(\tilde{\theta}|\theta^{(l)} S_2^{(l)}\right)}\right\}.$$

I endow the proposal distribution for the l^{th} iteration with the Gaussian form

$$q_\theta\left(\cdot|\theta^{(l)}, S_2^{(l)}\right) \sim \mathcal{N}\left(\theta^{(l)}, \Sigma\right), \tag{3.34}$$

where Σ is a covariance matrix fitted to attain a target jump rate throughout the iterations. For the empirical analysis, I aimed for a target jump rate of 0.3. This specification implies

$$q_\theta\left(\tilde{\theta}|\theta^{(l)}, S_2^{(l)}\right) = q_\theta\left(\theta^{(l)}|\tilde{\theta}, S_2^{(l)}\right). \tag{3.35}$$

Thus, the Metropolis-Hastings ratio simplifies to

$$r_\theta\left(\tilde{\theta}, \theta^{(l)}|S_2^{(l)}\right) = \min\left\{1, \frac{\mathbb{P}\left(\tilde{\theta}|S_2^{(l)}\right)}{\mathbb{P}\left(\theta^{(l)}|S_2^{(l)}\right)}\right\}, \tag{3.36}$$

and equation (3.31) yields the computable form

$$\frac{\mathbb{P}\left(\tilde{\theta}|S_2^{(l)}\right)}{\mathbb{P}\left(\theta^{(l)}|S_2^{(l)}\right)} = \frac{\mathbb{P}\left(\boldsymbol{D}^{t_0+1}\middle|\boldsymbol{D}^{t_0}, \boldsymbol{X}^{t_0}, S^{t_0}; \tilde{\theta}\right)\mathbb{P}\left(\boldsymbol{D}^{t_0+2}\middle|\boldsymbol{D}^{t_0+1}, \boldsymbol{X}^{t_0+1}, S^{t_0+1}; \tilde{\theta}\right)\pi_\theta\left(\tilde{\theta}\right)}{\mathbb{P}\left(\boldsymbol{D}^{t_0+1}\middle|\boldsymbol{D}^{t_0}, \boldsymbol{X}^{t_0}, S^{t_0}; \theta^{(l)}\right)\mathbb{P}\left(\boldsymbol{D}^{t_0+2}\middle|\boldsymbol{D}^{t_0+1}, \boldsymbol{X}^{t_0+1}, S^{t_0+1}; \theta^{(l)}\right)\pi_\theta\left(\theta^{(l)}\right)}. \tag{3.37}$$

We have

$$\theta^{(l+1)} = \begin{cases} \tilde{\theta} & \text{with probability } r_\theta\left(\tilde{\theta}, \theta^{(l)}|S_2^{(l)}\right) \\ \theta^{(l)} & \text{with probability } 1 - r_\theta\left(\tilde{\theta}, \theta^{(l)}|S_2^{(l)}\right). \end{cases} \tag{3.38}$$

3.5.3.2 Iterations of $S_2^{(l)}$

Let $\pi_2(\cdot)$ denote the prior of S_2. Assumption (3.27) and the specification of S^t yield

$$\begin{aligned}&\mathbb{P}\left(S_2|\boldsymbol{D}^{t_0}, \boldsymbol{D}^{t_0+1}, \boldsymbol{D}^{t_0+2}, \boldsymbol{X}^{t_0}, \boldsymbol{X}^{t_0+1}; \theta\right) \\ &\quad = \frac{\mathbb{P}\left(\boldsymbol{D}^{t_0+1}\middle|\boldsymbol{D}^{t_0}, \boldsymbol{X}^{t_0}, S^{t_0}; \theta\right)\mathbb{P}\left(\boldsymbol{D}^{t_0+2}\middle|\boldsymbol{D}^{t_0+1}, \boldsymbol{X}^{t_0+1}, S^{t_0+1}; \theta\right)\pi_2\left(S_2\right)}{\mathbb{P}\left(\boldsymbol{D}^{t_0+1}, \boldsymbol{D}^{t_0+2}\middle|\boldsymbol{D}^{t_0}, \boldsymbol{X}^{t_0}, \boldsymbol{X}^{t_0+1}; \theta\right)}.\end{aligned} \tag{3.39}$$

Given $\theta^{(l+1)}$ and $S_2^{(l)}$, let $\tilde{S}_2$ be the candidate for $S_2^{(l+1)}$ drawn from the proposal distribution

$$q_2\left(S_2\middle|S_2^{(l)}, \boldsymbol{D}^{t_0}, \boldsymbol{D}^{t_0+1}, \boldsymbol{D}^{t_0+2}, \boldsymbol{X}^{t_0}, \boldsymbol{X}^{t_0+1}; \theta^{(l+1)}\right). \tag{3.40}$$

Again, I suppress the notations for observed variables. Thus, $\mathbb{P}\left(S_2\middle|\theta\right)$ is equivalent to equation (3.39), and $q_2\left(S_2\middle|S_2^{(l)}, \theta^{(l+1)}\right)$ is equivalent to equation (3.40). The Metropolis-Hastings ratio for updating $S_2^{(l+1)}$ is given by

$$r_2\left(\tilde{S}_2, S_2^{(l)}\middle|\theta^{(l+1)}\right) = \min\left\{1, \frac{\mathbb{P}\left(\tilde{S}_2|\theta^{(l+1)}\right)q_2\left(S_2^{(l)}|\tilde{S}_2, \theta^{(l+1)}\right)}{\mathbb{P}\left(S^{(l)}|\theta^{(l+1)}\right)q_2\left(\tilde{S}_2|S_2^{(l)}, \theta^{(l+1)}\right)}\right\}. \tag{3.41}$$

The candidate draw $\tilde{S}_2$ is obtained by randomly permuting a fraction from each of $\left(S^{t_0}, S^{t_0+1}\right)^{(l)}$ For the empirical analysis, I chose the fraction to attain a target jump rate of 0.3. The specification of $\tilde{S}_2$ yields $q_2\left(\tilde{S}_2\middle|S_2^{(l)}, \theta^{(l+1)}\right) = q_2\left(S_2^{(l)}\middle|\tilde{S}_2, \theta^{(l+1)}\right)$. Moreover because S_2 is endowed with the discrete uniform distribution, the values of $\pi_2(\cdot)$ are equal over its support. Then the Metropolis-Hastings ratio simplifies to

$$r_2\left(\tilde{S}_2, S_2^{(l)}\middle|\theta^{(l+1)}\right) = \min\left\{1, \frac{\mathbb{P}\left(\boldsymbol{D}^{t_0+1}, \boldsymbol{D}^{t_0+2}\middle|\boldsymbol{D}^{t_0}, \boldsymbol{X}^{t_0}, \boldsymbol{X}^{t_0+1}, \tilde{S}_2; \theta^{(l+1)}\right)}{\mathbb{P}\left(\boldsymbol{D}^{t_0+1}, \boldsymbol{D}^{t_0+2}\middle|\boldsymbol{D}^{t_0}, \boldsymbol{X}^{t_0}, \boldsymbol{X}^{t_0+1}, S_2^{(l)}; \theta^{(l+1)}\right)}\right\}, \tag{3.42}$$

, and equation (3.30) yields a computable form. We have

$$S_2^{(l+1)} = \begin{cases} \tilde{S}_2 & \text{with probability } r_2\left(\tilde{S}_2, S_2^{(l)}\middle|\theta^{(l+1)}\right) \\ S_2^{(l)} & \text{with probability } 1 - r_2\left(\tilde{S}_2, S_2^{(l)}\middle|\theta^{(l+1)}\right) \end{cases} \tag{3.43}$$

3.6 Empirical Analysis: Network of Loyalty Programs

3.6.1 Setup and Preliminary Data Analysis

The network of loyalty programs is composed of of 3 credit card issuers, 7 hotel chains, and 43 airlines, and an additional 10 airlines without firm-level data. The data contain annual observations on transfer partnerships among the firms (snapshots of the network) from the fourth quarter of 2014 to the fourth quarter of 2018 and quarterly observations on their firm-level characteristics, from the first quarter of 2014 to the fourth quarter of 2018. Firm-level characteristics include key performance indicators (KPIs) of firm, characteristics of their loyalty programs, and geographic information for airlines. Table B.5 provides the list of included firms. Chapter 2 provides details on the data collection procedure and definitions of the variables. Among the collected KPIs, the empirical analysis utilizes three KPIs of credit card issuers, four KPIs of hotel chains, and three KPIs of airlines.

In addition to the fitted bids and potential transfer ratios obtained in section 3.4.2, the empirical analysis on network formation utilizes observations over two periods, where each period contains 8 calendar quarters[7]. Period 1 denotes the eight quarters from the first quarter of 2015 to the fourth quarter of 2016, and Period 2 denotes the eight quarters from the first quarter of 2017 to the fourth quarter of 2018. The initial and ending states in period 1 are the states of the network observed in the fourth quarter of 2014 and in the fourth quarter of 2016, respectively. The initial and ending states in period 2 are the states of the network observed in the fourth quarter of 2016 and in the fourth quarter of 2018, respectively. For each period, the initial state of the network is equal to the ending state in the previous period. The origin state of the network denotes the initial state in the earliest period (period 1), which is the observation in the fourth quarter of 2014. For all key performance indicators (KPIs) of firms and characteristics of loyalty programs, I averaged the relevant quarterly observations to construct period-level observations. For completeness, this subsection also presents KPIs of firms and characteristics for period 0, which denotes the four quarters of 2014.

[7] I chose to use 8 quarters after scrutinizing the history of changes in transfer partnerships of credit card issuers. The history of changes is given in table B.1 in the appendix

Figure C.2 in the appendix reports three KPIs of the credit card issuers and their Number of Transfer Partners (size of portfolios of transfer partners), which includes both hotel chain and airline partners. AMEX consistently possessed a larger portfolio of transfer partners than the other two firms although it did not possess the largest Credit Card Purchases (total amount of credit card purchases processed) . On the other hand, the customers of AMEX possessed overall better credit quality, indicated by lower Delinquency Rate (fraction of loans past due for 30 or more days) and Writeoff Rate (fraction of loans written off).

Figure C.3 in the appendix reports three KPIs of the hotel chains and their Number of Transfer Partners (size of portfolios of transfer partners), which only includes airline partners. MAR consistently possessed the Hotel Revenue (market size of lodging services) and the largest portfolio of transfer partners. On the other hand, HYT had the largest RevPar, indicating that, on average, consumers were willing to pay more for rooms in its hotel properties. Hotel chains generally possessed more transfer partners than credit card issuers, with more than 35 transfer partners for MAR.

Table C.2 in the appendix reports summary statistics of KPIs of the airlines. On average, Passenger Revenue (market size of passenger transportation services) fell in Period 1 and then increased in Period 2. On average, RPK (total flight distance of sold seats) and ASK (total flight distance of all seats) increased steadily over the periods. RPK is a measure of quantity demanded for flight services, and ASK is a measure of supply or capacity of flight services. For all periods, the distribution of each KPI exhibits a long right tail, indicating that there were a small number of airlines with large market size. The large standard deviation, as well as the $[P_{25}, P_{75}]$ and $[P_{10}, P_{90}]$ percentile ranges, indicate that there was substantial variability in the market size of airlines.

I note that all variables in equation (3.7) (in section 3.4.3), except for the constant term (corresponds to θ_{0c}), are endogenous in the network formation process. They are endogenous in the sense that the variables depend on the chooser's and other firms' portfolios of transfer partners, which are endogenous.

3.6.2 Discussion of Results

Table 3.4 reports the estimation result for the parameters of the credit card issuer's objective function. C.3. A detailed explanation of the estimation procedure is provided in appendix C.2. Table C.3 in the appendix reports the estimation result for the parameters of the hotel chain's objective function; I do not discuss this result because it is not the focus of this chapter.

θ_{0c} corresponds to the constant term, and $\theta_{1c}, \theta_{21c}, \theta_{22c}, \theta_{23c},$ and θ_{3c} correspond to the control variables. The variables of interest are *Mileage, Routes, Competitor,* and *Transitivity*. I make inferences based on a credit card issuer's attitude towards adding an airline transfer partner. Consider a meeting between credit card issuer i and airline k_1, that is not already in i's portfolio. Now, hold everything fixed and consider a meeting between i and a different airline k_2, that is also not in i's portfolio. Assume that k_1 and k_2 are equal in every aspect except for exactly one of the following:

1. Adding k_1 improves redemption options of loyalty points for flights (smaller *Mileage*) offered by i, adding k_2 does not.

Table 3.4: Estimation Results (Credit Card Issuer)

Estimand	Variable	Mean	Median	$[\boldsymbol{P_{2.5}}, \boldsymbol{P_{97.5}}]$
θ_{0c}	Constant term	0.3141	0.0887	[-0.3203,1.1028]
θ_{1c}	Size of Portfolio	-0.5381	-0.4253	[-1.8700,0.7010]
θ_{21c}	Passenger Revenue (incl. in *Performance*)	-0.2233	-0.3045	[-0.6589,0.3340]
θ_{22c}	Revenue Passenger Km (incl. in *Performance*)	-0.0834	0.0025	[-0.6042,0.2937]
θ_{23c}	Available Seat Km (incl. in *Performance*)	0.2304	0.1218	[-0.3017,0.9099]
θ_{3c}	*GeoHub*	-0.1431	-0.1294	[-0.5185,0.3309]
θ_{4c}	*Mileage*	-0.9683**	-0.9792	[-1.3119,-0.6260]
θ_{5c}	*Routes*	-0.1999**	-0.2097	[-0.3370,-0.6021]
θ_{6c}	*Competitor*	0.5100*	0.5605	[-0.0392,1.1371]
θ_{7c}	*Transitivity*	0.7848**	0.7398	[0.1476,1.4663]

This table reports the result of MCMC iterations. The first column ("Estimand") lists the components of θ_c, the parameter of the credit card issuer's objective function. The second column ("Variable") lists the covariates included in the objective function (see section 3.4.3 for definitions). The third column ("Mean") reports the mean of the MCMC iterations. The fourth column ("Median") reports the median of the iterations. The last column ("$[P_{2.5}, P_{97.5}]$") reports the 2.5 - 97.5 percentile range of the iterations. ** indicates that the 2.5 - 97.5 percentile range does not contain zero. * indicates that the 5 - 95 percentile range does not contain zero. The mean, median, and percentile range were computed after removing the first half of the iterations (after the "burn-in" process).

2. k_1 has more diverse routes for reward flights (larger *Routes*) than k_2 (I emphasize that adding either airline grants the same redemption options for flights offered by i).

3. k_1 is a partner of another credit card issuer, k_2 is not.

4. k_1 is a partner of i's partner hotel chain, k_2 is not.

The odds ratio of i adding k_1 relative to adding k_2 is used for interpretation. Similar to equation (3.18), define

$$\Delta g_{c+}(k;\theta_c) = g_c(P_i \cup \{k\}; b_i, w_i, \boldsymbol{A}, \boldsymbol{D}_{-i}, \theta_c) - g_c(P_i; b_i, w_i, \boldsymbol{A}, \boldsymbol{D}_{-i}, \theta_c) \tag{3.44}$$

The probability ratio of adding k_1 relative to adding k_2 is given by

$$\frac{1 + \exp(-\Delta g_{c+}(k_2;\theta_c))}{1 + \exp(-\Delta g_{c+}(k_1;\theta_c))} \tag{3.45}$$

A probability ratio larger than 1 implies that i is more likely to add k_1 to its portfolio than k_2. Corresponding to the four cases above,

1. If $\theta_{4c} < 0$, then the probability ratio is larger than 1.

2. If $\theta_{5c} > 0$, then the probability ratio is larger than 1.

3. If $\theta_{6c} > 0$, then the probability ratio is larger than 1.

4. If $\theta_{7c} > 0$, then the probability ratio is larger than 1.

The estimation results indicate the following. Other things equal,

1. There is statistical evidence that a credit card issuer is more likely to add an airline transfer partner that improves the redemption options for flights offered by i.

2. There is statistical evidence that a credit card issuer is less likely to add an airline transfer partner with more diverse routes for reward flights.

3. There is statistical evidence that a credit card issuer is more likely to add an airline transfer partner that is a transfer partner of another credit card issuer.

4. There is statistical evidence that a credit card issuer is more likely to add an airline transfer partner that is a transfer partner of its hotel partner.

Recall that *Routes* counts all routes of reward flights, with multiplicity for the same flight route granted by different airline partners. Thus, results 1 and 2 suggest that a credit card issuer does not necessarily favor an airline partner with more diverse routes for reward flights but instead an airline partner that better complements the redemption options of its other airline partners. In other words, a credit card issuer tends to pursue resource complementarity when choosing its airline partners, rather than their individual resources. While this result does not imply that a credit card issuer chooses the most cost-effective (in terms of redemption rates of loyalty points) portfolio of transfer partners, holding other things constant, it does provide evidence that how it chooses the airline partners aligns with the welfare of their customers. Result 3 suggests that a credit card issuer tends to pursue a transfer partnership with an airline that is a transfer partner of another credit card issuer. This result is not surprising because the credit card issuers already possess different sets of transfer partners via exclusive co-brand partnerships. Moreover, imitating the competition is a commonly observed business strategy. Lieberman and Asaba (2006) provides a survey of academic research on such behavior of firms. Finally, result 4 suggests that a credit card issuer tends to pursue a transfer partnership with an airline that is a transfer partner of its hotel partner. Although I cannot provide details without speculating, the result suggests that there exists certain benefits in sharing a common partner with a partner.

3.7 Concluding Remarks

A policy discussion by the Federal Reserve Bank of Boston points out that credit card rewards transfer wealth from the poor to the rich, as credit card spending and rewards are positively associated with income (Schuh et al., 2010). Economic theory explains how consumers, with varying degrees of credit card usage, share the cost of issuing credit card rewards. Yet, we understand little about the mechanics of credit card rewards. Credit card rewards are complicated, with stakeholders from a diverse pool of industries, and policy design for credit card rewards must be found on a profound understanding of the relationship among the stakeholders.

This chapter took the first step by studying how a credit card issuer chooses its airline partners to provide travel rewards to customers. The study revealed the significance of resource complementarity in partner choice. The study also revealed that the network of firms has a significant effect on partner choice. However, the study lacks insights into why the network effect exists. Moreover, the simple model of bid determination by airlines left opportunities for improvement. Future research should remedy these weaknesses and more thoroughly examine the dynamics of partnerships in the network of loyalty programs.

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Appendix A

Appendix to Chapter 1

A.1 Additional Tables

Table A.1: Community-Based Density (Largest Four Communities)

Year	Intra-Density	Inter-Density (Out)	Inter-Density (In)
2003	[0.066, 0.077, 0.181, 0.581]	[0.006, 0.002, 0.004, 0.003]	[0.004, 0.009, 0.003, 0.002]
2004	[0.069, 0.118, 0.147, 0.603]	[0.005, 0.002, 0.003, 0.003]	[0.002, 0.005, 0.004, 0.002]
2005	[0.092, 0.110, 0.221, 0.581]	[0.005, 0.001, 0.002, 0.003]	[0.002, 0.006, 0.003, 0.001]
2006	[0.092, 0.099, 0.176, 0.559]	[0.002, 0.005, 0.003, 0.002]	[0.006, 0.002, 0.003, 0.002]
2007	[0.085, 0.110, 0.147, 0.507]	[0.003, 0.003, 0.003, 0.002]	[0.003, 0.004, 0.003, 0.002]
2008	[0.081, 0.114, 0.188, 0.496]	[0.003, 0.003, 0.002, 0.002]	[0.002, 0.004, 0.003, 0.002]
2009	[0.077, 0.096, 0.188, 0.460]	[0.003, 0.003, 0.002, 0.002]	[0.002, 0.005, 0.003, 0.002]
2010	[0.103, 0.147, 0.232, 0.460]	[0.002, 0.003, 0.002, 0.002]	[0.005, 0.002, 0.003, 0.002]
2011	[0.136, 0.176, 0.257, 0.515]	[0.002, 0.004, 0.002, 0.002]	[0.003, 0.002, 0.003, 0.002]
2012	[0.199, 0.202, 0.298, 0.474]	[0.002, 0.002, 0.002, 0.002]	[0.003, 0.002, 0.002, 0.001]
2013	[0.232, 0.283, 0.268, 0.449]	[0.001, 0.002, 0.002, 0.002]	[0.003, 0.002, 0.002, 0.001]
2014	[0.228, 0.265, 0.290, 0.537]	[0.002, 0.002, 0.002, 0.001]	[0.002, 0.002, 0.001, 0.002]

This table reports density measures accompanying table 1.2. The entries in each bracket correspond to the $\left[4^{\text{th}}, 3^{\text{rd}}, 2^{\text{nd}}, 1^{\text{st}}\right]$ largest communities. The second column ("Intra-Density") reports the density of intra-community edges. The third ("Inter-Density (Out)") and fourth ("Inter-Density (In)") columns report the density of inter-community edges using out-edges and in-edges, respectively. Each density mesure was obtained by dividing the number of edges by the appropriate number of possible edges.

Table A.2: NAICS Codes Definition

NAICS Code	Definition	Examples (from Network)
32521	Resin and Synthetic Rubber Manufacturing	DuPont, Eastman Chemical
33411	Computer and Peripheral Equipment Manufacturing	Broadcom, Sandisk, Western Digital
33441	Semiconductor and Other Electronic Component Manufacturing	AMD, Micron, Nvidia
42343	Computer and Computer Peripheral Equipment and Software Merchant Wholesalers	CDW, Ingram Micro, Tech Data
51121	Software Publishers	Electronic Arts, Red Hat, Salesforce,
51913	Internet Publishing and Broadcasting and Web Search Portals	AOL, Chegg, Twitter
53112	Lessors of Nonresidential Buildings	Digital Realty, Lexington Realty, Rexford Realty
54151	Computer Systems Design and Related Services	FalconStor, Teradata, Unisys
56149	Other Business Support Services	Startek, Convergys, West Corp

This table is a dictionary for the NAICS codes that appear in table 1.4. The first column lists the NAICS codes, and the second column contains the definitions. The third column provides exmaples of firms with the NAICS code, observed in the supplier-buyer network.

Table A.3: Top 4 Ranking by Centrality (Downstream)

Year	Degree	Katz	PageRank	Closeness	Betweenness
2003	[IBM, MSFT, DELL, INVE]	[IBM, MSFT, NVDA, AKAM]	[IBM, MSFT, DELL, SOFO]	[IBM, DELL, MSFT, PLUS]	[IBM, MSFT, DELL, XLNX]
2004	[IBM, MSFT, DELL, SOFO]	[IBM, MSFT, ON, NVDA]	[IBM, MSFT, DELL, SOFO]	[IBM, DELL, MSFT, AAPL]	[IBM, MSFT, DELL, XLNX]
2005	[IBM, MSFT, DELL, ZIGO]	[IBM, MSFT, ELX, ON]	[IBM, MSFT, DELL, ZIGO]	[IBM, MSFT, DELL, AAPL]	[IBM, MSFT, DELL, XLNX]
2006	[IBM, MSFT, DELL, VRSN]	[IBM, MSFT, INTC, ON]	[IBM, MSFT, DELL, AMKR]	[IBM, MSFT, DELL, AAPL]	[IBM, MSFT, DELL, ORCL]
2007	[IBM, MSFT, DELL, SOFO]	[IBM, TTGT, SMTC, MSFT]	[IBM, MSFT, SOFO, PLCM]	[IBM, MSFT, DELL, AAPL]	[IBM, MSFT, PLCM, SOFO]
2008	[IBM, MSFT, DELL, SOFO]	[IBM, MSFT, ATML, TTGT]	[IBM, MSFT, DELL, SOFO]	[IBM, MSFT, DELL, TECD]	[IBM, MSFT, DELL, AAPL]
2009	[IBM, MSFT, DELL, SOFO]	[IBM, MSFT, ATML, IRF]	[IBM, MSFT, DELL, SOFO]	[IBM, MSFT, DELL, TECD]	[IBM, MSFT, DELL, SOFO]
2010	[IBM, MSFT, DELL, SOFO]	[IBM, MSFT, ATML, TTGT]	[IBM, MSFT, DELL, SOFO]	[IBM, MSFT, DELL, AAPL]	[IBM, MSFT, DELL, SOFO]
2011	[IBM, MSFT, DELL, ZIGO]	[IBM, MSFT, ATML, STX]	[IBM, MSFT, DELL, ZIGO]	[MSFT, IBM, DELL, AAPL]	[MSFT, IBM, DELL, AAPL]
2012	[MSFT, IBM, DELL, AAPL]	[MSFT, IBM, NXPI, AMD]	[MSFT, IBM, DELL, AAPL]	[IBM, MSFT, AAPL, DELL]	[IBM, MSFT, DELL, RCMT]
2013	[MSFT, IBM, DELL, AAPL]	[IBM, MSFT, NVDA, AMD]	[IBM, MSFT, DELL, AAPL]	[MSFT, DELL, IBM, AAPL]	[IBM, MSFT, AAPL, DELL]
2014	[MSFT, IBM, AAPL, DELL]	[IBM, MSFT, MU, CHKP]	[MSFT, IBM, AAPL, DELL]	[MSFT, AAPL, DELL, IBM]	[MSFT, IBM, AAPL, DELL]

This table reports ticker symbols of the four firms with the largest degree, Katz, PageRank, closeness, and betweenness centrality in the downstream channel (significance as a supplier). The first column lists the years. The entries in each bracket indicate the ticker symbol of the firm with the $\left[1^{\text{st}}, 2^{\text{nd}}, 3^{\text{rd}}, 4^{\text{th}}\right]$ largest centrality.

Table A.4: Top 4 Ranking by Centrality (Upstream)

Year	Degree	Katz	PageRank	Closeness	Betweenness
2003	[IBM, DELL, MSFT, AAPL]	[IBM, MSFT, DELL, PLUS]	[IBM, MSFT, DELL, AAPL]	[IBM, MSFT, MECK, DNB]	[IBM, MSFT, DELL, XLNX]
2004	[IBM, MSFT, DELL, AAPL]	[IBM, MSFT, DELL, UIS]	[IBM, MSFT, DELL, AAPL]	[IBM, MSFT, DELL, AAPL]	[IBM, MSFT, DELL, XLNX]
2005	[IBM, MSFT, DELL, AAPL]	[IBM, MSFT, DELL, PLUS]	[IBM, MSFT, DELL, AAPL]	[IBM, MSFT, ATML, STX]	[IBM, MSFT, DELL, XLNX]
2006	[IBM, MSFT, DELL, AAPL]	[IBM, MSFT, DELL, PLUS]	[IBM, MSFT, DELL, AAPL]	[IBM, MSFT, ATML, ON]	[IBM, MSFT, DELL, ORCL]
2007	[IBM, MSFT, DELL, AAPL]	[IBM, MSFT, DELL, MCRS]	[IBM, MSFT, DELL, AAPL]	[IBM, MSFT, TTFT, ATML]	[IBM, MSFT, PLCM, SOFO]
2008	[IBM, MSFT, DELL, AAPL]	[MSFT, IBM, DELL, MSCR]	[IBM, MSFT, DELL, AAPL]	[IBM, MSFT, TTGT, ATML]	[IBM, MSFT, DELL, AAPL]
2009	[IBM, MSFT, DELL, AAPL]	[IBM, MSFT, DELL, MCRS]	[IBM, MSFT, DELL, AAPL]	[IBM, MSFT, ATML, TTGT]	[IBM, MSFT, DELL, SOFO]
2010	[IBM, MSFT, DELL, AAPL]	[IBM, MSFT, DELL, PLUS]	[IBM, MSFT, AAPL, DELL]	[IBM, MSFT, ATML, TTGT]	[IBM, MSFT, DELL, SOFO]
2011	[IBM, MSFT, DELL, AAPL]	[MSFT, IBM, DELL, PLUS]	[IBM, MSFT, AAPL, DELL]	[IBM, MSFT, ATML, STX]	[MSFT, IBM, DELL, AAPL]
2012	[IBM, MSFT, AAPL, DELL]	[MSFT, DELL, TECD, IBM]	[IBM, MSFT, AAPL, DELL]	[IBM, MSFT, NXPI, NVDA]	[IBM, MSFT, DELL, RCMT]
2013	[IBM, AAPL, DELL, MSFT]	[MSFT, DELL, AAPL, PLUS]	[AAPL, IBM, DELL, MSFT]	[IBM, MSFT, NVDA, AMD]	[IBM, MSFT, AAPL, DELL]
2014	[MSFT, IBM, AAPL, DELL]	[MSFT, AAPL, DELL, PLUS]	[AAPL, MSFT, IBM, DELL]	[IBM, MSFT, MRVL, GUID]	[MSFT, IBM, AAPL, DELL]

This table reports ticker symbols of the four firms with the largest degree, Katz, PageRank, closeness, and betweenness centrality in the upstream channel (significance as a buyer). The first column lists the years. The entries in each bracket indicate the ticker symbol of the firm with the $\left[1^{\text{st}}, 2^{\text{nd}}, 3^{\text{rd}}, 4^{\text{th}}\right]$ largest centrality.

Table A.5: Top 4 Ranking by Modular Centrality (Downstream)

Year	Degree	Katz	PageRank	Closeness	Betweenness
2003	[IBM, MSFT, DELL, SOFO]	[IBM, MSFT, NVDA, SIGM]	[IBM, MSFT, DELL, SOFO]	[IBM, MSFT, PLUS, ANSS]	[IBM, MSFT, XLNX, DELL]
2004	[IBM, MSFT, DELL, ZIGO]	[IBM, NVDA, ON, EQIX]	[IBM, MSFT, DELL, ZIGO]	[IBM, MSFT, DELL, ANSS]	[IBM, MSFT, DELL, XLNX]
2005	[IBM, MSFT, DELL, NVDA]	[IBM, SMTC, NVDA, ELX]	[IBM, MSFT, DELL, ATML]	[IBM, XLNX, PLXT, SPRT]	[IBM, MSFT, XLNX, DELL]
2006	[IBM, MSFT, DELL, INTC]	[IBM, MSFT, INTC, SMTC]	[IBM, MSFT, DELL, VRSN]	[IBM, MSFT, JKHY, ANSS]	[IBM, MSFT, DELL, VRSN]
2007	[IBM, MSFT, DELL, SOFO]	[IBM, ATML, SMTC, AKAM]	[IBM, MSFT, DELL, SOFO]	[IBM, DELL, MSFT, CTCT]	[IBM, MSFT, DELL, AAPL]
2008	[IBM, MSFT, DELL, SOFO]	[MSFT, ATML, IRF, SMTC]	[IBM, MSFT, DELL, SOFO]	[IBM, DELL, MSFT, SNX]	[IBM, MSFT, DELL, AVT]
2009	[IBM, MSFT, DELL, SOFO]	[IBM, ATML, IRF, TTGT]	[IBM, MFST, DELL, SOFO]	[IBM, DELL, MSFT, PFSW]	[DELL, IBM, MSFT, SOFO]
2010	[IBM, MSFT, DELL, SOFO]	[IBM, ATML, TTGT, IRF]	[IBM, MSFT, DELL, SOFO]	[IBM, MSFT, DELL, NSIT]	[MSFT, IBM, DELL, SOFO]
2011	[IBM, MSFT, DELL, ZIGO]	[IBM, MSFT, AMD, DAEG]	[IBM, MSFT, DELL, ZIGO]	[DELL, IBM, MSFT, CSPI]	[MSFT, IBM, DELL, CTXS]
2012	[MSFT, IBM, DELL, AAPL]	[MSFT, IBM, NXPI, RCMT]	[MSFT, IBM, DELL, AAPL]	[IBM, DELL, AAPL, MSFT]	[MSFT, IBM, DELL, RCMT]
2013	[MSFT, IBM, DELL, AAPL]	[MSFT, IBM, RCMT, STX]	[MSFT, IBM, DELL, AAPL]	[AAPL, IBM, DELL, MSFT]	[MSFT, IBM, DELL, AAPL]
2014	[MSFT, IBM, AAPL, DELL]	[MSFT, NVDA, IBM, SCOR]	[MSFT, IBM, AAPL, DELL]	[AAPL, DELL, IBM, MSFT]	[IBM, MSFT, DELL, AAPL]

This table reports ticker symbols of the four firms with the largest modular centrality corresponding to degree, Katz, PageRank, closeness, and betweenness centrality in the downstream channel (significance as a supplier). The first column lists the years. The entries in each bracket indicate the ticker symbol of the firm with the $\left[1^{\text{st}}, 2^{\text{nd}}, 3^{\text{rd}}, 4^{\text{th}}\right]$ largest modular centrality.

Table A.6: Top 4 Ranking by Modular Centrality (Upstream)

Year	Degree	Katz	PageRank	Closeness	Betweenness
2003	[DELL, IBM, MSFT, AAPL]	[IBM, DELL, MSFT, PLUS]	[IBM, DELL, MSFT, AAPL]	[IBM, MSFT, DELL, WDC]	[DELL, IBM, MSFT, XLNX]
2004	[IBM, DELL, MSFT, AAPL]	[IBM, DELL, MSFT, IM]	[IBM, MSFT, DELL, AAPL]	[IBM, MSFT, WDC, INTC]	[MSFT, IBM, DELL, IM]
2005	[IBM, DELL, DMSFT, AAPL]	[IBM, DELL, MSFT, MCRS]	[IBM, MSFT, DELL, AAPL]	[IBM, MSFT, FFIV, ORCL]	[MSFT, IBM, DELL, XLNX]
2006	[IBM, DELL, MSFT, AAPL]	[IBM, DELL, MSFT, MANH]	[IBM, MSFT, DELL, AAPL]	[IBM, MSFT, ELX, FLWS]	[IBM, MSFT, DELL, ORCL]
2007	[IBM, MSFT, DELL, AAPL]	[IBM, BA, DELL, JKHY]	[IBM, MSFT, DELL, AAPL]	[IBM, MSFT, FLWS, LIOX]	[IBM, MSFT, DELL, INTC]
2008	[IBM, MSFT, DELL, AAPL]	[IBM, MSFT, DELL, SNX]	[IBM, MSFT, DELL, AAPL]	[IBM, MSFT, ATTU, LIOX]	[IBM, MSFT, DELL, SPRT]
2009	[IBM, MSFT, DELL, AAPL]	[IBM, MSFT, DELL, MCRS]	[IBM, MSFT, DELL, MCRS]	[IBM, MSFT, DELL, APPL]	[DELL, MSFT, IBM, AVT]
2010	[IBM, DELL, MSFT, AAPL]	[IBM, MSFT, DELL, PLUS]	[IBM, MSFT, DELL, AAPL]	[IBM, MSFT, DELL, ACTG]	[DELL, MSFT, IBM, SOFO]
2011	[IBM, MSFT, DELL, AAPL]	[IBM, MSFT, SNX, PLUS]	[IBM, MSFT, DELL, AAPL]	[IBM, MSFT, AMD, EDGW]	[MSFT, IBM, DELL, CTXS]
2012	[IBM, DELL, MSFT, AAPL]	[MSFT, IBM, SNX, TECD]	[IBM, MSFT, AAPL, DELL]	[MSFT, IBM, ACTG, MG]	[MSFT, IBM, DELL, RCMT]
2013	[DELL, IBM, MSFT, AAPL]	[MSFT, IBM, TECD, PLUS]	[IBM, AAPL, DELL, MSFT]	[MSFT, IBM, ORCL, RPXC]	[MSFT, IBM, DELL, AAPL]
2014	[IBM, DELL, MSFT, AAPL]	[MSFT, AAPL, PLUS, TECD]	[IBM, AAPL, MSFT, DELL]	[MSFT, IBM, NVDA, PLCM]	[IBM, MSFT, DELL, AAPL]

This table reports ticker symbols of the four firms with the largest modular centrality corresponding to degree, Katz, PageRank, closeness, and betweenness centrality in the upstream channel (significance as a buyer). The first column lists the years. The entries in each bracket indicate the ticker symbol of the firm with the $\left[1^{\text{st}}, 2^{\text{nd}}, 3^{\text{rd}}, 4^{\text{th}}\right]$ largest modular centrality.

Appendix B

Appendix to Chapter 2

B.1 Additional Figures and Tables

Figure B.1: Example of Distance-Based Redemption Chart

JAPAN AIRLINES

Redeeming Mileage

JMB Partner Airlines Award Ticket Chart

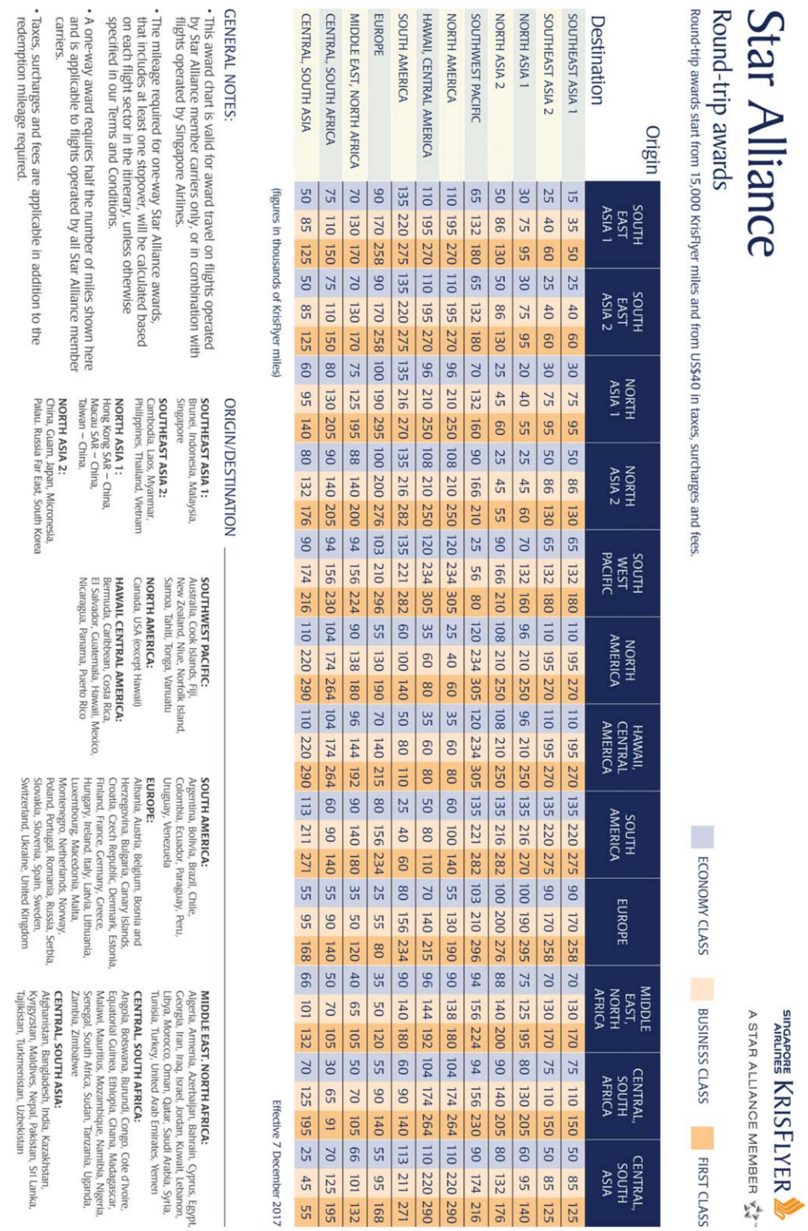
Distance Scheme Award Sector Mileage Calculator
You can check the "Total Sector Mileage(TPM)" by using Distance Scheme Award Sector Mileage Calculator.

Distance Scheme Award (UNIT:miles)

Total trip distance (mile)			Until November 19, 2018 Economy class	From November 20, 2018 Economy class	Until November 19, 2018 Premium economy class	From November 20, 2018 Premium economy class	Until November 19, 2018 Business class *1	From November 20, 2018 Business class *1	Until November 19, 2018 First class *2	From November 20, 2018 First class *2
1	-	1,000	15,000	12,000	25,000	17,000	32,000	24,000	55,000	36,000
1,001	-	2,000	20,000	15,000	27,500	21,000	35,000	30,000	60,000	45,000
2,001	-	4,000	21,000	23,000	31,500	30,000	42,000	42,000	65,000	65,000
4,001	-	6,000	37,000	37,000	48,500	46,000	60,000	60,000	90,000	90,000
6,001	-	8,000	39,000	45,000	51,000	59,000	63,000	80,000	100,000	120,000
8,001	-	10,000	40,000	47,000	52,500	62,000	65,000	85,000	105,000	135,000
10,001	-	12,000	50,000	50,000	65,000	70,000	80,000	100,000	115,000	145,000
12,001	-	14,000	55,000	55,000	70,000	77,000	85,000	110,000	135,000	165,000
14,001	-	20,000	60,000	70,000	80,000	94,000	100,000	130,000	155,000	190,000
20,001	-	25,000	85,000	90,000	105,000	112,000	125,000	145,000	200,000	220,000
25,001	-	29,000	110,000	110,000	135,000	135,000	160,000	160,000	250,000	250,000
29,001	-	34,000	130,000	130,000	160,000	160,000	190,000	190,000	290,000	290,000
34,001	-	50,000	150,000	150,000	180,000	180,000	210,000	210,000	330,000	330,000

This is a points (mileage) redemption chart of Japan Airlines. It is an example of a distance-based redemption chart. (Japan Airlines. https://www.ar.jal.co.jp/ar/en/jalmile/use/partner_air/p_jmb/jmb_mile_ar.html. Accessed December 15, 2018.)

Figure B.2: Example of Zone-Based Redemption Chart



Star Alliance

Round-trip awards

Round-trip awards start from 15,000 KrisFlyer miles and from US$40 in taxes, surcharges and fees.

SINGAPORE AIRLINES KRISFLYER

A STAR ALLIANCE MEMBER

ECONOMY CLASS | BUSINESS CLASS | FIRST CLASS

Destination \ Origin	SOUTH EAST ASIA 1			SOUTH EAST ASIA 2			NORTH ASIA 1			NORTH ASIA 2			SOUTH WEST PACIFIC			NORTH AMERICA			HAWAII, CENTRAL AMERICA			SOUTH AMERICA			EUROPE			MIDDLE EAST, NORTH AFRICA			CENTRAL, SOUTH AFRICA			CENTRAL, SOUTH ASIA		
SOUTHEAST ASIA 1	15	35	50	25	40	60	30	75	95	50	86	130	65	132	180	110	195	270	110	195	270	135	220	275	90	170	258	70	130	170	75	110	150	50	85	125
SOUTHEAST ASIA 2	25	40	60	25	40	60	30	75	95	50	86	130	65	132	180	110	195	270	110	195	270	135	220	275	90	170	258	70	130	170	75	110	150	50	85	125
NORTH ASIA 1	30	75	95	30	75	95	20	40	55	25	45	60	70	132	160	96	210	250	96	210	250	135	216	270	100	190	295	75	125	195	80	130	205	60	95	140
NORTH ASIA 2	50	86	130	50	86	130	25	45	60	25	45	55	90	166	210	108	210	250	108	210	250	135	216	282	100	200	276	88	140	200	90	140	205	80	132	176
SOUTHWEST PACIFIC	65	132	180	65	132	180	70	132	160	90	166	210	25	56	80	120	234	305	120	234	305	135	221	282	103	210	296	94	156	224	94	156	230	90	174	216
NORTH AMERICA	110	195	270	110	195	270	96	210	250	108	210	250	120	234	305	25	40	60	35	60	80	60	100	140	55	130	190	90	138	180	104	174	264	110	220	290
HAWAII, CENTRAL AMERICA	110	195	270	110	195	270	96	210	250	108	210	250	120	234	305	35	60	80	35	60	80	50	80	110	70	140	215	96	144	192	104	174	264	110	220	290
SOUTH AMERICA	135	220	275	135	220	275	135	216	270	135	216	282	135	221	282	60	100	140	50	80	110	25	40	60	80	156	234	90	140	180	60	90	140	113	211	271
EUROPE	90	170	258	90	170	258	100	190	295	100	200	276	103	210	296	55	130	190	70	140	215	80	156	234	25	55	80	35	50	120	55	90	140	55	95	168
MIDDLE EAST, NORTH AFRICA	70	130	170	70	130	170	75	125	195	88	140	200	94	156	224	90	138	180	96	144	192	90	140	180	35	50	120	40	65	105	50	70	105	66	101	132
CENTRAL, SOUTH AFRICA	75	110	150	75	110	150	80	130	205	90	140	205	94	156	230	104	174	264	104	174	264	60	90	140	55	90	140	50	70	105	30	65	91	70	125	195
CENTRAL, SOUTH ASIA	50	85	125	50	85	125	60	95	140	80	132	176	90	174	216	110	220	290	110	220	290	113	211	271	55	95	168	66	101	132	70	125	195	25	45	55

(figures in thousands of KrisFlyer miles)

Effective 7 December 2017

GENERAL NOTES:

- This award chart is valid for award travel on flights operated by Star Alliance member carriers only, or in combination with flights operated by Singapore Airlines.
- The mileage required for one-way Star Alliance awards, that includes at least one stopover, will be calculated based on each flight sector in the itinerary, unless otherwise specified in our Terms and Conditions.
- A one-way award requires half the number of miles shown here and is applicable to flights operated by all Star Alliance member carriers.
- Taxes, surcharges and fees are applicable in addition to the redemption mileage required.

ORIGIN/DESTINATION

SOUTHEAST ASIA 1: Brunei, Indonesia, Malaysia, Singapore

SOUTHEAST ASIA 2: Cambodia, Laos, Myanmar, Philippines, Thailand, Vietnam

NORTH ASIA 1: Hong Kong SAR – China, Macau SAR – China, Taiwan – China.

NORTH ASIA 2: China, Guam, Japan, Micronesia, Palau, Russia Far East, South Korea

SOUTHWEST PACIFIC: Australia, Cook Islands, Fiji, New Zealand, Niue, Norfolk Island, Samoa, Tahiti, Tonga, Vanuatu

NORTH AMERICA: Canada, USA (except Hawaii)

HAWAII, CENTRAL AMERICA: Bermuda, Caribbean, Costa Rica, El Salvador, Guatemala, Hawaii, Mexico, Nicaragua, Panama, Puerto Rico

SOUTH AMERICA: Argentina, Bolivia, Brazil, Chile, Colombia, Ecuador, Paraguay, Peru, Uruguay, Venezuela

EUROPE: Albania, Austria, Belgium, Bosnia and Herzegovina, Bulgaria, Canary Islands, Croatia, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Ireland, Italy, Latvia, Lithuania, Luxembourg, Macedonia, Malta, Montenegro, Netherlands, Norway, Poland, Portugal, Romania, Russia, Serbia, Slovakia, Slovenia, Spain, Sweden, Switzerland, Ukraine, United Kingdom

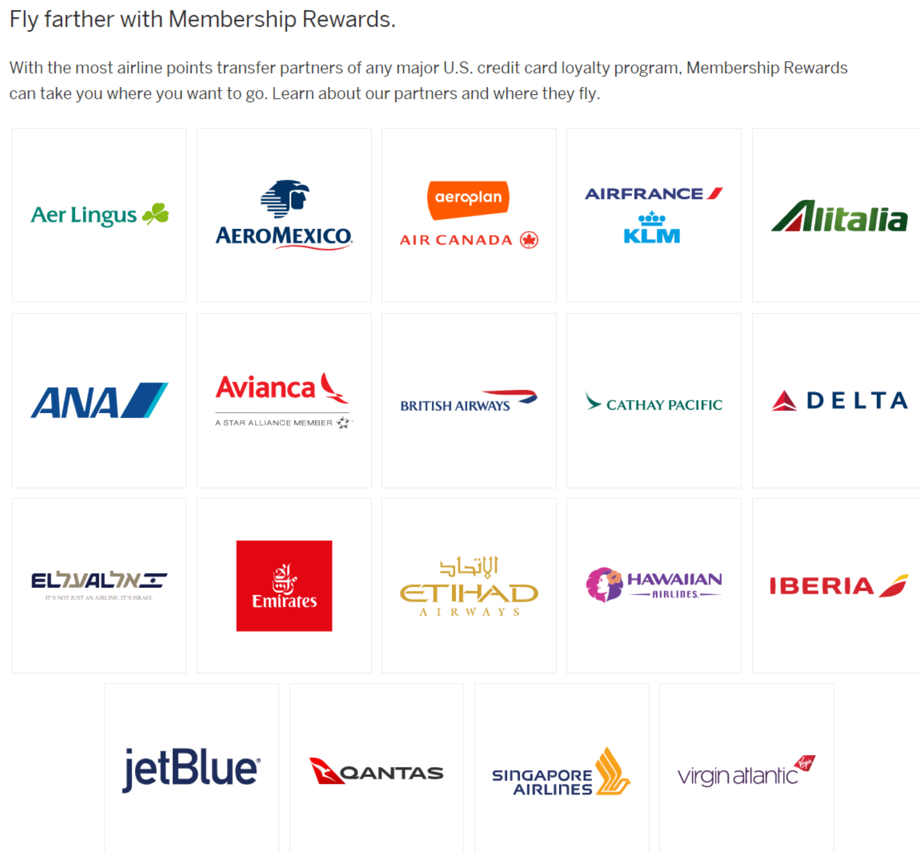
MIDDLE EAST, NORTH AFRICA: Algeria, Armenia, Azerbaijan, Bahrain, Cyprus, Egypt, Georgia, Iran, Iraq, Israel, Jordan, Kuwait, Lebanon, Libya, Morocco, Oman, Qatar, Saudi Arabia, Syria, Tunisia, Turkey, United Arab Emirates, Yemen

CENTRAL, SOUTH AFRICA: Angola, Botswana, Burundi, Congo, Cote d'Ivoire, Equatorial Guinea, Ethiopia, Ghana, Madagascar, Malawi, Mauritius, Mozambique, Namibia, Nigeria, Senegal, South Africa, Sudan, Tanzania, Uganda, Zambia, Zimbabwe

CENTRAL, SOUTH ASIA: Afghanistan, Bangladesh, India, Kazakhstan, Kyrgyzstan, Maldives, Nepal, Pakistan, Sri Lanka, Tajikistan, Turkmenistan, Uzbekistan

This is a points (mileage) redemption chart of Singapore Airlines for flights accessible via Star Alliance. It is an example of a zone-based points redemption chart. Zone definitions are clearly stated below the chart. (Singapore Airlines. https://www.singaporeair.com/saar5/pdf/ppsclub_krisflyer/charts/StarAlliance_RoundTrip.pdf. Accessed December 16, 2018.)

Figure B.3: Example of Airline Transfer Partners



Membership rewards is the loyalty program of American Express Company. The portfolio of transfer partners is actively used as a marketing tool. (American Express Company. https://www.americanexpress.com/us/rewards/membership-rewards/redeem/airline-partners/partner-airlines.html?linknav=us-loy-mr-mrair-home-airlines. Accessed September 9, 2019.)

Table B.1: History of Credit Card Issuers' Transfer Partners

Time	AMEX	JPMC	CITI
2013 Q2		Adds VS (Jun.)	
2013 Q3			
2013 Q4	Adds EK (Oct.)		
2014 Q1			
2014 Q2		Adds SQ (May)	Adds CX (Jul.), BR (Jul.), EY (Jul.), GA (Jul.), QR (Jul.), SQ (Jul.), TG (Jul.), MH (Aug.), AF (Aug.)
2014 Q3			
2014 Q4		Loses KE (Nov.)	
2015 Q1	Loses F9 (Jan.)	Adds KE (Jan.)	Adds VS (Jan.), QF (Feb.)
2015 Q2			
2015 Q3			
2015 Q4	Updates BA[1] (Oct.)		
2016 Q1			
2016 Q2	Adds EY (Apr.)	Adds AF (May.)	
2016 Q3	Adds MAR (Sep.); Loses SPG (Sep.)[2]		
2016 Q4			Adds B6 (Oct.)
2017 Q1			Removes VX[3] (Jan.)
2017 Q2	Updates BA[4](Jul.)		Adds 9W (Apr.)
2017 Q3			Adds TK (Aug.)
2017 Q4	Removes VX (Nov.)	Adds EI (Nov.), IB (Nov.)	Adds AV (Nov.); Loses HLT (Dec.)
2018 Q1	Updates HLT[5] (Jan.)		
2018 Q2			
2018 Q3	Adds EI (Aug.)	Loses KE (Aug.); Adds B6 (Aug.)	Updates B6[6] (Sep.)
2018 Q4	Adds AV (Nov.)		
2019 Q1	Adds QF (May)		
2019 Q2			
2019 Q3		Adds EK (Aug.)	Loses GA (Aug.)

This table reports the history of changes to transfer partnerships possessed by AMEX, JPMC and CITI, from the second quarter of 2013 to the third quarter of 2019.

Table B.2: Preliminary List of Firms

Industry	Firm
Credit Card Issuer	American Express Company (AMEX), J.P. Morgan Chase (JPMC), Citibank (CITI)
Hotel Chain	Best Western, Choice Hotels, Radisson Hotels, Hilton Hotels and Resorts, Hyatt Hotels, International Hotels Group, Marriott Hotels and Resorts, Starwood Hotels and Resorts, Wyndham Hotels and Resorts
Airlines (IATA Code)	9W, A3, AA, AB, AC, AF, AM, AS, AV, AY, AZ, BA, BR, CA, CI, CM, CX, CZ, DL, EK, EY, FI, G3, GA, GF, HA, HU, JL, KE, LA, LH, LY, MH, MU, NH, NZ, OK, OZ, PR, QF, QR, SA, SK, SQ, SU, SV, TG, TK, TP, UA, UL, VA, VS

This table reports the preliminary list of firms. Some firms were excluded after defining the market. Small regional airlines and airlines that use loyalty programs of other airlines were excluded. The first column ("Industry") lists the three industry types, and the second column ("Firm") reports the firms in each industry type.

[1]The transfer ratio was updated from 1 to 0.8.

[2]MAR acquired SPG. 3:1 transfer between them. SPG was removed from the network of loyalty programs and treated as a part of MAR.

[3]AS acquired VX in December 2016.

[4]The transfer ratio was updated from 0.8 to 1.

[5]The transfer ratio was updated from 1.5 to 2.

[6]The transfer ratio was updated from 0.8 to 1.

Table B.3: List of Zones and Destinations

Zone	Departure 1	Departure 2	Destination
U.S. (including Alaska) and Canada	JFK	ORD	LAX
Hawaii	LAX	JFK	HNL
Mexico	LAX	JFK	MEX
Caribbean	LAX	JFK	SJU
Central America	LAX	JFK	SJO
Northern South America	LAX	JFK	BOG
Southern South America	LAX	JFK	GRU
Western Europe	LAX	JFK	CDG
Eastern Europe	LAX	JFK	OTP
Middle East	LAX	JFK	DMM
North Africa	LAX	JFK	CAI
Central Africa	LAX	JFK	NBO
South Africa	LAX	JFK	JNB
Central Asia (Indian subcontinent)	LAX	JFK	DEL
Southeast Asia	LAX	JFK	SIN
East Asia	LAX	JFK	ICN
Oceania	LAX	JFK	SYD

The first column ("Zone") reports the 17 geographic zones that were used to compute the number of points required to redeem a reward flight for zone-based redemption charts. The next three columns report the departure and destination airports that were used to compute the number of points required to redeem a reward flight for distance-based charts. The second ("Departure 1") and third ("Departure 2") columns report the departure airports for each zone. For each zone, two departure airports were used to account for the difference in distance to the destination depending on the departure location within the U.S. The fourth column ("Destination") reports the destination airport for each zone. All numbers were computed using U.S. as the departure location.

Table B.4: List of Geographic Zones

Airline Hub Zones		**Flight Redemption Zones**	
Zone	Description	Zone	Description
1	U.S. (including Alaska and Hawaii) and Canada	1	U.S. (including Alaska) and Canada
2	Mexico, Caribbean, Central America, and Northern South America (e.g. Colombia)	2	Hawaii
3	Southern South America (e.g. Brazil, Chile)	3	Mexico, Caribbean, Central America, and Northern South America
4	North and West Europe (e.g. Finland, Germany, Italy)	4	Southern South America
5	East Europe (e.g. Greece, Russia)	5	North and West Europe
6	Middle East and North Africa (e.g. Egypt, Israel, Saudi Arabia, and Turkey)	6	East Europe
7	Central and South Africa (e.g. Ethiopia, South African Republic)	7	Middle East and North Africa
8	Central Asia (e.g. India, Sri Lanka)	8	Central and South Africa
9	Southeast Asia (e.g. Philippines, Singapore, Thailand)	9	Central Asia
10	East Asia (East of China)	10	Southeast Asia
11	Oceania (e.g. Australia and New Zealand)	11	East Asia
		12	Oceania

The "Airline Hub Zones" column reports the 11 airline hub zones used to assign geographic hub locations to airlines. The "Flight Redemption Zones" column reports the 12 geographic zones used to assign required number of points for flights. The required number of points were collected using the 17 zones in table B.3 and then aggregated to the 12 zones.

Table B.5: List of Firm Names and Abbreviations

ID	Name	Hub	ID	Name	Hub
AMEX	American Express Company	-	FI	Icelandair	4
CITI	Citibank	-	GA	Garuda Indonesia	9
JPMC	J.P. Morgan Chase Bank	-	GF	Gulf Air	6
CHO	Choice Hotels International	-	HA	Hawaiian Airlines	1
HLT	Hilton Hotels and Resorts	-	HU	Hainan Airlines	10
HYT	Hyatt Hotels	-	JL	Japan Airlines	10
IHG	Intercontinental Hotels Group	-	KE	Korean Air Lines	10
MAR	Marriott Hotels and Resorts	-	LA	LATAM Airlines	3
SPG	Starwood Hotels and Resorts	-	LH	Lufthansa	4,5
WYD	Wyndham Hotels and Resorts	-	LY	El Al Israel Airlines	6
9W	Jet Airways	8	MH	Malaysia Airlines	9
A3	Aegean Airlines	5	MU	China Eastern Airlines	10
AA	American Airlines	1	NH	All Nippon Airways	10
AB	Air Berlin	4	NZ	Air New Zealand	11
AC	Air Canada	1	OK	Czech Airlines	5
AF	Air France/KLM	4,5,7	OZ	Asiana Airlines	10
AM	Aeromexico	2	PR	Philippine Airlines	9
AS	Alaska Airlines	1	QF	Qantas Airways	11
AV	Avianca	2	QR	Qatar Airways	6
AY	Finnair	4	SA	South African Airways	7
AZ	Alitalia	4	SK	Scandinavian Airlines	4
BA	British Airways	4	SQ	Singapore Airlines	9
BR	EVA Air	10	SU	Aeroflot	5
CA	Air China	10	SV	Saudia	6
CI	China Airlines	10	TG	Thai Airways	9
CM	Copa Airlines	2	TK	Turkish Airlines	6
CX	Cathay Pacific Airways	10	TP	TAP Air Portugal	4
CZ	China Southern Airlines	10	UA	United Airlines	1
DL	Delta Air Lines	1	UL	SriLankan Airlines	8
EK	Emirates	6	VA	Virgin Australia	11
EY	Etihad Airways	6,5	VS	Virgin Atlantic	4

This table provides a dictionary for abbreviations of firm names. For airlines, their hub zones (see table B.4) are also reported.

Appendix C

Appendix to Chapter 3

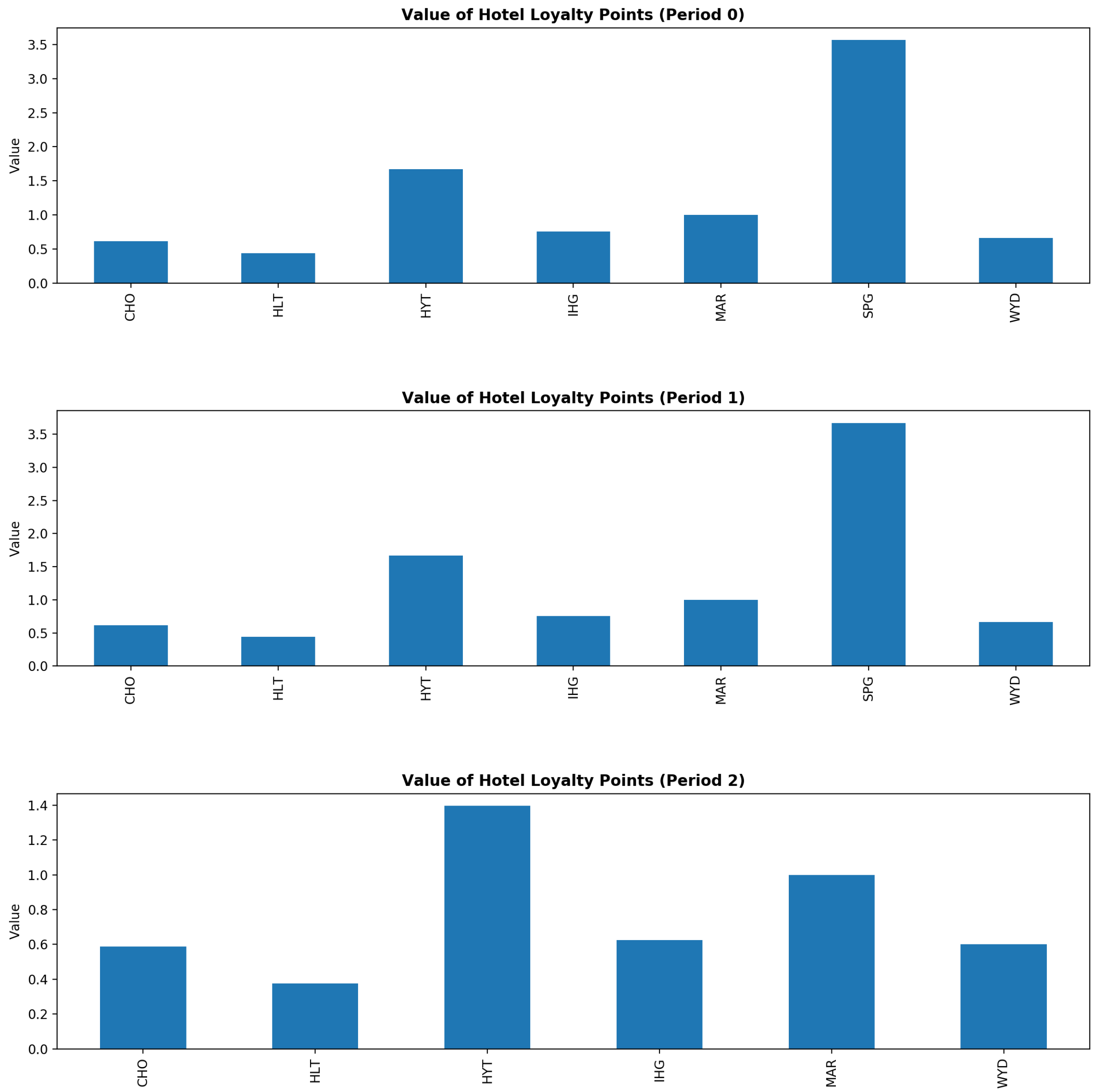
C.1 Additional Figures and Tables

Table C.1: Summary Statistics of Airline Point Values

Period	N	Mean	SD	10^{th}	25^{th}	Med.	75^{th}	90^{th}
0	43	1.830	6.248	0.615	0.764	0.935	1.016	1.078
1	43	1.828	6.248	0.612	0.773	0.917	1.016	1.069
2	41	1.873	6.399	0.590	0.770	0.935	1.024	1.072

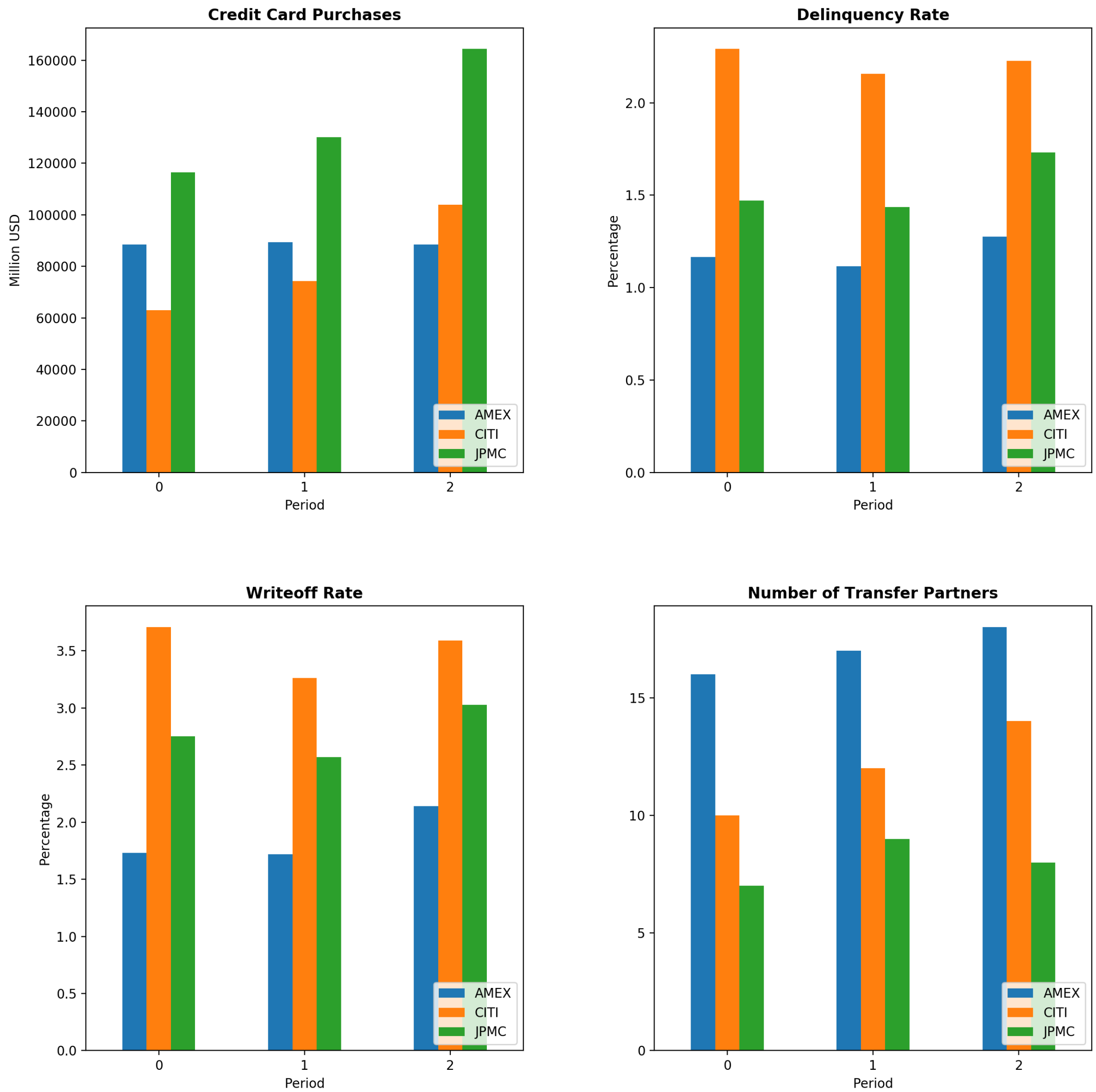
This table reports summary statistics of the values of airline loyalty points. Periods 0, 1, 2 are the 4 quarters of 2014, the 8 quarters of 2015-2016, and the 8 quarters of 2017-2018, respectively. All measures are averages over the quarters, for each period. All values were normalized using the value of United Airline's loyalty points. A value larger (smaller) than 1 indicates that, as an average over the 12 geographic zones (see "Flight Redemption Zones" in table B.4), it costs more (less) points to redeem for flights than United Airlines.

Figure C.1: Value of Hotel Loyalty Points



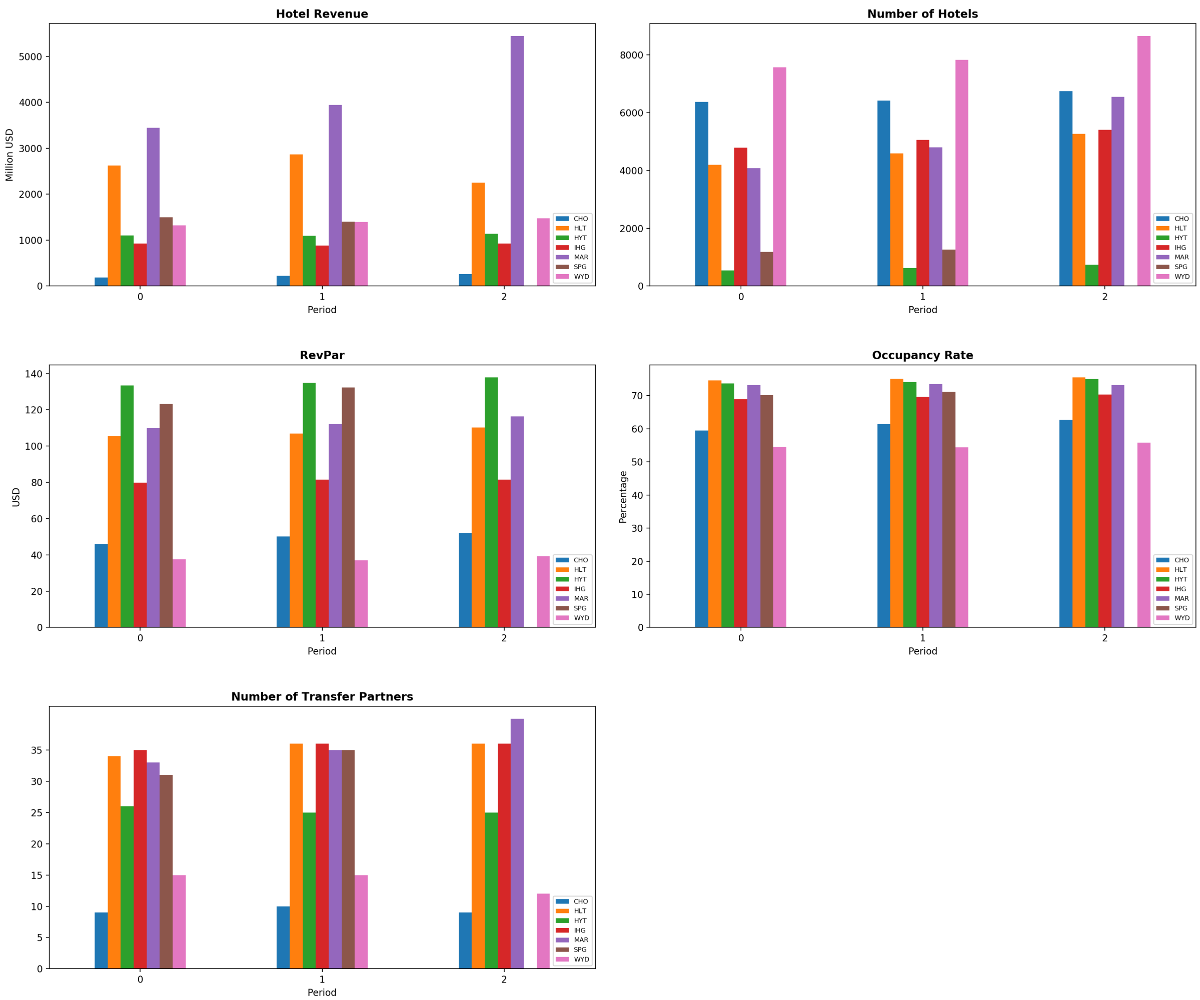
This figure reports summary statistics of the values of hotel chain loyalty points. Periods 0, 1, 2 are the 4 quarters of 2014, the 8 quarters of 2015-2016, and the 8 quarters of 2017-2018, respectively. All measures are averages over the quarters, for each period. All values were normalized using the value of MAR's (Marriott Hotels and Resorts) loyalty points. A value larger (smaller) than 1 indicates that, as an average over 7 categories of hotel properties, it costs more (less) points to redeem for a standard room than MAR. Note that SPG disappears in period 2 because it was acquired by MAR, and their loyalty programs completely integrated.

Figure C.2: KPIs for Credit Card Issuers (Quarterly Average)



This figure reports summary statistics of key performance indicators (KPIs) for credit card issuers. Periods 0, 1, and 2 are the 4 quarters of 2014, the 8 quarters of 2015-2016, and the 8 quarters of 2017-2018, respectively. All measures are averages over the quarters, for each period. Credit Card Purchase is the total amount of purchases made using the firm's credit card products. Delinquency Rate is the percentage of outstanding loans that are past due for at least 30 days. Writeoff Rate is the share of net-writeoff in outstanding loans. Only the measures for U.S. consumers were included. Number of Transfer Partners is the number loyalty programs of hotel chains and airlines to which points in the credit card issuer's loyalty program can be transferred to.

Figure C.3: KPIs for Hotel Chains (Quarterly Average)



This figure reports summary statistics of key performance indicators (KPIs) for hotel chains. Periods 0, 1, 2 are the 4 quarters of 2014, the 8 quarters of 2015-2016, and the 8 quarters of 2017-2018, respectively. All measures are averages over the quarters, for each period. Hotel Revenue is the total operating revenue of the hotel chain, including revenue from rooms and franchise fees. Number of Hotels is the number of worldwide hotel properties owned and leased by the hotel chain. RevPar (revenue per available room) is room revenue (from both owned and leased properties) divided by the number of available rooms. It is a measure of average consumer willingness to pay for lodging services offered by the hotel chain. Occupancy Rate is the number rooms sold divided by the number of available rooms. It is a measure of demand for the hotel chain's rooms relative to capacity. Number of Transfer Partners is the number loyalty programs of airlines to which points in the hotel chain's loyalty program can be transferred to.

Table C.2: Summary Statistics of KPIs for Airlines (Quarterly Average)

Period	N	Variable	Mean	SD	10^{th}	25^{th}	Med.	75^{th}	90^{th}
0	43	Passenger Revenue (Million USD)	2,390	2,562	515	731	1,189	2,800	7,182
		Revenue Passenger Km (Million)	23,447	22,680	6,194	7,931	14,299	27,887	56,824
		Available Seat Km (Milllion)	29,206	27,286	7,838	10,200	20,742	34,642	71,323
1	43	Passenger Revenue (Million USD)	2,173	2,329	499	667	1,078	2,593	5,623
		Revenue Passenger Km (Million)	25,614	23,933	6,133	9,250	15,414	30,750	63,342
		Available Seat Km (Milllion)	31,764	28,989	8,073	11,635	21,065	38,733	74,668
2	41	Passenger Revenue (Million USD)	2,562	2,682	600	765	1,250	2,959	6,882
		Revenue Passenger Km (Million)	29,747	26,276	8,176	9,707	19,750	35,765	69,758
		Available Seat Km (Milllion)	36,342	31,715	9,914	12,168	24,759	44,388	84,039

This table reports summary statistics of key performance indicators (KPIs) for airlines. The first column ("Period") lists the periods. Periods 0, 1, and 2 are the 4 quarters of 2014, the 8 quarters of 2015-2016, and the 8 quarters of 2017-2018, respectively. The second column ("N") reports the number of airlines. Other columns report summary statistics using averages over the quarters, for each period. Passenger Revenue is airline's revenue from scheduled and chartered flights. Revenue passenger Km (RPK) is total flight distance (in kilometers) of paying passengers; it is a measure of demand for an airline's flight services. Available Seat Km (ASK) is total flight distance (in kilometers) of available passenger seats; it is a measure of supply or capacity of an airline's flight services.

C.2 Estimation Procedure

The estimation procedure uses transitions of the network over two periods. A period denotes the time frame for the transition of the network from an initial state to an ending state. Period 1 denotes the eight quarters from the first quarter of 2015 to the fourth quarter of 2016, and Period 2 denotes the eight quarters from the first quarter of 2017 to the fourth quarter of 2018. The initial and ending states in period 1 are the states of the network observed in the fourth quarter of 2014 and in the fourth quarter of 2016, respectively. The initial and ending states in period 2 are the states of the network observed in the fourth quarter of 2016 and in the fourth quarter of 2018, respectively. For each period, the initial state of the network is equal to the ending state in the previous period. The origin state of the network denotes the initial state in the earliest period (period 1), which is the observation in the fourth quarter of 2014. Period 0 denotes the four quarters of 2014. For all key performance indicators (KPIs) of firms and characteristics of loyalty programs, I averaged the relevant quarterly observations to construct period-level observations.

C.2.1 Constructing Values of Nodes

The value of a node (loyalty program of a firm) is measure of the redemption value of its loyalty points. In addition, for each industry sector (airlines and hotel chains), I normalized the values of nodes relative to a pivot node so that the value of a pivot node is equal to 1. The pivot node among the airlines is UA, and the pivot node among the hotel chains is MAR. A value larger (smaller) than 1 indicates that, on average, the loyalty points of the node is more (less) valuable than the pivot node.

For airlines, I constructed the values of nodes using redemption rates of loyalty points for the 12 geographic zones (see table B.4) departing from the United States. The precise procedure was

1. For each of the 12 zones, divide the redemption rates of all airlines by the redemption rate of UA.

2. For each airline, average over the 12 zones.

3. Take the inverse.

In step 1, some airlines did not offer redemption for flights to certain zones (marked with zero). For the airlines, those zones were not used when computing the averages in step 2. The variable *Routes* (see section 3.4.3) accounts for the number of missing zones. Note that UA offered redemption for flights to all 12 zones.

The values of nodes for hotel chains were constructed similarly. The difference is that I used redemption rates for 7 hotel categories, classified by prestige of the hotel property, instead of the geographic zones. For each of the 7 categories, I divided the redemption rates of all hotel chains by the redemption rate of MAR. I then averaged over the 7 categories and then inverted the numbers.

For both airlines and hotel chains, I first computed values of nodes using quarterly observations. They were then averaged over the appropriate quarters to construct period-level observations.

For the credit card issuers, I could not find a reasonable method to derive the values of nodes from their own redemption options. Instead, I constructed the values of nodes by comparing the transfer ratios of loyalty points to the same airlines and hotel chains. In other words, I constructed the values of node using the relative transfer ratios to common transfer partners. For each of JPMC and CITI, I identified common transfer partners and then divided the transfer ratios by the matching transfer ratios of AMEX. I then averaged and inverted them to construct the values of nodes. Thus, a value larger (smaller) than 1 implies that, as an average over common transfer partners, the loyalty points of the credit card issuer is more (less) valuable than AMEX.

C.2.2 Constructing Bids

I first constructed the observed bids from transfer ratios and values of nodes using equation (3.1). Then I matched the observed bids with period-level KPIs. Note that I applied logarithmic transformations for all KPIs except for those in percentage terms. Then separately for (credit card issuer, airline) and (hotel chain, airline) as (chooser, bidder) pairs, I estimated the parameters of equation (3.2) using ordinary least squares (OLS). Note that I pooled the observations for all three periods (periods 0, 1, and 2) to computed the OLS estimates. I then used the parameter estimates and equation (3.2) to predict bids for all (chooser, bidder) pairs. I also constructed potential transfer ratios for all (chooser,bidder) pairs using equation (3.1). I used the predicted bids and potential transfer ratios for the Markov Chain Monte Carlo estimation.

C.2.3 Constructing *Mileage*

Each airline possessed different accessibility and redemption rates for flights to the 12 geographic zones. Accessibility is whether or not points in the airline's loyalty program could be used to redeem for flights to the geographic zones, and redemption rates are equal to the required number of points to redeem for the flights. *Mileage* is a measure of redemption options, which accounts for both accessibility and redemption rates, granted by the credit card issuer's portfolio of airline partners. A smaller (larger) value of *Mileage* indicates better (worse) redemption options. I employed the following procedure to construct *Mileage*. Given a credit card issuer's portfolio of airline partners,

1. For each airline, multiply the its redemption rates to the 12 geographic zones by the potential transfer ratio from the credit card issuer to the airline. The result gives the required number of points to the geographic zones, denominated in the credit card issuer's loyalty points.

2. Using the result of step 1, for each geographic zone, select three smallest required number of points then compute the average. Any missing redemption options are not counted towards computing the average. For example, if a portfolio of airline partners grants only two redemption options for a zone, compute the average of the two required number of points.

3. Average the result of step 2 over the geographic zones.

4. Count the number of missing redemption options in step 2. Subtract 36 (3 times the number of geographic zones) by the count. Then divide by 36. Take the inverse.

5. Multiply the result of step 3 by the result of step 4.

Note that I calculated *Mileage* whenever the portfolio of airlines was updated in the Markov Chain Monte Carlo estimation.

C.2.4 Markov Chain Monte Carlo

The Markov Chain Monte Carlo (MCMC) estimation utilizes observations on the state of the network and firm-level characteristics from periods 1 and 2. Note that I applied logarithmic transformations for all components of *Performance* in equation (3.7). I specified the prior distribution of θ as $\mathcal{N}(0, 100 \times \boldsymbol{I}_{20})$, where $\boldsymbol{I}_{20}$ denotes the 20×20 identity matrix. I executed the MCMC estimation in two stages. In the initial stage, I determined the the covariance of the proposal distribution for θ (henceforth *covariance*) and fraction of the sequence of meeting to be permuted (henceforth *fraction*) and . In the main stage, I used the covariance and the fraction to sample the sequence of meetings and to compute iterations of θ. I utilized the multi-sequence method of (Gelman and Rubin, 1992) in both stages. In particular, I sampled 10 starting values of θ and separately iterated 10 MCMC sequences in each stage. In the first stage, I computed 1,000 MCMC iterations of θ (after the burn-in process) for each MCMC sequence, and in the second stage, I computed the iterations until the convergence criterion of (Gelman and Rubin, 1992) was satisfied. The following describes the procedure I employed for the MCMC estimation.

Initial Stage:

1. Set the proposal distribution for θ as $\mathcal{N}(\mathbf{0}_{20}, 0.0005 \times \boldsymbol{I}_{20})$, where $\mathbf{0}_{20}$ denotes the 20×1 vector of zeros. Set the fraction to 0.2. I determined the fraction and the covariance by trial and error to obtain a target jump rate of 0.3, for each of $\theta^{(l)}$and $S_2^{(l)}$ in the following steps.

2. Sample 10 starting values of $\theta^{(0)}$ from $\mathcal{N}(\mathbf{0}_{20}, 0.05 \times \boldsymbol{I}_{20})$, which was obtained by multiplying the covariance of the proposal distribution by 100. Generate 10 starting sequences of meetings $S_2^{(0)}$ by permuting a sequence of all (credit card issuer, airline) and (hotel chain, airline) pairs.

3. Compute 2,000 iterations of $\theta^{(l)}$ and $S_2^{(l)}$, for each of the 10 MCMC sequences. Each MCMC sequence corresponds to one of the 10 starting values $\left(\theta^{(0)}, S_2^{(0)}\right)$.

4. Calibrate the covariance and the fraction using the later 1,000 iterations.

    (a) Compute the covariance matrix of $\theta^{(l)}$ for each MCMC sequence. Set the covariance of the proposal distribution for θ to $0.25\hat{\Sigma}$, where $\hat{\Sigma}$ denotes the element-wise average of the covariance matrices over the 10 MCMC sequences. I chose the tuning parameter 0.25 by trial and error to obtain a jump rate of 0.3 for $\theta^{(l)}$ in the later 1,000 iterations.

    (b) Set the fraction to 0.3. I chose it by trial and error to obtain a target jump rate of 0.3 for $S_2^{(l)}$ in the later 1,000 iterations.

Main Stage:

1. Let $\hat{\theta}_0$ be the average of $\theta^{(l)}$ for the later 1,000 iterations from the initial stage (total $10 \times 1,000$ iterations). Let $\hat{\Sigma}$ denote the covariance matrix from step 4.(a) above. Define

$$\hat{p}(\theta) = (2\pi)^{-\frac{\dim(\theta)}{2}} \det\left(\hat{\Sigma}\right)^{-\frac{1}{2}} \exp\left(-\frac{1}{2}\left(\theta - \hat{\theta}_0\right)' \hat{\Sigma}^{-1}\left(\theta - \hat{\theta}_0\right)\right) \tag{C.1}$$

2. Sample 1,000 draws of θ from $\hat{p}$. Divide each draw by a draw from $\mathcal{X}_4^2$ and then multiply by 4. They are overdispersed draws from an estimate of the posterior. The underlying density for the overdispersed draws is proportional to

$$p^*(\theta) = \det\left(\hat{\Sigma}\right)^{-\frac{1}{2}} \left(4 + \left(\theta - \hat{\theta}_0\right)' \hat{\Sigma}^{-1}\left(\theta - \hat{\theta}_0\right)\right)^{-\frac{\dim(\theta)+4}{2}} \tag{C.2}$$

3. Let θ^* denote an overdispersed draw from step 2. Compute the importance ratios $\hat{p}(\theta^*) / p^*(\theta^*)$ for each of the 1,000 overdispersed draws. Using the importance ratios, select 10 starting values $\theta^{(0)}$ by sampling from the overdispersed draws without replacement. Generate 10 starting sequence of meetings $S_2^{(0)}$ by permuting a sequence of all (credit card issuer, airline) and (hotel chain, airline) pairs.

4. With the 10 starting values $\left(\theta^{(0)}, S_2^{(0)}\right)$, separately compute iterations $\left(\theta^{(l)}, S_2^{(l)}\right)$ for the 10 MCMC sequences using the covariance and the fraction obtained in step 4 of the initial stage. Continue until the criterion suggested by Gelman and Rubin (1992) is satisfied. That is, using the later half of the iterations,

   (a) Compute the mean of $\theta^{(l)}$ for each of the 10 MCMC sequences. For each component of θ, compute the variance of the means. *Between-Var* denotes the variance of the means.

   (b) For each MCMC sequence, compute the variance of $\theta^{(l)}$ (for each components of θ). Compute the mean of the variances. *Within-Var* denotes the mean of the variances.

   (c) Continue MCMC iterations until

$$\max\left(\frac{\textit{Between-Var}}{\textit{Within-Var}}\right) < 0.1. \tag{C.3}$$

   Between-Var/Within-Var is an element-wise division, and the maximum is over the components of θ.

C.3 Estimation Results for Hotel Chains

Table C.3: Estimation Results (Hotel Chains)

Estimand	**Variable**	**Mean**	**Median**	$[\boldsymbol{P_{2.5}}, \boldsymbol{P_{97.5}}]$
θ_{0h}	Constant term	0.5152**	0.5341	[0.0663,0.8100]
θ_{11h}	Size of Portfolio	-1.6273**	-1.7723	[-2.1376,-0.5865]
θ_{12h}	Passenger Revenue (incl. in *Performance*)	0.8543**	0.8323	[0.5138,1.1762]
θ_{13h}	Revenue Passenger Km (incl. in *Performance*)	-0.2898*	-0.2957	[-0.5436,0.0214]
θ_{2h}	Available Seat Km (incl. in *Performance*)	0.0472	0.0243	[-0.1943,0.3308]
θ_{3h}	*GeoHub*	-1.0087**	-1.0148	[-1.2977,-0.6702]
θ_{4h}	*Mileage*	-0.0386**	-0.0374	[-0.0817,-0.0018]
θ_{5h}	*Routes*	0.0638*	0.0668	[-0.0070,0.1164]
θ_{6h}	*Competitor*	2.1022**	2.1444	[1.5285,2.5603]
θ_{7h}	*Transitivity*	1.3304**	1.3328	[0.9639,1.7671]

This table reports the result of MCMC iterations. The first column ("Estimand") lists the components of θ_h, the parameter of the hotel chain's objective function. The second column ("Variable") lists the covariates included in the objective function (see section 3.4.3 for definitions). The third column ("Mean") reports the mean of the MCMC iterations. The fourth column ("Median") reports the median of the iterations. The last column ("$[P_{2.5}, P_{97.5}]$") reports the 2.5 - 97.5 percentile range of the iterations. ** indicates that the 2.5 - 97.5 percentile range does not contain zero. * indicates that the 5 - 95 percentile range does not contain zero. The mean, median, and percentile range were computed after removing the first half of the iterations (after the "burn-in" process).