American University

Using Time-Series Data to Measure the Impact of the Silver Line Phase 1 Expansion on Commuter Behavior

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Abstract:

Metropolitan commuting and the infrastructure built to support the flow of traffic in and out of major urban hubs like Washington D.C. impact the lives of millions, and have an impact on the economic, social, and environmental makeup of the places we live and work. Much research has been done on the impact of transit in a time where commutes are increasing as urban development spreads out.

The main goal of this research is to use time series data from the American Communities Survey to build a difference-in-differences regression model predicting the impact that the opening of the 11 mile Silver Line Phase 1 Expansion of the WMATA Metro had on commuting behaviors in a select set of census tracts surrounding the rail expansion. While gaps in ACS reporting limit my ability to present statistically significant models, my research askes compelling questions that, given a series of transit expansions currently under construction in the Greater Washington Area, deserve continued exploration.

Keywords: Commuting, Difference-in-Differences Testing, Silver Line, WMATA Metro, Spatial Data, United States Census, American Communities Survey, Commuter Behavior, Case Study

1. Introduction:

In July of 2014, Phase 1 of the Washington Metropolitan Area Transportation Association's (WMATA) Silver Line expansion welcomed its first riders. More than 20 years in the making, these five new metro rail stops, stretching 11.4 miles in length, open up a new transit corridor in Northern Virginia (Berkowitz & Chow, 2014). In a list of enumerated goals, WMATA hoped to promote local development in the area surrounding each metro stop and based revenue calculations on ridership eclipsing 1,500 daily active commuters at each of the five new stops.

Ultimately, massive infrastructure projects like the Silver Line, with a preliminary cost of $2.9 billion for the first half of the line alone, alter the communities that surround them (WMATA, Silver Line, 2015). Examining the impact of large-scale infrastructure projects and developing tools and metrics which support such research, are crucial components to informed large-scale urban planning. Without meaningful independent research into the impact of past transit improvements, civic organizations and local government leaders are forced to rely solely on reporting from the transit system operators themselves, whose reporting is often clearly skewed to support their project and its commercial value.

My work, which examines the impact of Silver Line Phase 1 on local communities based on ridership growth and changes to household income, contributes to a body of research grounded in analyzing the broader effects of transit infrastructure on communities and neighborhoods. While some researchers focus on broad trends in the economic, social, and environmental impacts of communities impacted by large commuting flows, others seek to explore how specific projects and/or policies impact the behavior of local residents in an attempt to measure a project's financial value. Prior researchers vary in their methods and purpose. They use datasets that vary in the length of their time series data between 5 years and 30 years, and while most researchers rely on government-collect census data, some count on ridership data reported by the agency in charge of the operation of the transit system in question. All in all, the most important takeaway from the current literature is that time series data is an effective resource for measuring the impact of transit improvements at the national, regional, and local level.

In this research paper, I utilize annual data from the United States Census American Communities Survey (ACS) to examine short-term trends and changes in transit use for census tracts nearest to the new Silver Line. Data from both before and after the opening of the Silver Line, in addition to a large sample of Northern Virginia census tracts whose residents commute into Washington DC in large quantities, allow me to conduct linear regression modeling on the heterogeneous treatment effects of time and geographic proximity to the Silver Line.

While my models fall short of top-tier statistical significance, the question of neighborhood impact calls for further research as longer term time series data becomes available.

2. Literature Review:

My research and literature review was conducted with the goal of identifying major trends in the methods and discourses within published works related to commuting and transportation. Commonly used keyword search terms included "transit", "commuting", "Washington D.C.", and "new transit case study."

In my review I subset my literature into three groups. The first is a group of studies and reports that use time series data and spatial variables to explore questions related to commuting and urban development. My second group of literature is more narrowly focused on public transportation. I present research that uses the census and its demographic variables to measure transit equity and ridership trends across different social groups. Finally, the third features case studies that examine the impact of new transit improvements and transportation policies.

Group 1: Time-Series Data and Spatial Variables

One of the most commonly studied metrics relates to the imbalance between job and housing access (Yang, 2007; Axisa, Newbold, & Scott, 2012; Horner & Schleith, 2012). This imbalance creates a natural separation between the theoretical minimum commuting needed based on current job availability and affordable housing units (Yang, 2007). Yang uses Boston and Atlanta as two cities which are representative of this problem. With census data from 1980, 1990, and 2000, Yang is able to model actual commuting by theoretical minimum commuting. More importantly, this model shows how commuting flows, the pathways that commuters use, grew longer in distance and travel time from 1980-2000 (Yang, 2007). Both Boston and Atlanta show steady decade-by-decade increases in commute time, commute distance, and excess commuting, highlighting, according to Yang, the importance of developing a better balance of jobs and housing at a more localized level as “dispersed development” requires planners to be more intentional about relating housing and job availability than they needed to in the past (Yang, 2007).

Yang's work is the clearest example of long-run data being utilized to relate the impact of contemporary trends on difficult problems. While Yang speaks to geographic problems and incorporates spatial factors into his models, he elected not to use any geographic mapping in his report, limiting the reader's ability to visualize and relate to the true gap between residential sectors and work centers. Yang also makes no note of what form of transportation commuters elect to use, only average travel time and distance as his model variables.

Unlike Yang, other researchers lean heavily on geographic visualizations in exploring their research questions (Kalia, 2015; Lee, Choi, & Jung, 2017; Wu et.al, 2017; Ganning, 2018). Kalia uses heat maps to show nation-wide commuting flows that highlight the pull of major economic centers like London, England and Rio de Janeiro, Brazil (Kalia, 2015). Lee, Choi, & Jung also use mapping at the national level. Using data on the spread of the H1N1 virus in South Korea, their research maps the spread from more rural and isolated parts of the city into the metropolitan centers, where it then spreads out broadly across the nation over a series of months (Lee, Choi, & Jung, 2017). Their research, like Kalia's, highlights the power of mapping for large-population research. Next steps for their work could include expanding the depth of their variables to demonstrate impact at the neighborhood, block, and census tract level.

Ganning takes advantage of localized datasets to build tract level maps. She explores commuting patterns using transit card data to map a series of specific riders to and from home. Conducted over time with the same users, Ganning is able to draw clear lines of individual commuting flows in addition to population-wide mapping (Ganning, 2018).

In another study, Horner and Schleith use nine years of the Longitudinal Employer–Household Dynamics (LEHD) census database to map urban density and transit distance in medium-sized urban areas in Florida (Horner & Schleith, 2012). Exploring a very similar question to that of Yang in his Boston and Atlanta commuting study, Horner's team takes advantage of a newly available census database that features clearly developed spatial information which allows for the creation of census tract level maps of density, travel mileage, and household income (Horner & Schleith, 2012).

Group 2: Impact of transit and transit equity

Another well-documented discourse within transit research is focused on the environmental impact of transit generally, and of commuting specifically (Lawnicki, 2002, Yang, 2007; João-Pedro Ferreira & Cruz, 2014; Fan et.al, 2014; Lee & Wohar, 2016). These authors and their research questions speak to the importance of understanding how commuting impacts our society and our world, and they present compelling evidence for the need to make sustainable growth a priority for planners.

In addition to excess commuting (Yang, 2007), studies point to "extreme commuting," defined as regularly commuting 90 or more minutes to work, as a discouraging trend in modern commuting flows (Rapino & Fields, 2012). Opposite Rapino and Fields, other researchers narrow in on local commuting, which includes walking, biking, busing, and rail transit. Research on "active commuting" which consists mainly of walking and biking, is a metric used to show balanced housing and job markets, as well as being a sign of concentrated density and multi-use zoning. Active commuting policies include multi-use development and high density construction patterns broadly referred to as smart growth urbanism, where sustainability in an enumerated goal of strategic urban planning (Fan et.al, 2014).

Furthermore, multiple studies point to the environmental impact of “excess commuting”. João-Pedro Ferreira and Cruz (2014), measure the economic costs of excess transit in terms of GDP and tax subsidies for travel and infrastructure. They also present driving private vehicles to work as an important part of household energy use. In Portugal, where they conducted their research, the percentage of fuel usage from driving can reach 24% of household energy consumption (João-Pedro Ferreira & Cruz, 2014).

While Ferreira and Cruz did not relate their work back to the United States, in conjunction with the work of Rapino & Fields, Yang, and others, the body of research on the impact of poor commuting infrastructure on the environment and on the neighborhoods we live in are important to understand.

Group 3: Case Studies

Finally, I find it important to highlight the work of researchers who study the impact of specific transit systems and the impact of new commuting policies on commuters' daily lives. This is the style of research I am most interested in replicating and modeling in my research. In this section I highlight two published studies that speak to the utility of using both spatial data and time series data to draw conclusions about the impact that transportation changes can have on not only commuters, but on the communities they live and work in as well.

The first case study was conducted by Rivers and Plumptre (2016) titled, "The effectiveness of public transit tax credits on commuting behaviour and the environment." In this study, Rivers and Plumptre use six years of data from the 2006 Census and a 2011 household survey to explore the impact of a tax program that subsidized the cost of using public transit.

The data includes spatial data which is paired with basic demographic characteristics to quantify behavioral changes in commuting and transit ridership across different regions and different social groups (Rivers & Plumptre, 2016). In their findings, the research showed that while the tax credit system increased ridership by approximately one percentage point, the cost of the program was between $1,500 and $3,000 per one additional new rider. The study concluded that while, "public policy [like the tax credit] aimed at increasing ridership does indeed fulfill its purpose," in this instance there is a high cost to pay for what the researchers describe as only marginal benefits to traffic congestion, carbon emissions, and economic growth (Rivers & Plumptre, 2016). The credit was discontinued in 2017 after their report was written.

The report is intuitive in its merging of two unique citizen surveys, taking pieces from each to build a more informative model that has true policy impacts and statistical significance even within a small time series frame of six years, far short of the multi-decade research conducted by Yang (2007) and others.

The second transit impact case study relates to the research in Belgium regarding the impact of location policy on commuting choices (Verhetsel & Vanelslander, 2009). Contracted by the Belgian government, Verhetsel and Vanelslander used, "Quite exceptionally...the individual census data from nearly all 1, 2 million Flemish commuters" in mapping their transportation use to measure the impact that installing new bus or rail ways can have on ridership (Verhetsel & Vanelslander, 2009). The researchers conclude that while personal cars remain the overwhelming choice of commuters regardless of how close they live to transit lines, rail lines in particular outperform bus stops and bike lanes as being the most impactful form of transit infrastructure on commuter behavior (Verhetsel & Vanelslander, 2009).

Unlike the work of Rivers and Plumptre in Canada, Belgium lacks the necessary data to conduct time series data, which they openly state is the ideal method for measuring impact (Verhetsel & Vanelslander, 2009).

I find work like that of Rivers and Plumptre (2016) and Verhetsel & Vanelslander (2009), to be incredibly important for planners, policy makers, and civic organizations to have at their disposal. Gathering meaningful data and using models to measure variables of interest before and after the roll-out of new transit policies and transit infrastructure are a must if we hope to spend funding adequately and provide public services to citizens in an efficient and equitable manner.

There is a deep and consistent body of work that lays out the impact of commuting on our infrastructure, on our environment, and on our communities. Much of this work is done at a national or regional level, where data can become crowded and variables can be difficult to isolate. Thanks to time-series data and spatial variables available in surveys like the United States Census, there is an expanding body of data that can be used to better understand our transit systems and commuter behaviors today and help us plan on building a better tomorrow.

3. Methods:

Data Gathering:

My research centers around the central question of how effectively tract-level census data can measure the impact of the Silver Line Phase 1 on transit ridership and economic growth in a select group of census tracts that encompass the new line. How does ridership data in these tracts compare to a wider set of tracts in Northern Virginia with high numbers of daily commuters? Does the multi-billion dollar project lead to a change in common economic prosperity metrics like household income? What statistically significant conclusions can be drawn using the most current data available, which provides only six years of data points and only two years of separation between the Silver Line's opening and the most current data point?

The primary source of my data is the American Community Survey (ACS) conducted by the United States Census Bureau. The Census Bureau describes the ACS, which is sent to 3.5 million homes a year, as a project that, "helps local officials, community leaders, and businesses understand the changes taking place in their communities" (United States Census Bureau, 2018).

The section from which I glean the majority of my data is the 'Journey to Work' category, which was omitted from the 2010 Census and did not exist in its current form until 2012. From the available data I pulled survey results from three years: 2012, 2014, and 2016 which spans a total of six years. This paper's methods will only become more effective and informative as more localized commuting data becomes available.

The relevant data I pulled from these years consist of the following variables gathered at the census-tract level: the spatial data signifier 'GEOID'; total population; number of residents who report commuting to work using public transportation; the average household income for each tract; and the year from which the data was gathered.

From this data I developed five new variables for each observation from which I use to build my models. Three of the new variables are quantitative while the other two are binary variables used in grouping and subsetting. The new quantitative variables are: the percentage of residents who use public transit to commute to work; the growth rate in transit usage from 2012 to 2016; and the change in average household income from 2012 to 2016. My two binary variables are: whether or not the tract is located within a mile of the new Silver Line; and whether the observation is from a survey before the Silver Line expansion opened (2012; 2014) or after (2016).

My dataset consists of 1,227 observations, three years of data from 409 individual census tracts. Firgure 3.1 provides an example cross-section of my dataset.

GEOID	pop12	pop14	pop16	transit12	transit14	transit16	hhincome12	hhincome14	hhincome16	incomegrowth	silver	pred	year	pcttransit	income	after
5159471000	2078	2122	2058	343	345	408	143438	140880	141950	-0.010373820	0	0.05978785	pcttransit16	0.198250729	-1.0373820	1
5159471100	7223	7772	6797	574	345	248	101417	109643	108750	0.072305432	0	0.05978785	pcttransit16	0.036486685	7.2305432	1
5159471201	3251	3205	3670	70	138	169	94315	90987	86750	-0.080209935	1	0.08402270	pcttransit16	0.046049046	-8.0209935	1
5159471202	4728	5190	5222	436	609	657	101543	94476	101977	0.004274051	1	0.08402270	pcttransit16	0.125813864	0.4274051	1
5159471301	3609	4274	4435	409	468	339	94135	91250	95000	0.009188931	0	0.05978785	pcttransit16	0.076437430	0.9188931	1
5159471303	3966	4052	4415	358	466	536	95708	99922	93063	-0.027636143	0	0.05978785	pcttransit16	0.121404304	-2.7636143	1
5159471304	1694	1838	1927	179	136	178	179103	149844	148516	-0.170778826	0	0.05978785	pcttransit16	0.092371562	-17.0778826	1
5159471401	3542	3641	4129	231	227	466	102791	96929	99844	-0.028669825	0	0.05978785	pcttransit16	0.112860257	-2.8669825	1
5159471402	3509	3391	3630	212	267	390	74630	79052	97813	0.310639153	0	0.05978785	pcttransit16	0.107438017	31.0639153	1
5159480100	4300	4371	4142	16	16	24	237656	231406	250001	0.051944828	0	0.05978785	pcttransit16	0.005794302	5.1944828	1
5159480201	3976	4417	4607	13	60	82	221250	250001	220469	-0.003529944	1	0.08402270	pcttransit16	0.017799002	-0.3529944	1

Figure 3.1. Dataset contains 1,227 observations of 17 variables.

Sample Selection:

The census tracts of interest were selected using the 2010 Commuting Flows Census Archives (Commuting Flows, Table 2, 2010). The qualifiers for selection into the general tract pool were that the tract come from a county in which the WMATA Metro has at least one stop: Fairfax County, Alexandria, Arlington, and Loudoun County.

My method for selection of the census tracts impacted by the Silver Line Phase 1 expansion, I used the fairfax County GIS and Mapping Services tool to select only the census tracts and their identification codes for the 20 tracts where the Silver Line passed through (Fairfax County, Mapping Services).

There are several alternative selection criteria that can be used in creating similar models. I elected to use one that works to compare the focused sample in relation to census tracts of a similar region. Other samples could have included information across both Maryland and Virginia as both have access to the WMATA Metro. I elected against that method and in favor of selecting only a subset of Virginia instead of the whole state to ensure that the difference-in-difference coefficients measured in my models were not representative of the whole region. If this research was to be replicated, I would think critically into how the most equitable and fair population and sample population could be selected.

Figure 3.2 Sample Population Area mapped by volume of public transit commuters.

Linear Regression Models:

My analysis consists of three linear regression models. Each rely on time series data to make predictions and measure differences in how the census tracts directly impacted by the Silver Line Phase 1 expansion changed overtime in relation to the broader sample. The three models are listed below and each measures a different variable in relation to change from before and after the opening of the five new Silver Line stops. The three variables explicitly measured are: percentage of residents who commute to work using public transit; growth rate in the number of riders who use transit to commute; and average household income. Figure 3.2 notes the linear regression formula and the variables used in this study.

Figure 3.2:

Linear Regression Formula for Heterogeneous Treatment Effects:

$Y_i = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_1 * X_2 + e$

Percentage of Residents Who Commute to Work Using Public Transit:

$\textit{Percentage Transit}_i = \beta_0 + \beta_1 \text{(Silver)} + \beta_2 \text{(After)} + \beta_3 \text{(Silver)} * \text{(After)} + e$

Growth Rate in the Number of Residents who Commute to Work Using Transit:

$\textit{Transit Growth}_i = \beta_0 + \beta_1 \text{(Silver)} + \beta_2 \text{(After)} + \beta_3 \text{(Silver)} * \text{(After)} + e$

Average Household Income:

$$\textit{Household Income}_i = \beta_0 + \beta_1 \text{(Silver)} + \beta_2 \text{(After)} + \beta_3 \text{(Silver)} * \text{(After)} + e$$

4. Results:

My quantitative findings fell short of established standards for statistical significance. The limits of the ACS dataset, present in its current form for only six years, complicated the returns of the modeling and prevent the drawing meaningful empirical conclusions.

My primary model, which predicts change in the percent of residents who use public transit in the group of tract-level data points that are A) next to the Silver Line and B) measured after the line opened, returned the following results with a P-value of 0.786. The model showed that the Silver Line impacted tracts had a lower average transit usage percentage than the data set as a whole by approximately a third. While the coefficient of interest, change in transit usage after the opening of the Silver Line, showed an estimated increase by one half of one percent, the estimate was smaller than the standard error, effectively returning no difference.

Figure 4.1 shows the percent of transit usage for each census tract split by whether the data was before or after the Silver Line opening and whether or not the data point was in the Silver Line group.

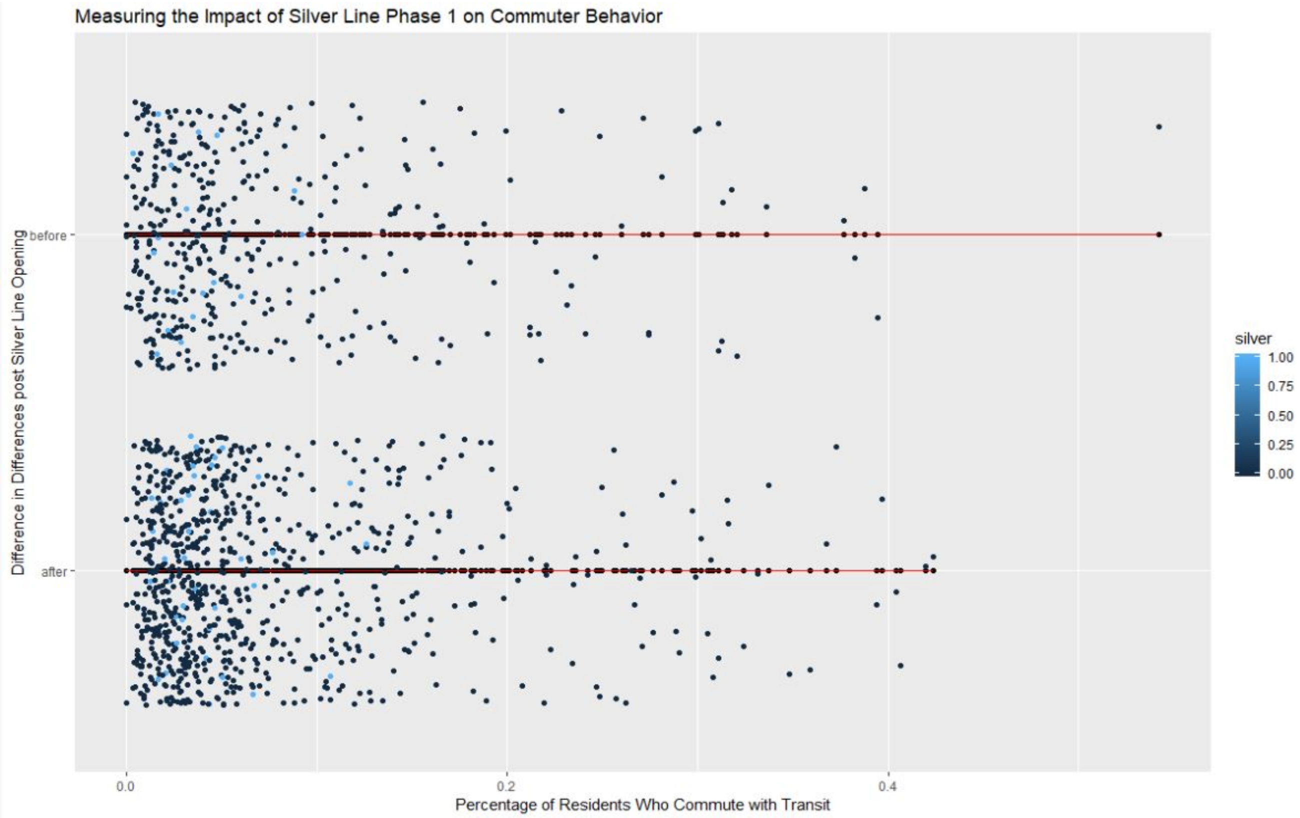

Figure 4.1

The two other difference-in-differences models also lacked P-values of statistical significance. These models asked whether or not the Silver Line expansion impacted the growth rate of transit ridership or the household income of the 20 census tracts closest to the new metro stops. What can be taken from this study is that important questions remain when it comes to using commuting data from the American Communities Survey to measure the impact of new transit systems on commuter behavior.

5. Discussion and Conclusion:

The goal of my research project was to use geographic and spatial data to better understand and map the impact of transit-oriented infrastructure on commuter behavior. More specifically, I had an interest in better understanding the impact that the Silver Line Phase 1 expansion have on local communities. Limited by a lack of long-term time series data, as the ACS has been around in its current form for less than a decade, and by my own limited understanding of complex mathematical modeling, my project, while grounded in a larger body of data-based research and model-based case studies, largely failed to yield any statistically significant results. That being readily acknowledged, what this project demonstrates quite clearly, is that there is a real opportunity to expand on our knowledge base when it comes to measuring and assigning empirical value to our public transit infrastructure. In this worthy pursuit, the Greater Washington Area, particularly at this moment in time, is a crucial case study.

While Phase 1 of the Silver Line opened in 2014, Phase 2, which connects the line to Dulles Airport consists of six new metro stations and is set to open in 2020 (Dulles Metro, 2017). In Montgomery County Maryland, plans for 14 miles of dedicated-lane bus routes have finally passed the County Council after years of research and push back from some community groups. The plan will draw the periphery of the Washington D.C. transit network further north than ever before with a stated goal of helping re-connect poorer regions in Eastern Maryland an efficient pathway into the city and its expansive job market (Shere, 2018).

Also in Montgomery County, the much-maligned Purple Line, a Maryland only Metro Line that connects the two arms of the Red Line, creating a currently absent express connection between Bethesda in Montgomery County to New Carrollton in Prince George's County (Purple Line Project, 2018).

On top of all of these new transit projects stands the immense task of integrating Amazon’s new HQ2 office in Crystal City, Virginia and the 25,000 projected jobs it will bring to the Greater Washington Area (McCartney & Shaver, 2018). HQ2 has already made an impact on the region’s transit infrastructure, as many credit last years trilateral agreement between D.C., Maryland, and Virginia to approve $500 million in dedicated funding for the Metro, a steady income source the system has lacked since its inception (Emerson, 2018).

For all the exciting growth and change that comes with HQ2, the influx on new jobs and new workers will put added strain on an already burdened transportation network. As more census data becomes available related to commuting behaviors, it is important that policy makers, urban planners and engineers, and engaged citizens and civic groups take advantage of the opportunity to explore the impacts of our region’s newly developed transit infrastructure on our environment, on individual commuter behavior, and on the neighborhoods where we work and call home. While the models in this study were far from conclusive, the methodology and the broader purpose and goal of this research project can be generalized to fit a variety of different cases as a process to use time series data from the census to make meaningful conclusions about the impact of public transit improvements on commuter behavior in local neighborhoods.

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