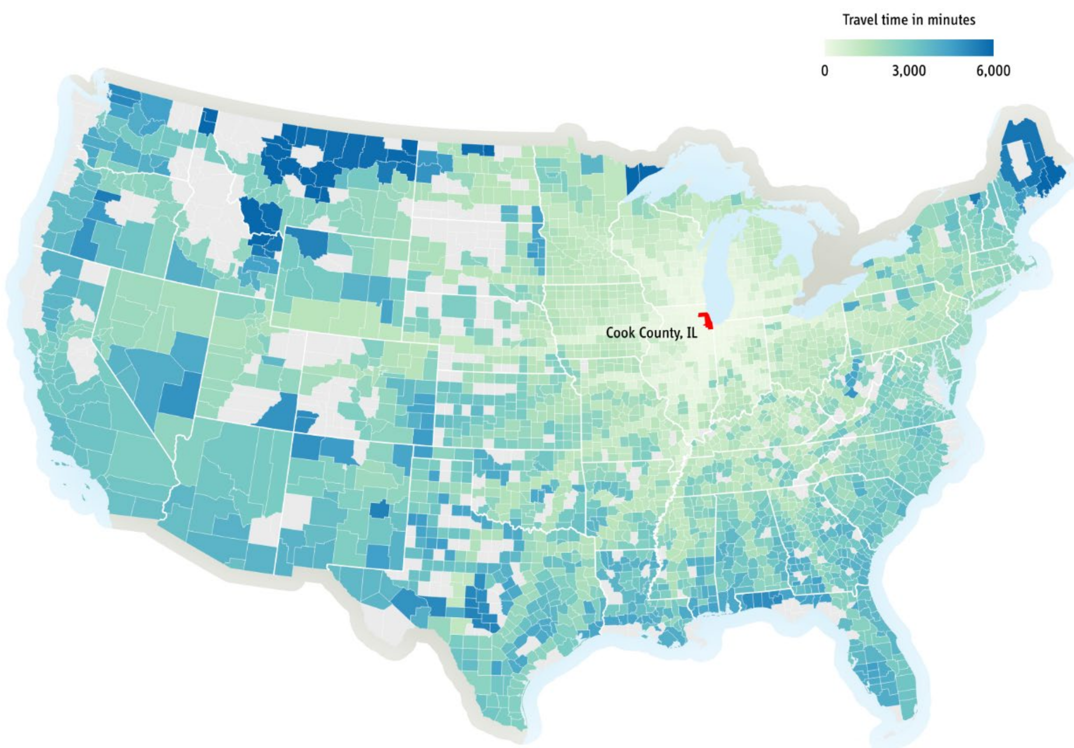
BTS ATRI FREIGHT MOBILITY INITIATIVE: COUNTY-TO-COUNTY TRAVEL TIMES

1. OVERVIEW

Figure 1. Median Travel Times for Freight Trucks Departing Cook County, IL



Source: BTS.
Note: This map illustrates the travel times for all trucks with a minimum of 100 movements (as defined in Section 4).

As part of the Bureau of Transportation Statistics (BTS) American Transportation Research Institute (ATRI) Freight Mobility Initiative (FMI), BTS has developed an experimental product comprising county-to-county travel times for freight trucks. Unlike most web-based navigation tools, which forecast expected travel times between a selected origin and destination, this product estimates travel times by referencing a Global Positioning System (GPS) dataset for a sample of freight trucks that have been moving around the United States since 2018. Because this product is exclusively based on observed truck probe GPS trajectories, BTS can analyze the actual travel experiences of freight trucks and their drivers, reflecting the myriad conditions truckers experience that may affect their mobility.

This product provides an estimated travel time for every county pair in the dataset, describing the directed travel between each unique combination of an origin county and a destination county. Currently, estimates reflect the travel times freight trucks experienced as they moved between counties during 2023, but BTS has commensurate GPS data for other years and, using the methodology described in Section 4, may release the same statistic for other those years or shorter periods.

BTS is planning future iterations of this product that will aim to provide better travel-time estimates with more refined methodologies.

2. SUGGESTED USES

This product could be used for many activities, including the following:

- Estimating actual travel times from one county to another, inclusive of time spent moving, stopped, and in traffic
- Identifying which county pairs were connected by freight truck behavior during the provided period
- Highlighting the travel-time efficiencies provided by major interstates
- Observing the geographic accessibility provided by freight trucking across the Nation
- Showcasing disparities in travel times between county pairs frequently traveled by trucks and county pairs served more irregularly

This tool is not a substitute for exact travel times from specific locations within a given county as it simply reflects the total amount of time between the moment a truck leaves an origin county and enters the destination county. It does not differentiate between time spent stopped versus moving and does not account for travel prior to the origin county's border or beyond the destination county's border.

3. DATA SOURCES

Data sources used to develop this product include the following:

- **Freight Truck GPS Data:** BTS hosts the FMI database of GPS pings collected and provided by ATRI. This database currently features over 345 billion pings, each of which is represented in the database as one row with five core elements: unique, anonymized truck identifier (ID); timestamp; recorded speed; latitude; and longitude. Since October 1, 2018, BTS has been harvesting pings from the freight trucks in ATRI's sample as they travel around North America (i.e., the contiguous United States, Alaska, Hawaii, and 5 miles into Canada and Mexico). This dataset is a subset of freight truck activity in the United States and does not provide information on the type of cargo being transported, purpose of travel, or industry being served. Though these characteristics are unknown, they have potential impacts on the travel times of the trucks observed moving between all prospective county pairs.
- **County Boundaries:** The 2023 Census county boundaries at the 1:5,000,000 scale, from the U.S. Census Bureau [2025], contain polygon representations of the geographic boundaries of all 3,144 counties, parishes (Louisiana), and boroughs (Alaska) in the 50 states and District of Columbia during 2023 (excluded from this study are counties and county-equivalents in American Samoa, Guam, the Mariana Islands, Puerto Rico, and the U.S. Virgin Islands). When BTS adds county-to-county travel-time estimates for other years, it will use the Census county boundaries for the corresponding years and note the year of the geographic unit and/or shape within the downloadable dataset.

4. METHODOLOGY

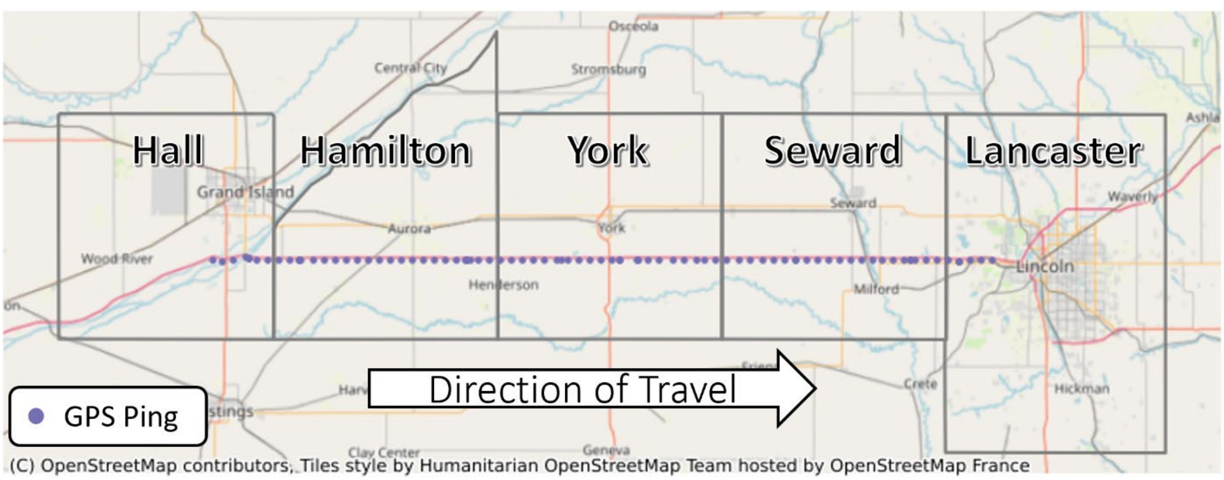
Section 4.1 through Section 4.5 describe BTS' methodology for measuring the travel times represented in this experimental product. Accumulated travel time was measured between the last recorded ping before a truck left a county and the first recorded ping after a truck entered another county regardless of whether the truck made a stop along its trajectory.

Every instance of a truck traveling between two counties is hereafter referred to as a "movement." Each movement produced a travel time, and the collection of these travel times for any given county pair can be aggregated or summarized to provide travel-time estimates based on all instances of trucks observed moving between those two counties.

BTS uses the term "movement" in lieu of the term "trip" as the latter carries larger meaning within the realm of transportation planning that presupposes a stop event (i.e., a cluster of consecutive GPS points from a single truck that remains relatively stationary over a set period) demarcating the origin and destination of a given travel time. In contrast, movements only look at elapsed time between spatially designated pings regardless of whether those trucks were stopped or moving along the way.

To aid in explaining this methodology, Figure 2 illustrates a sample trajectory that showcases the steps used to identify county-to-county movements. In this example, the GPS pings representing the trajectory of a freight truck start in Hall County, NE, and then drive eastward toward Lancaster County, NE, passing through three other Nebraska counties (Hamilton, York, and Seward) along the way. Once pings were assigned to their respective counties, the next step was to build pairs of county exit and entry events. For each truck and for each county visited, the first (entry) ping and last (exit) ping were identified. If a single truck entered and left the same county multiple times, that travel was considered multiple, distinct visits, each with its own first and last pings.

Figure 2. Trajectory of a Freight Truck's GPS Pings



Source: OpenStreetMap, modified by BTS.

4.1. Step 1: County Assignment

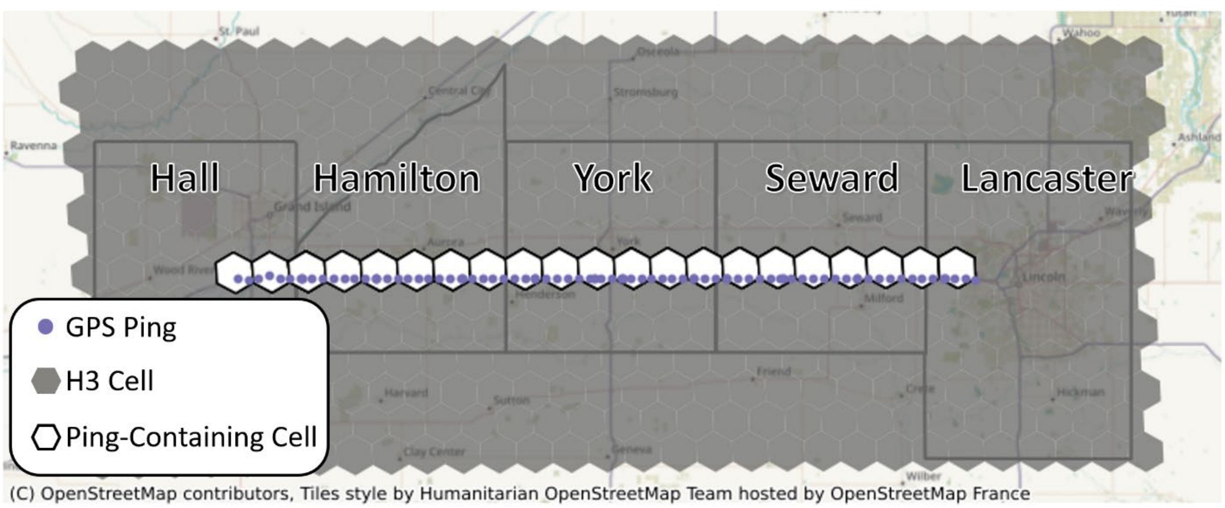
To begin the process of estimating county-to-county travel times, each ping along a truck's trajectory was assigned to a county. To optimize the assignment of pings to counties at scale, the project team used Uber's Hexagonal Hierarchical Spatial Index (H3) tiling [Brodsky 2018].

All pings were assigned to H3 cells based on their latitude and longitude coordinates, and counties were assigned H3 cells based on overlap, referencing their boundaries as defined by the Census Bureau for the corresponding year. Matching features with H3 cells can significantly speed up any spatial matching in comparison to traditional spatial joins (one paper found it reduced computation costs by 40 to 90 percent [Marten, Johns, Karavelas 2022]). While spatial accuracy decreased with hexagonal tiling because county boundaries do not align perfectly with H3 cells, the net computational efficiency gained from the H3 architecture outweighs data losses (i.e., the precision loss from using the predesignated cell boundaries and not directly using ping coordinates) when working with a database as large as BTS' FMI.

For these county-to-county estimates, BTS used a base H3 resolution of 8, which tiled the world into hexagonal cells approximately 0.28 square miles (0.73 square kilometers) in size and was further optimized by using H3's compact feature function to make joins more computationally efficient.

Figure 3 illustrates how the counties and pings from Figure 2 were assigned to H3 cells. Each ping was assigned to a county and corresponding H3 cell.

Figure 3. Example H3 Cell Tiling



Source: OpenStreetMap, modified by BTS.
Note: For illustration purposes, this visualization uses cells with a resolution of 6. They are approximately 49 times as large as the resolution 8 cells nested inside them.

4.2. Step 2: Exits and Entries

After assigning each ping to a county using H3, the pings comprising each truck's trajectory were separated by truck ID and ordered by time (as shown in Table 1). Once sorted, each ping record was compared to its immediately preceding and succeeding records to see if the assigned county changed.

Table 1. Timestamped Pings by Location

Truck ID	Ping	Timestamp	County	Exit	Entry
1234	1	1/1/2023 11:00	Hall	N	N
1234	2	1/1/2023 11:05	Hall	N	N
…	…	…	…	…	…
1234	46	1/1/2023 11:58	Hall	N	N
1234	47	1/1/2023 12:00	Hall	Y	N
1234	48	1/1/2023 12:01	Hamilton	N	Y
…	…	…	…	…	…
1234	63	1/1/2023 12:21	Hamilton	Y	N
1234	64	1/1/2023 12:22	York	N	Y
…	…	…	…	…	…
1234	84	1/1/2023 12:42	York	Y	N
1234	85	1/1/2023 12:43	Seward	N	Y
...	...	...	...	...	...
1234	104	1/1/2023 13:02	Seward	Y	N
1234	105	1/1/2023 13:03	Lancaster	N	Y
...	...	...	...	...	...

Y = Yes; N = No.
…Rows skipped to emphasize GPS pings immediately before and after the truck crossed a county boundary.

If consecutive pings were identified as being in different counties, the second ping record was categorized as the entry event for that vehicle into that county. For example, Table 2 summarizes just the entry events observed in Table 1.

Table 2. Entry Events

Truck ID	County	Entry timestamp
1234	Hamilton	1/1/2023 12:01
1234	York	1/1/2023 12:22
1234	Seward	1/1/2023 12:43
1234	Lancaster	1/1/2023 13:03

Meanwhile, the ping record preceding each entry event (i.e., the last ping in a county before the first ping in another county) was categorized as an exit event for that truck.

Beyond noting the timestamp of each truck's exit from a county, an additional column was created to note prospective times of reentry. The reentry value defaulted to 9999-12-31 23:59:59 and was either updated with the time the truck reentered the county or remained in place for those that never made a return visit.

Reentry timestamps were important because each was the upper-bound timestamp to look for a truck's entry events into other counties before coming back to the county it just departed. In other words, this timestamp was a bounding window in which the algorithm looked for other county visits, especially those that may have had a significant impact on the overall travel-time estimation process (i.e., avoided double-counting when the same exit event could be attached to repetitive reentry events in the same county).

Ultimately, the purpose of collecting entry and exit events was to build a master list of all county-pair movements made by the trucks in the FMI database. The elapsed times represented by these movements are all a function of the cumulative time between specified pairs of entry and exit events.

To aid with computation, entry and exit events were saved as separate tables (i.e., Table 2 and Table 3).

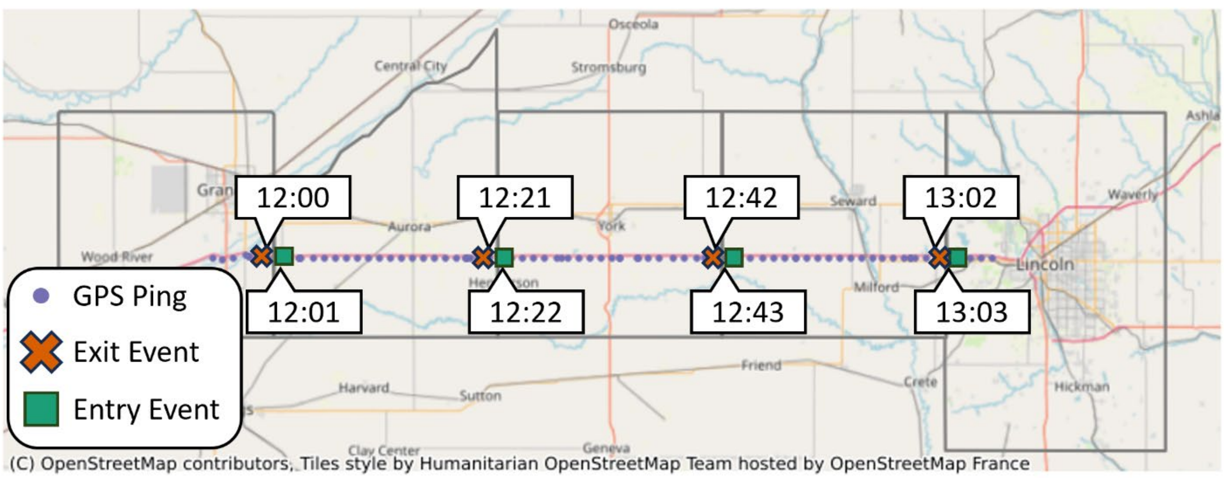
Table 3 summarizes a sample of exit events.

Table 3. Exit Events

Truck ID	County	Exit timestamp	Upper-bound timestamp
1234	Hall	1/1/2023 12:00	12/31/9999 23:59
1234	Hamilton	1/1/2023 12:21	1/7/2023 19:57
1234	York	1/1/2023 12:42	2/5/2023 8:32
1234	Seward	1/1/2023 13:02	1/2/2023 6:02

Figure 4 illustrates the results of detecting exit and entry events using the same example trajectory through Nebraska as Figure 2.

Figure 4. Exit- and Entry-Event Detection



Source: OpenStreetMap, modified by BTS.

4.3. Step 3: Crossings and Travel Time

After identifying the exit and entry events, the associated event tables were joined for each truck, linking each county entry event with a preceding exit event that took place between the time that truck left a prior county and the upper-bound timestamp for the country it just entered.

Table 4 shows example exit and entry events in one table.

Table 4. Combined Entry and Exit Events

Truck	County	Entry time	Exit time
1234	Hall	—	12:00
1234	Hamilton	12:01	12:21
1234	York	12:22	12:42
1234	Seward	12:43	13:02
1234	Lancaster	13:03	—

—Not applicable.

For any movement between two counties, the elapsed travel time was calculated simply as the difference between the exit timestamp from the former county and the entry into the latter.

Once joined, this table was filtered down so that, for each exit event, only the first entry event into each subsequent county was considered, a step that eliminated indirect or duplicative movements that were incongruent with this product's goal of capturing intended travel between two counties. For example, if a truck departed County A, entered County B, entered County C, and then returned to County B, the only A–B movement with a counted travel time would be the initial crossing from A into B (not the time that elapsed between the initial departure from A and the second arrival in B, which could have been interpreted as an A–B movement otherwise).

The contents of Table 5 and Table 6 further illustrate the ways county-to-county movements were extracted from trucks' entry and exit timestamps. Table 5 illustrates the combinations of movements that could have been logged from a sample truck trajectory, while Table 6 summarizes the number of movements attributed to each county pair produced by the truck.

Table 5. Example of County Pairs and Crossings

Visited counties	A	B	A	C	D	A	C
Enumerated county visits	1st visit to A	1st visit to B	2nd visit to A	1st visit to C	1st visit to D	3rd visit to A	2nd visit to C
Movements	A1*	B1**	—	—	—	—	—
	—	B1*	A2**	—	—	—	—
	—	B1*	—	C1**	—	—	—
	—	—	A2*	C1**	—	—	—
	—	B1*	—	—	D1**	—	—
	—	—	A2*	—	D1**	—	—
	—	—	—	C1*	D1**	—	—
	—	—	—	C1*	—	A3**	—
	—	—	—	—	D1*	A3**	—
	—	—	—	—	D1*	—	C2**
	—	—	—	—	—	A3*	C2**

*Exit event that kicked off a captured county-pair movement (also indicated by orange shading).
**Entry event ending a county-pair movement (also indicated by green shading).
—Not applicable.

Table 6. Example of County Pairs and Crossings Collected

County pair	Movements	Exit–entry event combinations
A–B	1	A1 to B1
A–C	2	A2 to C1 A3 to C2
A–D	1	A2 to D1
B–A	1	B1 to A2
B–C	1	B1 to C1
B–D	1	B1 to D1

Table 5 shows the different and sometimes complicated ways a multicounty truck trajectory can produce travel-time estimates for multiple county-pair movements (including, of course, return visits to counties the truck previously encountered). More specifically, it shows all the exit and entry events produced by a truck along its trajectory (a truck starts in County A before going through Counties B, A, C, D, and A before ending back in C), illustrating all the measurable county-to-county movements.

While this truck produced movements each time it crossed a border (A1–B1, B1–A2, A2–C1, C1–D1, D1–A3, and A3–C2), it also produced five county-pair movements for nonadjacent counties (B1–C1, B1–D1, A2–D1, C1–A3, D1–C2), where the trajectory passed exclusively through a series of unique counties before returning to one it had previously exited.

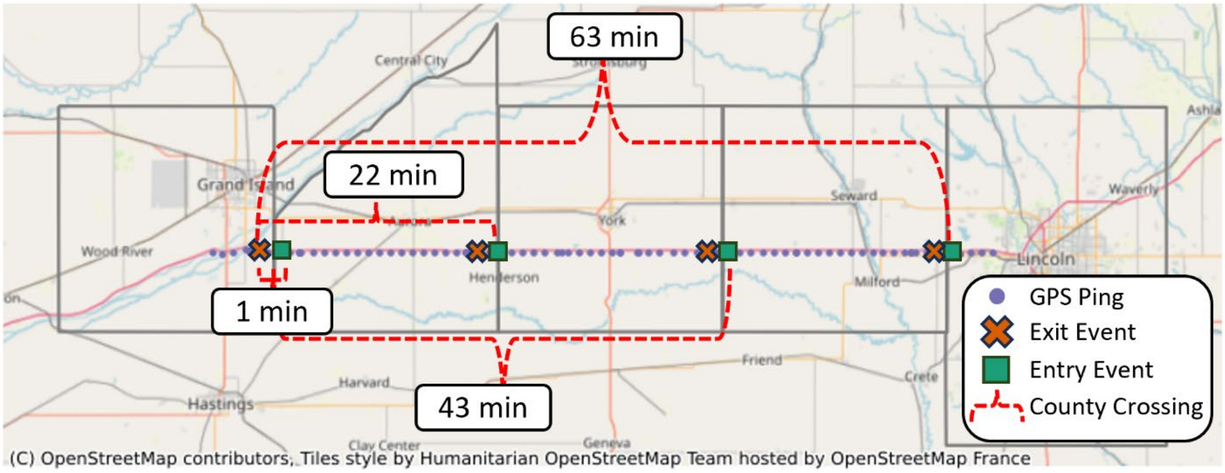
Conversely, Table 5 also shows several examples of how a captured movement ended once that truck returned to a prior county. For instance, exit event, A1, has only one corresponding entry event, B1, because that truck immediately returned to County A. While this return movement (B1–A2) produced a standalone travel-time estimate, all subsequent movements for that truck from County A were based on its second exit event. In this instance, BTS is presuming that the second movement from County A was made with different intention than the first movement and, therefore, each subsequent movement should be considered separately.

Another illustration of how one trajectory can produce multiple movements is the subcomponent of this truck's journey that took it through Counties B, A, C, and D, which produced six total movements. Beyond the three moves logged as this truck moved over the three adjacent boundaries (B1–A2, A2–C1, and C1–D1), it simultaneously produced three qualifying movements for the three nonadjacent county pairs (B1–C1 via A, A2–D1 via C, and B1–D1 via A and C). Because this method does not care what the truck did in a county (it could have made a stop in A between B1 and C1 or driven through A and C without stopping while going from B to D), each of these county-pair movements and their corresponding exit-to-entry elapsed travel times were treated and logged equally.

Table 6, which summarizes the number of movements logged for each county pair by this truck over its trajectory, shows how one journey produced more than one valid travel-time estimate for the same county pair (A–C produced two moves: A2–C1 and A3–C2).

Figure 5 demonstrates how this movement-detection logic would be applied to the same Nebraska example depicted in Figure 2–Figure 4.

Figure 5. Movement Detection Example



Source: OpenStreetMap, modified by BTS.

In this instance, Hall County, which is the furthest west, was the origin county (akin to County A in the Table 5 example). Because the truck subsequently passed through four other counties (Hamilton, York, Seward, and Lancaster), it automatically registered four travel times for the four corresponding movements from Hall County (the four callout boxes in Figure 5). In each case, the county-pair travel time was the difference in time between the Hall County exit event and the entry event into each subsequent county (the times underlying these calculations are in the first four rows of Table 7).

The following are the four movements originating from Hall County:

1. Hall to Hamilton
2. Hall to York
3. Hall to Seward
4. Hall to Lancaster

While Hall County was the origin of this entire trajectory and Lancaster County was the destination, the same truck produced the following six travel times, which correspond to the additional county pairs formed by the three counties it passed through on its way to its ultimate destination in Lancaster (Hamilton, York, and Seward):

1. Hamilton to York
2. Hamilton to Seward
3. Hamilton to Lancaster
4. York to Seward
5. York to Lancaster
6. Seward to Lancaster

This list includes several movements for nonadjacent counties that qualified because the truck had not first doubled back into a county it had already visited. All 10 county-pair movements were counted in this product even though the truck may not have actually stopped in the interceding counties.

Table 7 lists all the county-pair movements produced by this truck along its trajectory, including the exit- and entry-event times that bookended each of those movements and produced a subsequent travel-time estimate.

Table 7. All County-Pair Movements

Origin county	Exit time	Destination county	Entry time	Travel time
Hall	12:00	Hamilton	12:01	1 minute
		York	12:22	22 minutes
		Seward	12:43	43 minutes
		Lancaster	13:03	63 minutes
Hamilton	12:21	York	12:22	1 minute
		Seward	12:43	22 minutes
		Lancaster	13:03	42 minutes
York	12:42	Seward	12:43	1 minute
		Lancaster	13:03	21 minutes
Seward	13:02	Lancaster	13:03	1 minute

Travel times between neighboring counties are typically low as they are often just the difference in time between the consecutive pings produced on either side of a boundary. Given that most trucks in the BTS FMI database produce a ping once every minute, this value is approximately 1 minute for most of these pairs. As such, the travel-time estimates for neighboring county pairs are not fully representative of all hypothetical travel times between all parts of the two neighbors (e.g., using Figure 5 as an example, trucks originating at the far western end of Hall County and arriving at the eastern end of Hamilton County, its eastern neighbor, would still produce a travel time of 1 minute even though complete trajectory was longer).

Relatedly, users should note—for lengthier trajectories in which trucks enter and exit the same counties repeatedly—only the travel time from the first unique movement along that county pair was recorded.

Referencing Figure 5, if the same truck were to depart Hall County and sequentially enter Hamilton and York, it would produce travel times for three county pairs:

1. Hall to Hamilton (1 minute)
2. Hall to York (22 minutes)
3. Hamilton to York (1 minute)

If that truck were to then reenter Hamilton County from York County, it would not produce a second movement from Hall County to Hamilton County (i.e., Hall to Hamilton to York to Hamilton). Instead, it would only produce one new movement, from York County to Hamilton County (likely also 1 minute). If the truck were to return to Hall County—the original start of its trajectory—in the future and then make a subsequent trip back into Hamilton or York, the travel times for all these new movements would be counted.

Future iterations of BTS' county-to-county travel-time product will aim to advance this methodology to capture travel times from neighboring counties with greater nuance, especially vis-à-vis detection and utilization of truck stop events.

Once all county-pair movements were identified across all full truck trajectories in the FMI database in 2023, their travel times were saved into a new table alongside the unique ID of the truck that produced each movement.

4.4. Step 4: Cleaning

Given that summarizing the travel times detected by this method is vulnerable to skew by trucks with highly irregular trajectories, data-cleaning procedures (described in Section 4.4.1 and Section 4.4.2) were performed to remove erroneous or inflated travel-time estimates, especially when the trajectories in question did not represent direct or intentional travel between a given county pair.

More explicitly, the adopted procedures targeted movements with travel times clearly affected by extremely long, indirect, or circuitous trajectories to remove travel-time estimates that were not appropriately comparable against those produced by trucks making intended, direct travel between those counties.

4.4.1. Method 1: Removal of GPS Noise

The initial set of travel times produced from the methodology (Section 4.1 through Section 4.5) included clear (albeit rare) instances of inaccurate travel times due to GPS noise: Truck routes with long gaps between consecutive pings (spatial and/or temporal) were inadvertently measured as single trajectories with implausibly short travel times (i.e., time-sequential GPS pings were hundreds of miles away from each other in a short period, resulting in an impossibly high calculated speed).

Trajectories producing these erroneous travel-time estimates were filtered out by removing all pings that had—relative to their preceding ping—a calculated Haversine Distance of over 1 mile and a calculated speed over 100 mph.

To prevent overcorrecting, both conditions had to be present to remove a ping since they can both occur on their own without indicating an error. For example, GPS pings are inherently noisy, and two consecutive pings with little time in between (e.g., 1 second) can lead to an exceptionally high calculated speed despite a nonsignificant change in distance.

Similarly, a lengthy temporal gap by itself is very plausible whether accompanied by a short or long spatial gap. The former would happen anytime a truck does not move from a single spot over a prolonged period, and the latter would occur if a truck made a movement at a standard speed but only pinged its location at the start and end of its move (i.e., if the temporal gap between these two pings is equivalent to the time it would have taken to make that movement, the calculated speed would not look out of the ordinary).

An example from the FMI data is when a truck departed one part of the United States into Canada and then reentered the country somewhere else; while the database did not log the pings from its trajectory inside Canada, the time and distance between its U.S. exit and entry events would not appear out of the ordinary.

Removing GPS noise ultimately dropped just 2.9 percent of the FMI pings from 2023, leaving 97.1 percent of the data available for further movement detection. While the underlying causes for these jumps in the data are not fully understood (potentially an artifact of the technology that produces these pings), this approach preserves most of the initially calculated travel-time data.

In future iterations of this product, an alternative approach to handling these jumps, when they are noticed, could be segmenting truck trajectories to isolate these anomalous data points. In these situations, the original trajectories would produce two or more new isolated subtrajectories belonging to the same individual truck, allowing BTS to use the data points contributing to that trajectory instead of having to throw them out as erroneous.

4.4.2. Method 2: Stop Detection

A second method of cleaning movement travel times hinged on stop events. While stops are not a central component of this product's county-pair travel-time algorithm, they were nonetheless helpful for breaking apart lengthy, indirect trajectories. Fang, et al. [2018], who attempted to identify trips and activities based on GPS observations, provide a model for breaking a truck trajectory into a subset of chained trip and stop events.

First, a stop-detection algorithm [Holguín-Veras, et al. 2020] was used to identify stops within each truck's trajectory. For this application, stops were defined by examining the pings from a truck within a rolling window of time, looking for a specified set of conditions assumed to characterize a truck that has paused its movement (based on a combination of calculated velocity, acceleration, and the length of time the truck's pings exhibited these conditions) for a deliberate reason within an allowable distance.

One modification was added to further group stop events, if they occurred, in spatiotemporal proximity of one another.

Table 8 contains the parameters used to identify stops.

Table 8. Parameters for Stop Identification

Parameter	Value
Time window	300 seconds
Velocity ceiling	5 mph
Acceleration ceiling	8.7 mi/h^2
Dwell minimum time	300 seconds
Dwell maximum distance	0.5 miles
Phase time allowance*	900 seconds
Phase distance allowance*	0.5 miles

*These parameters belong to modifications added to the original stop detection algorithm.

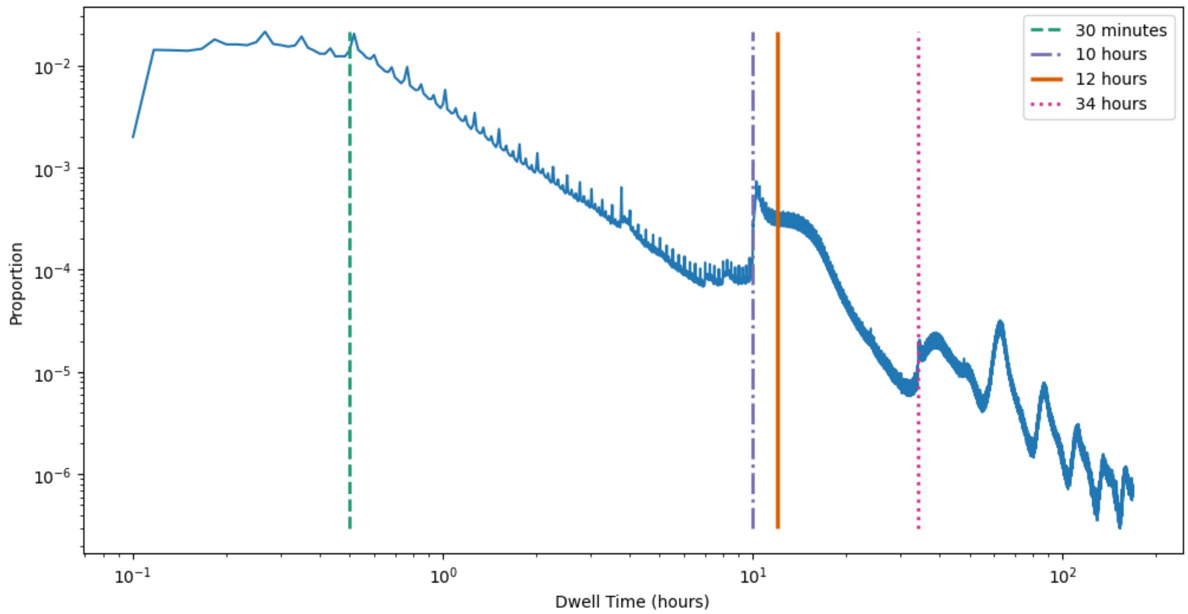
This approach initially identified over 260 million stops among the GPS trajectory data for 2023.

4.4.2.1. Long Stops Determination

A challenge with using a travel-time estimation approach centered on elapsed time, rather than on trip and stop events in corresponding counties, was that exceptionally long trajectories produced commensurately long lists of visited counties, especially if a trajectory persisted for over a month. In turn, such a lengthy trajectory, which presumably captures many intentional and direct trips, may cross hundreds, if not a thousand or more, counties in one year, with each corresponding county-pair movement producing its own travel-time estimate. Some of these county-pair movements, especially between uncommonly linked counties, may only incidentally be linked (i.e., not because of deliberate travel between them but because the truck completed two unrelated tours that happened to visit the counties in question).

Long stop events helped unlink disassociated, unrelated components of lengthy or circuitous trajectories while preserving the subcomponents that should be kept together. Yang, et al. [2022] provide a methodology to follow, whereby the dwell time for each collected stop event was bucketed into minute intervals, and the proportion of all stop events that fell into each bucket was plotted out (Figure 6).

Figure 6. Dwell Time and Proportion



Source: BTS.
Note: Dwell times greater than a week (>168 hours) are omitted.

As noted by Yang, et al., this approach doubles for detecting inflection points in truck drivers' stopping behaviors, illustrating the characteristics that separate short-, moderate-, and long-duration stops and providing a data-driven approach for classifying the longer stops that typically bookend a truck trip. In fact, the local peak for stops 10 hours long (a long stop that commonly dictates a trip end) aligns with Federal Motor Carrier Safety Administration (FMCSA) regulations that require truck drivers to take a 10-hour break after driving for a consecutive 14 hours [2022].

To capture long-distance movements (and not subdivide them prematurely), a 12-hour inflection point served as a trajectory-breaking parameter. Any trajectory with a stop over 12 hours (i.e., a "long stop") was split into two; all pings after this break were considered independent of those preceding the break, resetting the chain of county pairs for that given truck (all subsequent county entry events that occur after this stop event and any prior county exit events will not be accounted for in this subtrajectory).

In addition to the 14 hours of driving followed by a 10-hour stop pattern observed in the data (i.e., trucks conforming to FMCSA regulations), other patterns echoed additional FMCSA [2022] regulations. Examples include a required 30-minute break when driving a cumulative 8 hours and 34 consecutive hours off duty required after hitting a 60-hour limit in 7 consecutive days or a 70-hour limit in 8 consecutive days.

4.4.2.2. Handling Nondirect Routes

The original travel-time methodology outlined in Section 4.3 can be skewed by nondirect or circuitous routes that would otherwise inflate average travel times on given county pairs by improperly grouping unrelated, distinct movements that do not adequately reflect the intentional, directed travel between a county pair intended for representation in this product. In other words, even though travel times between two counties may vary for many reasons (e.g., business practices, truck driver choices, congestion, infrastructure, and logistic inefficiencies, need to stop for rests and gas), comparing incidental connections between two counties against those that appear intentional does not make sense.

To illustrate how indirect routes could be generated and inflate travel times for a given county pair, consider a truck that embarked on a tour from Wayne County, MI (Detroit), that subsequently headed into Canada and reentered the United States in Maine. In this instance, the methodology would produce a county-pair crossing between their respective exit and entry counties in Michigan and Maine (which are obviously nonadjacent). If the same truck was to then proceed from Maine to Cook County, IL (Chicago), it would generate county-pair movements not only from the county in Maine and Cook County (alongside the dozens of other counties encountered between the two) but also vis-à-vis Wayne County (as the movement from Michigan-to-Maine would otherwise still be seen as a valid link in that full trajectory). While the Maine-to-Cook County travel times would all be reasonable, the travel times from Wayne County to Cook County would all be likely be much higher than the travel times of movements made more directly between the two.

Without taking precautions to clean (and therefore split) this single trajectory, these Wayne County–Maine–Cook County travel times could substantially skew the measures of central tendency taken across the full set of Wayne County–Cook County movements observed from all trucks across 2023. While instances of these sorts of indirect routes are common (especially with less frequented counties due to fewer direct routes and tours existing), failing to account for them in any capacity would lead to travel-time estimates that stray excessively from the reality of travel between the two entities, especially when the goal is to represent travel time on directed, intentional travel between each county pair.

Several methods were implemented to deal with this concern and segment these trajectories into more meaningful county pairs, each involving the upper-bound timestamp assigned to each county exit event. Initial trials replaced the upper-bound timestamp placeholder value (9999-12-31 23:59:59) with one of the following values:

- A maximum of 14 days after the exit-event timestamp (i.e., if the exit event took place at 2023-01-01 12:00:00, the new upper-bound timestamp would be set to 2023-01-15 12:00:00)
- The next time that truck reentered that same county
- The timestamp of the truck's next long stop (i.e., a stop over 12 hours)

A combination of these methods was applied to every exit event, with the final upper-bound timestamp being set to whichever of these produced the minimum value.

Table 9 shows some instances in which the upper-bound timestamp was modified under one of these rules.

Table 9. Adjusted Exit Table

Truck ID	Exit county	Exit timestamp	Reentry timestamp	14 days ahead	Next long stop	Minimum of upper-bounds
1234	A	1/1/2023 0:00	1/2/2023 6:00	1/15/2023 0:00	1/15/2023 17:00	1/2/2023 6:00
1234	B	1/1/2023 1:30	1/1/2023 19:00	1/15/2023 1:30	1/15/2023 17:00	1/1/2023 19:00
1234	C	1/1/2023 3:30	1/17/2023 16:00	1/15/2023 3:30	1/15/2023 17:00	1/15/2023 3:30
…	…	…	…	…	…	…
1234	A	1/2/2023 6:00	12/31/9999 23:59	1/16/2023 6:00	1/15/2023 17:00	1/15/2023 17:00
…	…	…	…	…	…	…

…Rows skipped to emphasize exit events affected by the methodology to clean nondirect trips.

4.5. Step 5: Final Output and Modifications

Once all county-pair movements were identified from the GPS ping trajectories in the FMI database for 2023 and the resultant travel times estimated, three percentiles (25th, 50th, and 75th) were identified to summarize all the movements between each pair.

Table 10 provides an example row of the resultant table, which has one row for each directional county pair.

Table 10. Sample Row

Exit county	Entry county	Observed movements	25th-percentile travel time	50th-percentile travel time	75th-percentile travel time
A	B	10K-100K	35 minutes	43 minutes	52 minutes

To protect the confidentiality of the businesses operating the trucks represented in the FMI database, the following steps were taken:

1. Any county pair with fewer than 100 movements identified within this dataset was dropped.
2. The count of movements between each pair were binned into five groups based on powers of 10 (100–1,000, 1,000–10,000, 10,000–100,000, 100,000–1,000,000, and over 1,000,000). These movements are what was observed and captured through the methodology and do not represent every truck movement between each county pair.

While the first step dropped 56 percent of the summarized county pairs in the United States, the remaining pairs nevertheless represent 99 percent of the underlying, individual county-to-county movements, illustrating that most truck activity happens between a subset of all county pairs.

These travel-time estimates provide a baseline value for referencing the amount of time it takes freight trucks to travel between a provided county pair directly and intentionally when compared to pairs from other parts of the country. They also reveal patterns related to the directness of the routes taken between each county pair and the relative impact of stop events along their journeys.

Imbalances have been detected in movements observed and travel-time percentiles obtained when comparing A–B to B–A county pairs. In general, correlations between the directional movements observed are 0.99, 0.95, 0.93, and 0.91 for the 25th-percentile, 50th-percentile, and 75th-percentile time-travel estimates, respectively. However, some county pairs have their calculated metrics several magnitudes off in comparison to their opposite direction. Some part of this effect could be attributed to misaligned trajectory segmentation, freight flow practices, tour routing, and truck-infrastructure differences, but this imbalance can be further explored.

5. LIMITATIONS

The following are limitations of the methodology used to estimate the county-to-county travel times featured in this product:

- Neighboring-county travel times will often be short as time is measured based on the exit ping in the origin county and the entry ping in the destination county (i.e., merely the average ping frequency of a truck's GPS logger). Nevertheless, the travel-time estimates for neighboring counties are helpful in understanding the range of the volume of movement as well as revealing the county pairs with higher-than-expected median travel times (potentially showcasing either an unpopular trucking route or a lack of suitable trucking infrastructure).
- Many indirect and circuitous routes remain in the data despite attempts to avoid them, skewing the measures of central tendency of the estimated travel times.
- Gaps in all possible county pairs exist if enough crossings are not observed between them, providing an incomplete visual and analysis.
- The truck GPS probe data used do not include every freight truck, and biases may exist in the geographic coverage, industry, and types of freight being included that will differ from reality.

6. NEXT STEPS

The following sections outline future steps that could enhance and extend the travel-time estimates contained in this product.

6.1. Stop-Oriented Travel Times

Incorporating stop events into the methodology may provide more accurate travel-time estimates as they more closely align with activity that is based on trip purpose. For example, if a truck's trip between two counties is bookended with a stop of significant length, researchers can be more certain that travel was intended between that pair of counties.

All the while, looking only at travel between stops raises data-privacy concerns as it inherently reduces the number of identifiable movements between counties, especially for rural counties where there may only be a single business or establishment to which a truck could make a meaningful stop, thereby indirectly revealing that business' operations.

A potential workaround would merge this method with stop information in a way that preserves data anonymity. This approach, for instance, could handle trucks passing through a county without stopping (omitted for a stop-based method but included with this movement-based method). The timestamps of its entry and exit events would be averaged to produce an approximated event time that could be more comparable with approximated stop events in other, busier counties. For these stops, the first ping of the first stop within the county could be considered the entry-event time, and the last ping of the last stop within that county could be considered the exit-event time. Under this method, all travel-time estimates would use these new event times instead of the more simplistic entry and exit times used here.

6.2. Land-Use Data

Beyond incorporating stops, a future approach could also ingest land-use data. These data can help identify the industry or activity that produced a given trip and contextualize travel-time estimates when relevant, especially if they are affected by the type or category of freight carried by the truck, the purpose of its trip, or the locations where it parks, stops, or takes rest. In particular, identifying trip purpose and differentiating stops between ones that end trips and ones that are along trips through land-use data can greatly aid in segmenting trajectories.

7. FEEDBACK AND CONTACT US

Please contact the BTS ATRI FMI inbox to provide feedback or suggestions. We seek to improve upon this work to provide more accurate, nuanced travel-time estimates of county-to-county freight trucking throughout the United States.

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8. REFERENCES

Brodsky, Isaac. 2018. *H3: Uber's Hexagonal Hierarchical Spatial Index*. Washington, DC: Uber Blog. H3: Uber's Hexagonal Hierarchical Spatial Index | Uber Blog. Last accessed May 22, 2025.

Census. 2025. "2023, Cartographic Boundary Files by Scale," *Cartographic Boundary Files*. Washington, DC: U.S. Census Bureau. https://www.census.gov/geographies/mapping-files/time-series/geo/cartographic-boundary.2023.html#titlecore-c6fb02ef61. Last accessed May 22, 2025.

Fang, Zong, Lv Jian-yu, Tang Jin-jun, Wang Xiao, and Gao Fei. 2018. "Identifying activities and trips with GPS data," *IET Intelligent Transportation Systems*, 12, no. 8, pp. 884–890. Hertfordshire, England: Institute of Engineering and Technology. https://doi.org/10.1049/iet-its.2017.0405. Last accessed May 22, 2025.

FMCSA. 2022. *Summary of Hours of Service Regulations*. Washington, DC: Federal Motor Carrier Safety Administration. https://www.fmcsa.dot.gov/regulations/hours-service/summary-hours-service-regulations. Last accessed May 22, 2025.

Holguín-Veras, José, Trilce Encarnación, Sofía Pérez-Guzmán, and Xia (Sarah) Yang. 2020. "Mechanistic Identification of Freight Activity Stops from Global Positioning System Data," *Transportation Research Record*, 2674, no. 4, pp. 235–246. Thousand Oaks, CA: Sage Journals. https://doi.org/10.1177/0361198120911922. Last accessed May 22, 2025.

Marten, Kent, Michael Johns, and Menelaos Karavelas. 2022. *Spatial Analytics at Any Scale With H3 and Photon: A Comparison of Discrete, Vector, and Hybrid Approaches*. San Francisco, CA: Databricks Blog. https://www.databricks.com/blog/2022/12/13/spatial-analytics-any-scale-h3-and-photon.html. Last accessed May 22, 2025.

Yang, Yitao, Bin Jia, Xiao-Yong Yan, et al. 2022. "Identifying intercity freight trip ends of heavy trucks from GPS data," *Transportation Research Part E: Logistics and Transportation Review*, 157. Amsterdam, Netherlands: Elsevier. https://www.sciencedirect.com/science/article/pii/S1366554521003458. Last accessed May 22, 2025.

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