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Network Analysis: A Novel Method for Mapping Neonatal Acute Transport Patterns in California

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Abstract

Objective—To use network analysis to describe the pattern of neonatal transfers in California, to compare empirical sub-networks with established referral regions, and to determine factors associated with transport outside the originating sub-network.

Study Design—This cross-sectional database study included 6546 infants <28 days old transported within California in 2012. After generating a graph representing acute transfers between hospitals (n=6696), we used community detection techniques to identify more tightly connected sub-networks. These empirically-derived sub-networks were compared to state-defined regional referral networks. Reasons for transfer between empirical sub-networks were assessed using logistic regression.

Results—Empirical sub-networks showed significant overlap with regulatory regions (p <0.001). Transfer outside the empirical sub-network was associated with major congenital anomalies (p<0.001), need for surgery (p=0.01), and insurance as the reason for transfer (p<0.001).

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Conclusion—Network analysis accurately reflected empirical neonatal transfer patterns, potentially facilitating quantitative, rather than qualitative, analysis of regionalized health care delivery systems.

Introduction

Admission rates to neonatal intensive care units (NICUs) in the United States have been increasing.[1] Care and outcomes for these newborns vary widely, which is not fully explained by differences in underlying clinical risk.[2] Differences in how neonatal care is organized across regionalized health care delivery networks may account for some of this variation.[3-8]

In order to optimally match patient need with neonatal care delivery capabilities, a program of regionalized care was implemented in the United States, beginning in the 1970s.[9] Regionalization involves a linking of hospitals in a coordinated system of communication, learning and response. Over the past several decades, these networks have been shaped by regulatory policy, financial incentives, and market forces.[4,5,8] For example, the Affordable Care Act has led to a wave of consolidation of care that is expected to have a significant effect on the shape of regionalized care delivery for newborns.[10]

A rich literature has documented the benefits of maternal transport and the adverse effects of acute inter-hospital transport on neonatal morbidity and mortality.[4,6,11-16] However, findings of a detrimental effect of neonatal transport have not been uniform.[17,18] This suggests that reasons for transport may vary, as do their consequences on outcomes. Previous attempts to assess the effect of regionalization on outcomes have been limited by their reliance on hospital-level characteristics or before-after study designs, rather than an understanding of the flow of patients through a care delivery system.[3,6,7,9,12,19,20] Accounting for the characteristics of the patients and their movement through the care delivery network would provide for a more granular understanding of the way care networks function for infants requiring acute transport.

Network analysis, which stems from graph theory in mathematics, analyzes the structure of relationships; it has been utilized in many fields, such as sociology, biology, and economics.[21,22] Network analysis has previously been used to examine the structure of adult intensive care unit transports in Texas,[23] but has not yet been applied to the field of neonatal regionalization. The goal of this study was to test the construct validity of network analysis as a tool to quantify the linkages between hospitals providing neonatal care in California.

Methods

Sample

We undertook a cross-sectional database study including all neonatal transfers (up to the age of 28 days) conducted by California Perinatal Quality Care Collaborative (CPQCC) member hospitals that occurred between January 1, 2012 and December 31, 2012.[24] Data are collected on infants by CPQCC member hospitals using any of the following inclusion criteria: birth weight 401 to 1500 grams, gestational age 22 0/7 weeks to 29 6/7 weeks, or for infants >1500 grams either death, surgery, intubation or positive pressure support for

more than 4 hours, readmitted for total bilirubin 25 and/or exchange transfusion, early bacterial sepsis, or acute transfer. Acute transfer was defined as an infant who requires acute resolution of medical problems and who is transferred in order to obtain care that is not provided, or that cannot be effectively provided at the referring institution (e.g., staffing/census issues, insurance).[25] Within the CPQCC dataset, the California Perinatal Transport System, a system of over 100 specialized NICUs that participate in the transport of critically ill infants in California, collects data on acute neonatal transports.[26] Transports originating from or traveling to hospitals not included in the CPQCC network, from outside the state of California, or from outside the United States, and infants admitted from home, were excluded from the cohort.

Analysis

Objective 1: Representation of neonatal transfers using a network graph—We employed techniques of network analysis to characterize the movement of patients across the system of hospitals.[21,22] This approach utilizes a network graph to represent mathematically the structure, direction, and intensity of relationships between distinct entities using a set of connected nodes. In this network graph, hospitals were represented by nodes; neonatal transfers between hospitals were represented as connections, or edges, between them. Edges between nodes can be represented either as arrows, representing the direction of the transfer between two hospitals (known as a "directed" network), or as simple lines, in which case the direction of the transfer is not denoted (an "undirected" or "symmetric" network). For clarity of presentation, we collapsed all transfers between each pair of hospitals into a single edge, and the network was symmetrized by removing the directionality of transfers.

There are several methods of representing the volume of transfers between each pair of hospitals, most commonly to proportionally widen the line as number of transfers increases. However, given the large size of this network and its relative density, we represented volume of transfers into each hospital by the size of the node. The American Academy of Pediatrics (AAP) level designation of each hospital, as derived in a 2012 survey of NICU directors,[27] was denoted by the shape of the node.

After establishing the network structure, we characterized the most interactive communities of the network – that is, those groups of hospitals between which transfers occur most frequently, or regional referral networks – using network community detection techniques.[28] Community detection separates the nodes of a network into groups (that is, communities) where there are many connections, while simultaneously attempting to minimize the number of connections between groups. In this way, community detection techniques break a network down along its most natural divisions. In our analysis, communities were identified using a hierarchical agglomeration algorithm for detecting community structure, a bottom-up approach that starts by considering each node as its own community, and successively merges pairs of communities.[29] We did not pre-specify a desired number of communities (henceforth termed "sub-networks"), thereby allowing the algorithm to determine the optimal number of clusters to maximize within-cluster transfers and minimize between-cluster transfers.

Objective 2: Comparison of empirical sub-networks with state-defined regulatory regions—In order to establish construct validity of the network analysis approach, we assessed whether the networks derived from the analysis would be consistent with our knowledge of existing transfer patterns across California. To this end, we compared the network analysis derived sub-networks (henceforth termed "empirical") to perinatal referral regions defined by the state of California (henceforth termed "regulatory"). The Regional Perinatal Programs of California (RPPC), established by the California Department of Public Health, has divided the state into perinatal referral regions.[30] Perinatal centers are tasked with conducting oversight and outreach on quality improvement to other hospitals in the region.[31,32] There are 9 RPPC-designated referral regions, as well as 2 regions defined by Kaiser Permanente (splitting the state between north and south, and here included under the designation "regulatory").[30] We generated a heat map, in which the row-by-column transports between empirical and regulatory regions were specified, to visualize the degree of alignment between these two types of networks. We quantified agreement between empirical sub-networks and regulatory regions using a chi-square test.

Objective 3: Identifying factors associated with transfer outside empirical sub-networks—In order to determine factors associated with cross-sub-network transfers, all transfers were coded according to whether they occurred between two hospitals within the same empirical sub-network or crossed sub-network boundaries. Variables included gestational age, birth weight, sex, race/ethnicity, major congenital anomaly, and documented reason for transfer (medical/diagnostic services, surgery, insurance, or bed availability). Congenital anomalies comprised central nervous system defects, congenital heart defects, gastrointestinal defects, genitourinary defects, chromosomal anomalies, pulmonary defects, vascular/lymphatic defects, and other conditions such as skeletal dysplasia, congenital diaphragmatic hernia, and hydrops fetalis.[33] We used multivariable logistic regression to assess cross-sub-network transfer, using $p<0.05$ as the threshold for significance. Network visualization and statistical analyses were undertaken with R using the igraph package (R Development Core Team, Vienna, Austria).[34] The study was approved by the institutional review boards of the investigators.

Results

Description of patient population

The sample included 6546 infants, representing 6696 inter-hospital transports. Characteristics of these patients and transfers are shown in Table 1. Of note, 14% (n=915) of infants were very low birth weight, 24% (n=1572) of the infants had a major congenital anomaly, and 2% (n=150) underwent more than one transfer. Of 296 hospitals, 167 were designated as Level 1, 24 as Level 2, 86 as Level 3, and 19 as Level 4 units. In 91% (n=6122) of transfers, the destination hospital was of a higher level than the originating hospital, while 6% (n=422) transferred to the same level of care (Table 2).

Objective 1: Representation of neonatal transfers using a network graph

The network graph of the neonatal transport network in California, overlaid onto a map of the RPPC regulatory regions, is shown in Figure 1.Node shape denotes AAP level of care, and node size reflects the number of transfers into that hospital.

The clustering algorithm empirically identified 11 sub-networks, the same number as the regulatory regions. Each sub-network is represented by a different node color. The largest of these empirical sub-networks included 46 hospitals, while the smallest included 7 hospitals. Nine of the 11 empirical sub-networks included at least one Level 4 NICU.

Objective 2: Comparison of empirical sub-networks with state-defined regulatory regions

Table 3 shows the number of hospitals coexisting in each pair of empirical sub-network and RPPC regulatory regions. The degree of overlap between the empirical sub-networks and the regulatory regions is significant (p<0.001). The minimum amount of mismatch (that is, the number of hospitals not falling into the largest overlapping cell per sub-network/regulatory region pair) was 0%, denoting perfect alignment of one RPPC regulatory region with one empirical sub-network. The greatest amount of mismatch for hospitals within the empirical sub-networks was 53% (that is, only 47% of that sub-network's hospitals fell into a single regulatory region), while the maximum mismatch was 43% when the analysis was based on regulatory regions. Of note, Kaiser North was the only regulatory region that did not map onto its own empirical sub-network; the empirical sub-networks with which it overlapped were more highly connected to other regulatory regions. Conversely, there were several empirical sub-networks that overlapped with the Los Angeles regulatory region; only the empirical sub-network with the largest number of overlapping hospitals (cyan) was considered as Los Angeles' best-matching sub-network.

Objective 3: Identifying factors associated with transfer outside empirical sub-networks

Overall, 91% (n=6086) of neonatal transports remained within their empirical sub-network, while 83% (n=5534) remained within their regulatory region (Table 4a and 4b). Comparison of characteristics between transports that stayed within an empirical sub-network compared to those that crossed empirical sub-network boundaries is shown in Table 5.Significant predictors of cross-sub-network transport included the presence of a major congenital anomaly (OR 1.79 [95% CI, 1.47-2.19], p<0.001), need for surgery (OR 1.42 [95% CI, 1.08-1.88], p=0.01), and insurance as the documented reason for transfer (OR 5.13 [95% CI, 3.89-6.76], p<0.001) (Table 5). Hispanic infants were significantly less likely to cross sub-network boundaries during transport (OR 0.81 [95% CI, 0.67-0.98], p=0.03).

Discussion

This paper describes the use of network analysis as a novel methodology for accurately visualizing regionalized neonatal health care delivery systems. By conducting the analysis in a highly regulated state in which the existing referral relationships are well understood, we have demonstrated that network analysis can accurately depict known transport patterns. Furthermore, we showed that infant transports out of an empirical sub-network are associated with patient factors, including the presence of a major congenital anomaly, need

for surgery, and insurance status; again aligning with our clinical expectations. Our findings are important, because they support the validity of network analysis as a tool to empirically quantify the degree of regionalization of neonatal care networks. Network analysis could thus be a powerful tool to define, analyze, and improve care at the network level in regions that lack a strong regulatory structure.

Taking an empirical network approach to neonatal regionalization addresses several limitations of prior studies of regionalization. First, definitions of NICU level of care vary considerably across the United States, confounding the definition of regionalization and, subsequently, studies based on these levels.[18,35] While network analysis can incorporate these levels of care, the visualization of the networks and the calculation of network metrics does not depend on them. Moreover, before-after studies of the impact of regionalization programs on neonatal outcomes fall prey to confounding by secular trends, inadvertently reflecting concurrent changes in the field.[9] Network analysis elucidates how the flow of patients changes over time, clarifying the impact of regionalization itself, regardless of other changes. Having a method to quantify neonatal care at a systems level represents a more rigorous and complete approach to assessing regionalization.

The finding of significant overlap between empirical and regulatory care networks suggests that hospitals are generally, but not always, transporting neonates in accordance with state-defined neonatal referral regions. Regulatory regions may mirror current practice because the regions are already optimally drawn, or hospitals may simply be working within their state-defined boundaries. While the two types of networks do overlap, empirical networks may represent a better unit of regional analysis, as they have fewer out-of-network transfers than the regulatory networks.

Although more than 90% of transports stay within their empirical sub-network, the patients who do cross sub-networks may illustrate factors shaping current neonatal care networks and may also identify suboptimal patterns of care delivery. Infants with major congenital anomalies, who comprised nearly a quarter of our patient population, typically require specialized care after delivery and thus frequently require transport to a regional referral center to receive subspecialty or surgical services. With prenatal ultrasound screening, most of these infants could be identified prenatally and their postnatal needs anticipated, allowing for delivery at an appropriate center. Likewise, patients who require surgery are more likely to be transported beyond their empirical sub-network, for related reasons of appropriate care availability. The high rate of transport across sub-network boundaries for these infants may indicate highly successful regionalization, as such subspecialized care cannot realistically be delivered by a larger number of centers. On the other hand, this could signify a breakdown in regionalization, if providers are bypassing closer, equally capable centers. For example, the clustering analysis detected real historical relationships between hospitals, showing that certain hospitals that are geographically disconnected from a regional referral center are a part of that center's empirical sub-network.

It is important to recognize that these findings do not directly address quality of care; however, they hold promise for optimizing care networks for efficiency and quality. Network analysis techniques that allow comparisons between sub-networks have the potential to

quantify the association between care delivery network structure and quality of care. For example, network analysis techniques can measure how tightly connected a network is; if such cohesiveness measures are correlated with neonatal outcomes, there may be opportunities to improve the quality of neonatal care by optimizing the networks in which care is delivered. Moreover, network analysis allows for visualization of care patterns that appear suboptimal, such as when infants are transported long distances, bypassing closer centers that could provide appropriate care. While many of these instances can be explained by historical relationships between hospitals or providers, visualizing these cases would allow policy makers to identify areas for improvement in the flow of neonatal patients through care networks.

Our findings thus have important health policy implications. Quantifying the degree of regionalization of neonatal care networks will allow between-network comparisons as well as measurement of changes over time. For example, while there have been descriptions of deregionalization in the United States, longitudinal comparison of network graphs will allow quantification of this deregionalization.[5] Furthermore, policy-makers will be able to measure the effects of new legislation such as the Affordable Care Act on care delivery systems. Also, as hospital network mergers and acquisitions occur, such quantitative approaches hold promise not only in evaluating the effects of shifting hospital systems, but also in informing such decisions prior to their execution.

This study must be viewed within the context of its design. Not all neonatal transports in California were included, as we excluded non-acute transports, as well as interstate and international transfers. We are currently working to incorporate non-acute transports for convalescent care and maternal transports into our analyses. Furthermore, because the data are based on self-report, some data may be missing or inaccurately classified. However, as the CPQCC database captures over 90% of neonates cared for in California NICUs, and the results reflect our expectations of the transport networks in California, this sample appears adequate. In addition, while we anticipate that network analysis techniques will be generalizable to less regulated states based on the adaptability of the underlying mathematical principles, these methods need to be empirically tested in other regions, particularly those with weaker regulatory oversight, differing geography, or known reliance on interstate transfer. Finally, these data do not assess the degree to which care is provided to meet specific goals, such as parental preference for a certain institution.

Even though Kaiser provides tightly integrated care, Kaiser North was not identified by our algorithm as a separate sub-network. We believe that this is likely a function of the cases we considered and how Kaiser is organized. Because Kaiser puts great emphasis on having mothers deliver at appropriate settings, many cases that would be neonatal transfers in other systems are antenatal referrals/transports and thus are not included in our data. Further, this exclusion shifts the balance of types of infants transferred by Kaiser to more complex cases that need subspecialty care provided at a small number of hospitals (e.g., cardiac surgery). Since Kaiser contracts with non-Kaiser hospitals for many of these types of cases, these appropriate referrals are, by definition, out of network, while transfers from many of the non-Kaiser hospitals who contract with the same tertiary hospitals will be in-network in our analyses. This is supported by additional analyses (not shown), showing that infants

transported outside of Kaiser North disproportionately required subspecialty care. Finally, although we have employed a well-established type of network community detection algorithm[29] that appears to accurately map transport sub-networks, it is possible that our network analysis algorithm was not a good tool to compare networks that are distributed by membership rather than location.

In conclusion, applying network analysis techniques to the field of neonatal regionalization offers an unprecedented view of how care delivery networks are shaped. In the future, such quantification of neonatal referral networks could be used to correlate network structure with patient outcomes. Network analysis has the potential to significantly influence regionalized neonatal care delivery systems.

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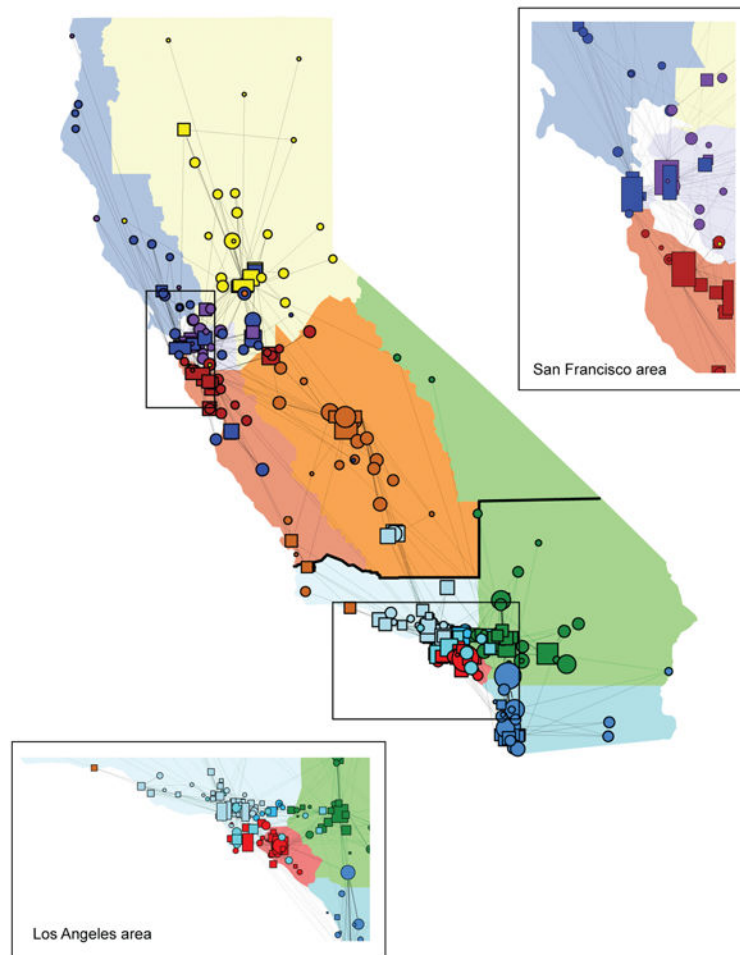
Figure 1. Network graph of acute neonatal transports in California
Empirical sub-networks overlaid onto RPPC regulatory regions. Empirical sub-networks are color-coded. Node size denotes number of transports into a hospital. Node shape denotes AAP level (circles - levels 1 and 2; squares - level 3; rectangles - level 4). The black line marks the division between Kaiser Permanente Northern and Southern regions. The San Francisco and Los Angeles areas have been enlarged for clarity.

Table 1

Sample characteristics of acutely transported infants in California, 2012

	Very low birth weight (n=915)	Not very low birth weight (n=5631)	Total (n=6546)
Gestational age, weeks [mean (SD[1])]	27.8 (3.0)	37.4 (2.7)	36.1 (4.3)
Birth weight, grams [mean (SD)]	995.1 (285.2)	2973.6 (758.8)	2697.0 (988.6)
Male sex [n (%)]	469 (51.3)	3270 (58.1)	3739 (57.1)
Maternal race [n (%)]			
Non-Hispanic White	227 (24.8)	1848 (32.8)	2075 (31.7)
Non-Hispanic Black	117 (12.8)	362 (6.4)	479 (7.3)
Hispanic	440 (48.1)	2743 (48.7)	3183 (48.6)
Asian/Pacific Islander	83 (9.1)	437 (7.8)	520 (7.9)
Native American/Alaskan	6 (0.7)	11 (0.2)	17 (0.3)
Other	37 (4.0)	169 (3.0)	206 (3.1)
Unknown	5 (0.5)	61 (1.1)	66 (1.0)
Major congenital anomaly [n (%)]	116 (12.7)	1456 (25.9)	1572 (24.0)
Two or more transfers [n (%)]	29 (3.2)	121 (2.1)	150 (2.3)

[1]SD – standard deviation

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Table 2

Originating hospital AAP[1] level versus receiving hospital AAP level

		Receiving Hospital Level			
		1	2	3	4
Originating Hospital Level	1	1	230	1538	2207
	2	23	25	222	338
	3	2	85	289	1587
	4	0	2	40	107

[1] AAP – American Academy of Pediatrics

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Table 3

Overlap between empirical sub-networks and RPPC[1] regulatory regions

Empirical Sub-Network	RPPC Regulatory Region											Percent Mismatch
	Northern California	Northeastern	SF[2] Bay Area	Central Coast	Central Valley	Los Angeles	Southern Inland	Orange County	San Diego	Kaiser North	Kaiser South	
Navy	18	7	1	3	1	0	0	0	0	8	0	53
Yellow	1	27	1	0	0	0	0	0	0	0	0	7
Purple	3	4	11	0	0	0	0	0	0	0	0	39
Brick	1	0	1	16	4	0	0	0	0	5	0	41
Tan	0	1	0	4	19	3	0	0	0	1	0	32
Cyan	0	0	0	0	4	42	0	0	0	0	0	9
Green	0	0	0	0	1	1	32	0	0	0	1	9
Red	0	0	0	0	0	13	0	18	0	0	0	42
Badger blue	0	0	0	0	0	0	2	0	20	0	1	13
Light blue	0	0	0	0	0	7	0	0	0	0	0	0
Grey	0	0	0	0	0	2	0	1	0	0	11	21
Percent Mismatch	22	31	21	30	19	38	6	5	0	43	15	

[1] Regional Perinatal Programs of California;

[2] San Francisco. The darker shaded cells represent hospitals where the empirical and regulatory regions align; the lighter shaded cells represent hospitals that do not. Absence of alignment may be with higher, lower, or equal quality of care delivery, depending on the context and selection of infants transported.

Table 4a

RPPC region of originating versus receiving hospital for all transports

		Receiving Hospital Region										
		Northern CA	North-eastern	SF Bay Area	Central Coast	Central Valley	Los Angeles	Southern Inland	Orange County	San Diego	Kaiser North	Kaiser South
Originating Hospital Region	Northern CA	146	2	10	14	2	0	0	0	0	5	0
	Northeastern	24	555	40	11	8	0	0	0	0	5	0
	SF Bay Area	11	1	240	34	1	0	1	0	0	8	0
	Central Coast	40	0	1	302	11	2	0	0	0	7	0
	Central Valley	5	0	3	45	933	36	15	1	0	1	9
	Los Angeles	0	0	0	5	10	1131	23	91	0	0	28
	Desert	0	3	0	0	0	30	810	56	294	0	7
	Orange County	0	0	0	2	0	34	1	599	1	0	14
	San Diego	0	0	0	0	0	3	1	0	509	0	14
	Kaiser North	26	5	9	9	30	0	0	0	0	152	1
	Kaiser South	0	0	0	0	0	33	39	25	15	0	157

RPPC – Regional Perinatal Programs of California; CA – California; SF – San Francisco

Table 4b

Empirical sub-network of originating versus receiving hospital for all transports

| | | Receiving Hospital Sub-Network | | | | | | | | | | |
		Navy	Yellow	Purple	Brick	Tan	Cyan	Green	Red	Dodger Blue	Light Blue	Slate Grey
Originating Hospital Sub-Network	**Navy**	456	13	33	34	5	0	0	0	1	0	0
	Yellow	8	421	1	9	0	0	0	0	0	0	0
	Purple	7	10	304	8	0	0	1	0	0	0	0
	Brick	28	0	5	386	1	0	0	0	0	0	0
	Tan	3	0	0	41	812	10	3	0	0	0	0
	Cyan	0	0	0	0	41	824	5	18	0	3	32
	Green	0	3	0	0	0	12	823	53	5	3	7
	Red	0	0	0	2	0	38	2	857	1	0	22
	Dodger Blue	0	0	0	0	0	2	53	4	826	0	4
	Light Blue	0	0	0	0	0	15	5	0	0	92	2
	Slate Grey	0	0	0	0	0	17	22	16	1	1	285

Table 5

Infant characteristics associated with transfer within versus out of empirical sub-networks

	Within network (n=6086)	Out of network (n=610)	Total (n=6696)	Odds ratio [95% CI[1]]	P-value
Gestational age, weeks [mean (SD[2])]	36.1 (4.3)	35.8 (4.6)	36.1 (4.3)	0.99 [0.95,1.03]	0.63
Birth weight, grams [mean (SD)]	2705 (989)	2619 (995)	2697 (989)	1.00 [1.00,1.00]	0.71
Male sex [n (%)]	3487 (57.3)	339 (55.6)	3826 (57.1)	0.94 [0.79,1.12]	0.48
Maternal race [n (%)]					
Non-Hispanic White	1,920 (31.5)	205 (33.6)	2125 (31.7)	Reference	
Non-Hispanic Black	436 (7.2)	53 (8.7)	489 (7.3)	1.07 [0.77,1.49]	0.67
Hispanic	2974 (48.9)	276 (45.2)	3250 (48.5)	0.81 [0.67,0.98]	0.03
Asian/Pacific Islander	489 (8.0)	44 (7.2)	533 (8.0)	0.81 [0.57,1.15]	0.24
Native American/Alaskan	16 (0.3)	4 (0.7)	20 (0.3)	2.33 [0.75,7.21]	0.14
Other	195 (3.2)	17 (2.8)	212 (3.2)	0.74 [0.44,1.25]	0.27
Unknown	56 (0.9)	11 (1.8)	67 (1.0)	1.66 [0.83,3.30]	0.15
Major congenital anomaly [n (%)]	1425 (23.4)	203 (33.3)	1628 (24.3)	1.79 [1.47,2.19]	<0.001
Reason for transfer [n (%)]					
Medical/Diagnostic	5237 (86.1)	441 (72.3)	5678 (84.8)	Reference	
Surgery	493 (8.1)	78 (12.8)	571 (8.5)	1.42 [1.08,1.88]	0.01
Insurance	214 (3.5)	85 (13.9)	299 (4.5)	5.13 [3.89,6.76]	<0.001
Bed availability	138 (2.3)	6 (1.0)	144 (2.2)	0.58 [0.25,1.32]	0.19

[1] CI – confidence interval,

[2] SD – standard deviation. Odds ratios obtained using multivariable logistic regression including all the variables shown.