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Abstract

This paper investigates the impact of the largest rail strikes in German history on intercity buses. Using unique booking data of bus services, we exploit variation in rail service cancellations across routes to show that the disruption in rail transport increases bus ticket sales. The effect persists beyond the strike, indicating that travellers do not return to their originally preferred mode of transport. It is particularly pronounced for passengers travelling on weekends. The findings suggest that customers were previously under-experimenting. From a policy perspective, our results highlight the need to incentivise experimentation to foster competition, facilitate transformative change and raise welfare.

JEL-Codes: D830, L920, R410.

Keywords: experimentation, inter-modal substitution, learning, optimisation, strike, switching costs, transport.

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1 Introduction

Once settled on a product, consumers do not usually revisit their choice for every purchase. After all, you do not evaluate whether your preferred e-mail provider, regular hairdresser, or favourite restaurant constitutes the optimal choice every time you make use of their services. Such behaviour might be a rational response to search costs and informational frictions, or it could be driven by inertia. Incumbent firms benefit from those habits, as they constitute a barrier to entry for new firms. Service interruptions, however, may force customers to experiment with substitutes, inducing some of them to permanently switch to competitors.

We test this hypothesis by exploiting a major strike in the German railway network as a quasi-natural experiment to investigate whether the resulting service disruptions caused customers to permanently switch from rail to bus travel. Travel is an experience good, which can only be adequately evaluated during or after consumption. Passengers accustomed to trains may hesitate to invest time in trying intercity buses. Our study reveals that such switching costs limit experimentation. Once these costs are removed, use of the alternative transport mode increases. This study is, to the best of our knowledge, the first to present systematic evidence of this mode-of-transport-switch.

The state-owned railway company, *Deutsche Bahn AG* (DB), monopolizes Germany's intercity high-speed railway services. A labour dispute in autumn 2014 halted most of DB's long-distance services, forcing travellers to seek alternative transportation. Less than two years before, Germany's passenger transport market experienced a phase of liberalization, allowing intercity buses to compete with DB's high-speed trains.[1] For some travellers, this led to a first encounter with intercity buses. In introducing new customers to the railway's key rival, the strike potentially resulted in new, long-term customers for buses. It thus serves as a quasi-natural experiment to examine enduring shifts in customer preferences after service disruptions. Unprecedented in geographic extent, the strike occurred on short notice, and it marked the first instance where buses were a viable alternative.

Our analysis employs a unique dataset: comprehensive booking records from a major intercity bus provider, MeinFernbus (MFB), encompassing all ticket sales across 33 large German cities over four months. We cross-reference this with web-crawled rail itineraries and emergency schedules. Our dataset details rail and bus connections among the 33 cities hourly, including trip duration, required transfers, and departure frequency during regular and strike periods.

Applying a difference-in-differences approach, we estimate the railway strike's impact on intercity bus usage, leveraging the varying exposure of different routes. Our findings reveal a substantial rise in bus ticket sales during the strike (averaging 32% in the initial wave). This

[1] Intercity buses are defined as regularly scheduled services exceeding a distance of 50 km. In the literature, they are also interchangeably referred to as 'inter-urban' or 'long-distance' buses.

is predominantly attributed to first-time customers who had not used bus services before the strike. Importantly, this effect continues post-strike, indicating a sustained shift as passengers adopt new modes of travel. Ticket sales on affected routes remain 8% higher on average after the strike. Notably, the post-strike influence is more pronounced for weekend travellers, indicating buses as a leisure travel alternative. Positive price effects imply increased demand due to the strike, rather than a supply-driven response (e.g., capacity expansion). Furthermore, our analysis highlights a shift primarily on shorter routes, where buses more effectively substitute for trains. The results imply that even short periods of forced experimentation may permanently foster competition, facilitate change and raise welfare.

The paper contributes to multiple literature strands. Firstly, it extends the classic literature on individual decision-making among alternatives. There is a long-standing debate on rational decision-making (Simon, 1955; Weitzman, 1979; Morgan and Manning, 1985) and factors like search costs (Baumol and Quandt, 1964; Ben-Akiva and Morikawa, 1990), information gaps, or habits, particularly in transport mode selection (Moser et al., 2018; Donna, 2021). Bus travel is an experience good, and its pre-consumption quality may often be underestimated by consumers (Riordan, 1986; Bergemann and Välimäki, 2006). Klemperer (1987) highlights welfare reduction in the presence of switching costs. Porter (1996) suggests exogenous shocks prompt optimal choices via experimentation. Therefore, although public transport strikes are often economically harmful (Kennan, 1986), they could enhance welfare by encouraging experimentation. Our paper aligns with this idea, wherein rail unavailability during strikes drives experimentation, which in turn helps consumers overcome switching costs.

Our findings amend the literature around effective intervention in the transport market. Urban agglomeration and negative externalities associated with car travel, such as congestion or environmental costs, might justify subsidies to boost the adoption of public transport (Glaister and Lewis, 1978; Parry and Small, 2009; Baum-Snow and Kahn, 2000). Our study underscores the significance of switching costs as a barrier to experimentation. Shapiro (1983) and Villas-Boas (2006) argue that firms can increase demand for experience goods by encouraging experimentation through low introductory prices. In the same spirit, governments may temporarily lower prices for certain types of transport through subsidies (Gohl and Schrauth, 2022). Our results suggest that any policy encouraging experimentation may facilitate a shift towards alternative transport modes.

Beyond specific policy objectives, Giulietti et al. (2005) argue that switching costs may cement market power, justifying regulation. Relatedly, we show that forced experimentation can have pro-competitive effects, as consumers overcome barriers preventing them from trying new products. In the case of transport, increased competition may even be advantageous for customers who stay with the incumbent, as it can increase the overall quality in the transport market (Fang et al., 2023).

Our study aligns with the literature exploring the impact of labour disputes in the transport sector. A review by van Exel and Rietveld (2001) notes increased private car usage during strikes, sometimes culminating in lasting mode shifts. Bauernschuster et al. (2017) examine public transport strikes as quasi-experimental shocks, assessing adverse externalities from heightened car traffic. Conversely, Chen and Whalley (2012) study positive effects of new rail transit on air pollution. Anderson (2014), Adler and van Ommeren (2016), and Adler et al. (2021) reveal strike-induced road congestion, emphasizing public transport's role in curbing it. Kreindler and Miyauchi (2023) find that strikes may reduce high-skill commuters' travel. Yang et al. (2022) link a London bike-sharing surge to Tube strikes. Yeung and Zhu (2022) show that the number of booked seats with BlaBlaCar - an intercity ride-sharing app - increased by 33% during a railway strike in France. Most of the above studies investigate contemporaneous effects or focus on urban transport. Our study uniquely quantifies rail-to-bus mode shifts during and after strikes, filling a literature gap for intercity travel.

For perfectly informed consumers, a strike should be just a temporary disruption, after which they return to their optimal mode of transport. However, Larcom et al. (2017) show that following a 2014 strike on the London Underground, up to 5% of commuters permanently altered their commuting route, indicating a suboptimal choice prior to the strike's experimental nudge. This aligns with Goodwin (1977), who posits that "the traveller does not carefully and deliberately calculate each morning anew whether to go to work by car or by bus". While Larcom et al. (2017) provide insights into route shifts within London's Transport Network, we demonstrate customers' switches across competing networks (from rail, operated by DB, to bus, operated by MFB). Our findings also relate to Fung et al. (2021), who reveal a sustained surge in bike-sharing trips in Glasgow post-temporary subway closure. In intercity travel, we identify a lasting strike-induced mode shift from rail to bus, suggesting under-experimentation on long-distance routes.

Finally, this paper contributes to the nascent literature examining the German long-distance bus market. Existing work focuses on the impact of German bus market liberalisation on rail ticket prices and services. Böckers et al. (2015) and Evangelinos et al. (2015) observe a stronger rail network effect at the network periphery. Bataille and Steinmetz (2013) present theoretical models on liberalisation's consequences, echoing earlier research on low-cost airline entry in Germany (Friebel and Niffka, 2009). Durr et al. (2015) study intercity bus market competition and assess the price impact of a significant MFB and Flixbus merger (also see Gagnepain et al. (2011) for broader bus market analysis). Neither considers recent German railway strikes. Empirical research often employs limited time-series data from price comparison sites. In contrast, our analysis utilizes detailed MFB booking data, significantly enhancing insights into this dynamic emerging market.

The remainder of the paper is structured as follows: Section 2 outlines our motivating model. Section 3 delves deeper into the 2014 railway strikes. Section 4 introduces datasets and provides novel intercity bus market statistics. Section 5 outlines our empirical approach and tackles estimation challenges. Section 6 presents our baseline results, followed by extensions and robustness checks in Section 7. Section 8 concludes.

2 Conceptual framework

We begin by sketching a simple model of the choice of transport mode, which constitutes the conceptual framework guiding our investigation.[2] Let there be two modes of travelling, train (T) and bus (B) and a continuum of travellers represented by the unity interval $[0, 1]$. Preferences of a representative traveller $x \in [0, 1]$ can be represented with the following equation:

$$U^x(m) = V^m - p^m - xC^m \tag{1}$$

with $m \in \{T, B\}$, where $U^x(m)$ is the net utility derived by passenger x from travelling on transport mode m. We denote V^m to be the gross utility of travelling on mode m, capturing utility derived from mode amenities, such as the existence of dining cars or wifi. Let p^m be the price of travelling on mode m and C^m the gross time cost of using transport mode m. Travellers have different valuations of time costs, represented by their location within the interval $[0, 1]$. Using transport mode m, traveller x incurs time costs of xC^m. The higher x, the more a traveller values time and hence the greater his or her travel time costs xC^m.

We make the following assumptions: First, $V^T > V^B$. Other things equal, it is more convenient to travel by train than by bus. Second, $p^T > p^B$, i.e. the train is more expensive than the bus.[3] Third, $V^B - p^B > V^T - p^T$, i.e. the net utility when excluding travel time is greater for the bus than for the train. Fourth, $C^T < C^B$, which says that gross time costs are lower for the (faster) train.[4] Fifth, $V^T - p^T - C^T > V^B - p^B - C^B$ i.e. the net utility for traveller $x = 1$ from using the train is greater than from using the bus. Note that the third assumption implies that the net utility for traveller $x = 0$ is greater when using the bus. Travellers choose m to maximise:

$$max_{m\in\{T,B\}}\{V^m - p^m - xC^m\} \tag{2}$$

[2] We partly build on Donna (2021), who models the use of public transport and car use, whereas we focus on two different types of public transport, namely rail and bus services.

[3] This assumption is supported by the data, see Section 4.

[4] Travel time on trains is indeed shorter than travel time on buses, as Figure 6 shows.

Given the above assumptions, travellers with an x close to zero will choose $m = B$ and those with an x close to one will choose $m = T$. Therefore, there exists a traveller $0 < \tilde{x} < 1$ who is indifferent between the two modes, such that

$$V^T - p^T - \tilde{x}C^T = V^B - p^B - \tilde{x}C^B \tag{3}$$

$$\Rightarrow \tilde{x} = \frac{V^B - p^B - V^T + p^T}{C^B - C^T} > 0 \tag{4}$$

Note that the third and fourth assumptions imply that $\tilde{x} > 0$. All travellers for whom $x < \tilde{x}$ will use the bus, whereas all travellers for whom $x > \tilde{x}$ will use the train. From (4) we can derive the following comparative statics:

$$\frac{\partial \tilde{x}}{\partial C^T} = \frac{V^B - p^B - V^T + p^T}{(C^B - C^T)^2} > 0 \tag{5}$$

$$\frac{\partial \tilde{x}}{\partial C^B} = -\frac{V^B - p^B - V^T + p^T}{(C^B - C^T)^2} < 0 \tag{6}$$

$$\frac{\partial \tilde{x}}{\partial V^T} = -\frac{1}{C^B - C^T} < 0 \tag{7}$$

$$\frac{\partial \tilde{x}}{\partial V^B} = \frac{1}{C^B - C^T} > 0 \tag{8}$$

$$\frac{\partial \tilde{x}}{\partial p^T} = \frac{1}{C^B - C^T} > 0 \tag{9}$$

$$\frac{\partial \tilde{x}}{\partial p^B} = -\frac{1}{C^B - C^T} < 0 \tag{10}$$

During the strike, the gross time cost of using the train C^T increases as trains are cancelled. At the same time, the gross utility from using trains V^T falls (e.g. because trains are crowded during strikes and seating is not guaranteed). Following (5) and (7), a higher C^T and lower V^T both increase $\tilde{x}$. Recall that all travellers for whom $x < \tilde{x}$ travel by bus. Therefore, the number of passengers travelling by train falls while the number of passengers travelling by bus increases.[5]

After the strike, we assume that C^T and V^T return to their original values. However, we propose two mechanisms that may prevent $\tilde{x}$ from falling back to its pre-strike level: Switching

[5] An increase in $\tilde{x}$ could also be induced by a rise in p^T or a fall in p^B (not the focus of our paper). In Section 7, we show that bus ticket prices on routes affected by the strike increased during the strike. Our findings are thus not driven by a fall in prices for bus tickets.

costs and uncertainty surrounding the gross utility of using the bus. In the presence of switching costs, the decision problem becomes

$$max_{m\in\{T,B\}}\{V^m - p^m - xC^m - \phi^m \mathbf{1}\{m^x_{t-1} \neq m^x_t\}\} \tag{11}$$

$\phi^m > 0$ captures switching costs to mode m and $\mathbf{1}\{\cdot\}$ is an indicator function, ensuring that switching costs are only incurred if a passenger switches transport mode between periods $t-1$ and t. Switching costs include search costs such as having to look up information on bus schedules, routes or transfers. In addition, transportation is an experience good. If a passenger has not used bus services before, he or she forms an expectation of V^B which we call $\tilde{V}^B$. The true V^B is, however, only revealed once travelling by bus is experienced.[6] For travellers who never used the bus before, the indifferent traveller is determined by

$$V^T - p^T - \tilde{x}C^T = \tilde{V}^B - p^B - \tilde{x}C^B - \phi^B \tag{12}$$

$$\Rightarrow \tilde{x} = \frac{\tilde{V}^B - p^B - V^T + p^T - \phi^B}{C^B - C^T} > 0 \tag{13}$$

Taking the partial derivative of $\tilde{x}$ with respect to ϕ^B yields:

$$\frac{\partial \tilde{x}}{\partial \phi^B} = -\frac{1}{C^B - C^T} < 0 \tag{14}$$

The higher the switching costs, the fewer travellers will choose the bus. Passengers who did switch to buses during the strike will, however, not have to incur switching costs again if they continue to use buses. Following Equation (14), ϕ^m dropping to zero implies an increase in $\tilde{x}$ and hence an increase in the number of passengers travelling by bus relative to the pre-strike equilibrium. In the absence of switching costs, the value of using buses starts to exceed that of using trains for some passengers, leading them to use bus services permanently.[7]

In light of the literature on inertia and experience goods discussed above, it is also possible that $V^B > \tilde{V}^B$. During the strike, passengers, who are forced to experiment with buses, realise that the experience is more pleasant than previously expected. From Equation (8) we know that $\tilde{x}$ is increasing in V^B, so the number of travellers using bus services increases once buses are experienced and $\tilde{V}^B$ is replaced by V^B. Note that V^B might vary across individuals and $V^B > \tilde{V}^B$ does not need to hold for all passengers in order for the number of bus travellers to increase.

[6]Note that introducing ϕ^B and $\tilde{V}^B$ does not change the general results of the previous comparative statics exercise.

[7]We could also add a cost for switching from bus to train, ϕ^T. However, this would not change the general predictions of the model.

To sum up, two predictions can be derived from the model: First, the number of passengers using bus services increases during the strike following a temporary decline in V^T and an increase in C^T. Second, some of this change persists even after the strike because ϕ^B disappears for those travellers that switched to buses during the strike and because $V^B > \tilde{V}^B$, at least for some passengers. These passengers used to travel by train, switched to buses during the strike and continue using buses also in its aftermath. In the remainder of the paper, we show that passenger numbers for bus services on affected routes indeed increase during the strike and that some of this change persists even after rail services resumed.

3 The German railway strikes of 2014-2015

High-speed railway services in Germany are almost exclusively provided by DB. The company controls the railway infrastructure and is legally shielded from competition. In the year 2013, it became legal to offer bus services in direct competition with existing railway connections.[8] Private bus operators entered the passenger transport market, offering intercity connections on routes more than 50 km apart.

The locomotive drivers' union (*Gewerkschaft Deutscher Lokomotivführer*; hereafter referred to as GDL) is relatively small but powerful and has a long history of disputes with DB. The 2014-2015 negotiations, however, constituted the most ferocious industrial action in the history of DB. Two factors contributed to the ferocity of the dispute: GDL was in a power struggle with a rival union, and new legislation was under review which threatened GDL's right to represent service personnel in future wage negotiations. Between September 2014 and May 2015, the dispute resulted in nine strike waves and 22 days affected by strikes – 354 hours of service disruptions. Because of the importance of the rail network to the economy, the dispute was followed closely by the German media and the public.[9]

We study the effects of three major waves in October and November 2014.[10] We disregard strikes after January 2015 as this is when MFB merged with rival competitor Flixbus. In addition, we disregard minor warning strikes, as they only lasted a few hours and were announced with many days advance warning. Our data suggest that those strikes were too short to have any measurable impact on the bus market. Figure 1 shows the timeline of disruptions caused by the three strike waves relevant to our study. In the week between 13 October and 19 October 2014, strikes disrupted rail services on Wednesday and Thursday, as well as on Saturday and

[8]The market was liberalised by law as of January 2013. Previously, the Passenger Transport Act only permitted intercity bus services if the state-owned railway company was unable to provide an acceptable service. Durr et al. (2015) provide more details on the liberalisation.

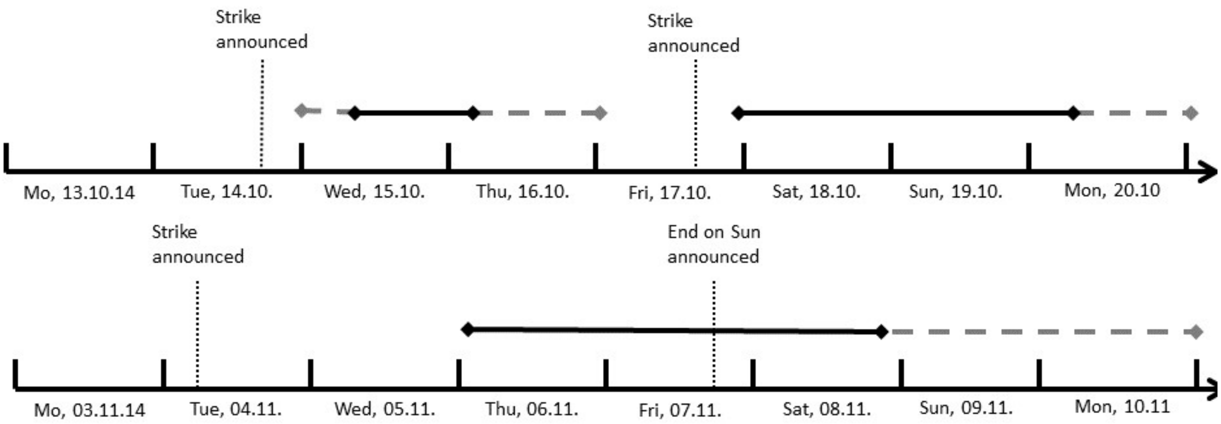
[9]This paper is concerned with passenger transport. Note, however, that the railway strikes affected both passenger and freight services by DB.

[10]Table A.1 provides a detailed account of the 2014/2015 public transport strikes.

Sunday. In the week between 3 November and 9 November, rail services were cancelled due to the strike from Thursday, 6 November onwards for three consecutive days.

The timing of the strikes was arguably exogenous. Strikes result from a breakdown of negotiations, the exact timing of which is unpredictable, as negotiations often collapse quickly and unexpectedly. Once negotiations have broken down, the exact timing of a strike remains unclear. It could be delayed by days, weeks, or months if the parties were hopeful of making progress or political pressure was exerted. The trade union centrally decides to go on strike after consulting its members. Importantly, there is no evidence to suggest that competition from buses played any role in the occurrence, timing, or length of the strikes. The strikes can be considered an exogenous positive demand shock to the German bus market. Having reached a decision, GDL usually announced strikes at short notice to maximise their impact. Each strike was announced no more than two days in advance.

Figure 1: Timeline of rail strike 13-20 October and 3-10 November 2014



Note: Grey dashed lines indicate strike-related service disruptions. Disruptions started before the first strike wave because DB adopted its emergency timetables at the beginning of the departure day to minimise the overall impact of the strike. Disruptions lasted beyond the duration of each strike wave as it took time to return to normal timetable operations. The third rail strike wave ended prematurely on Saturday, although it had initially been announced to last until Sunday. Following public pressure, GDL announced it would return to work on Sunday, 9 November to allow travellers to reach the anniversary festivities of the Fall of the Berlin Wall around the country.

GDL called for a strike nationwide. However, neither did GDL shut the network down entirely, nor were rail routes exposed to the same degree. GDL membership strength is weaker in West Germany because many West German train drivers have civil servant status – a relic of DB's historical status as a state company.[11] The emergency timetables operated during the rail strike reflect the varying power of GDL across Germany. The regional disparity in the change of service frequency specified in the emergency timetables was arguably exogenous to the bus

[11]German civil servants have by law no right to strike or unionise.

market. DB did not strategically focus rail services on routes which were under particular threat of competition from buses. The emergency timetables were the same in all strike waves in 2014-2015, and they are almost identical to those employed by DB in the last railway strikes of 2007-2008; i.e. long before the liberalisation of the intercity bus market in 2013.

Switching between rail and bus is rather easy.[12] Bus terminals are located directly next to the rail station in most cities (Guihéry et al., 2016). Tickets can be bought online or on the bus. Travellers could arrive at the rail station and easily transfer to intercity buses when the implications of the rail strike became clear to them.

4 Data and descriptive statistics

This paper combines data from three sources: detailed booking data for intercity buses provided by MFB, DB emergency timetables, and a data set of all rail itineraries. The latter data are collected using a web crawler linked to the website of a leading price comparison website. We combine the emergency timetables and travel itineraries to create a data set of service cancellations and expected delays caused by the rail strike.

MFB booking data: MFB is Germany's largest bus provider in the sample period, with a market share of then roughly 50%. In addition to being the key player in the German intercity bus market, MFB's service quality as well as strategic use of local bus partners are representative of the entire intercity bus industry.[13]

The data set provided by MFB contains the universe of MFB ticket sales between any combination of 33 large German cities for departure dates from 27 August to 16 December 2014. Figure 2 lists and maps all 33 cities in the sample. Any booking for a departure between these 33 cities is included, regardless of when the booking was made. The original data set contains about 2.2 million observations. Not all possible combinations of the 33 cities are actually routes served by bus services. Some routes are only served on weekdays or not at all. We restrict our sample to routes that were served by MFB during the strike. The panel composition does not change throughout our observation period.

A booking observation includes detailed information on the bus service such as the route, price, departure date, and time as well as an anonymised e-mail address under which the booking was made. The e-mail address identifies first-time and repeat bookings by the same account, and thus allows following a customer over time. The key variable of interest is the

[12] DB does not offer season passes on specific routes. It offers the *BahnCard* which grants fixed price reductions to cardholders. *BahnCard* subscriptions can be cancelled annually. This may have locked travellers in to DB services, in which case any lasting effect beyond the strike would not be visible until the medium or long term.

[13] For example, free wifi, luggage allowance, and legroom are almost identical across the industry. See Dürr et al. (2015) for a detailed introduction and comparison of players in the intercity bus market.

natural logarithm of the number of tickets sold at the route and departure day level.[14] We aggregate the individual bookings at the route and departure day level – the unit of analysis in this paper.[15] A route is the combination of an origin- and destination-city, meaning that different routes may be served by the same bus journey. For example, a bus ride from Munich to Berlin with a stop in Dresden serves three routes: Munich–Dresden, Munich–Berlin, and Dresden–Berlin.

Figure 2: Map and list of German cities in the sample

Cities:	
Augsburg	Heidelberg
Berlin	Karlsruhe
Bonn	Kassel
Braunschweig	Kiel
Bremen	Leipzig
Cologne	Mainz
Dortmund	Magdeburg
Dresden	Mannheim
Duesseldorf	Munich
Erfurt	Muenster
Essen	Nuremberg
Frankfurt (Main)	Rostock
Freiburg	Saarbruecken
Goettingen	Stuttgart
Hamburg	Ulm
Halle (Saale)	Wuerzburg
Hanover	

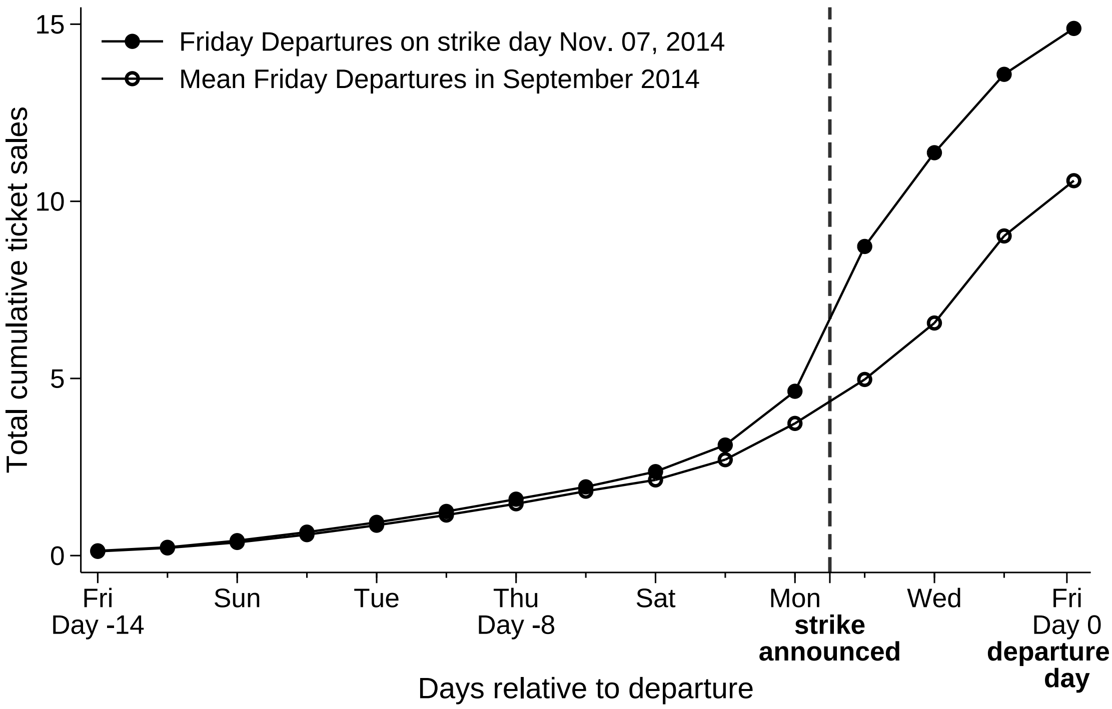
While rail strikes continued beyond the sample period to May 2015, we restrict the sample period to 2014. This is because MFB unexpectedly merged with rival bus provider Flixbus in

[14]The dependent variable is computed as $\ln(1 + \textit{tickets sold})$ at the route departure day level. This approach allows us to keep route-day observations with zero tickets sold. In the data set, zero observations only account for 0.3% of tickets sold and 7% of tickets sold to new customers.

[15]Note that there are two time dimensions to each individual booking: the date of booking and the date of departure. We aggregate ticket sales to the route and departure date dimension. 95% of bus travellers arrive at the same date as they depart.

January 2015. Any changes after this date may be driven by the effects of the merger and not the rail strike. The final panel contains 312 routes and roughly 35,000 observations at the route and departure day level. The data set is balanced in the sense that all routes are observed over the entire sample period and through all strike waves.[16] MFB entered the market with an aggressive pricing strategy, where the cheapest tickets sell at only €4.39 for a one-way trip. The average ticket price is €14.5 (median: €12). The maximum price is €63, but only 1% of tickets sell at a price higher than €46. An average bus ticket costs €3.5 per scheduled hour of travel.[17]

Figure 3: Mean cumulative bookings for Friday departures



Note: Data are split into bookings for Friday departures in September, the month just preceding the rail strike, and bookings for departures for strike day 7 November 2014. The strike was announced three days prior to the strike (as indicated by the dashed line). Note that ticket sales are not in log scale here.

The 2.29 million individual ticket sales we observe in the MFB data correspond to roughly 1.5 million ticket orders. In some cases, the order is made several months before the actual departure. On average, an order precedes a departure by around eight days. During the railway strike, we would expect an increase in tickets bought on short notice. Figure 3 compares cumulative bookings before departure for a day affected by a railway strike with a typical

[16] Note that, as a consequence, there are route-day combinations with zero ticket sales in our panel.

[17] A back of the envelope calculation: A DB *Sparpreis* (saver ticket) at €19 for the maximum travel distance of 250km at 200km/h travel speed would yield a per hour price of €15.2.

booking curve. The dashed vertical line indicates the moment of the strike announcement for the third strike wave on 7 November 2014. As is apparent, ticket sales only diverge from their usual trend after the rail strike was announced. The small sales departure from the usual trend before the announcement suggests that a few travellers booked bus tickets after negotiations had broken down, but before the strike was announced; i.e. very few travellers anticipated the strike. If travellers book bus tickets for departure days before the strike in anticipation, our results would be downward biased. Figure 3 provides strong descriptive evidence that rail strikes drove the peak in ticket sales on striking days.

During the strike, MFB experienced peaks in the number of bookings made by new customers. Figures A.1 and A.2 in the appendix illustrate the overall ticket sales during our observation period. We differentiate between three groups of tickets: all tickets, the subset of all tickets bought by first-time customers, and the subset of tickets bought no more than three days before departure (the spontaneous customers). A ticket is marked as a first-time sale when the booking was made with an e-mail address not yet registered with MFB.[18] For all three groups, there is a weekly pattern in ticket sales. Friday and Sunday departures sell the most tickets.

DB Emergency timetables and itineraries: Rail service cancellations varied by route. DB maintained rail services on key routes, partly with reduced frequency. A route's exposure to cancellations is exogenous to the MFB service on this route. To capture the route-varying effect of the strike, we deduce to what extent a route was affected by the rail strike from DB's emergency timetables. The DB emergency timetables list DB services at the *line level.* For example, ICE line 25 from Hamburg to Munich halved its operations from once every hour to once every two hours. However, a typical itinerary involves stopovers and hence uses multiple rail lines. We combine the emergency timetables provided by DB with DB travel itineraries, which were collected using a web crawler linked to a leading price comparison website. Using actual itineraries considers that some DB routes are served through different paths in the rail network. We can then recapitulate all possible railway connections between any of the 33 cities in our sample, including the departure times, the number and length of stopovers, and the lines used. We deem a connection unfeasible if it uses more than five trains or requires a waiting period of more than 120 minutes. To the remaining connections in our sample, we assign a strike exposure, measuring the fraction of services cancelled during the strike along all connections that would regularly be available on this route.

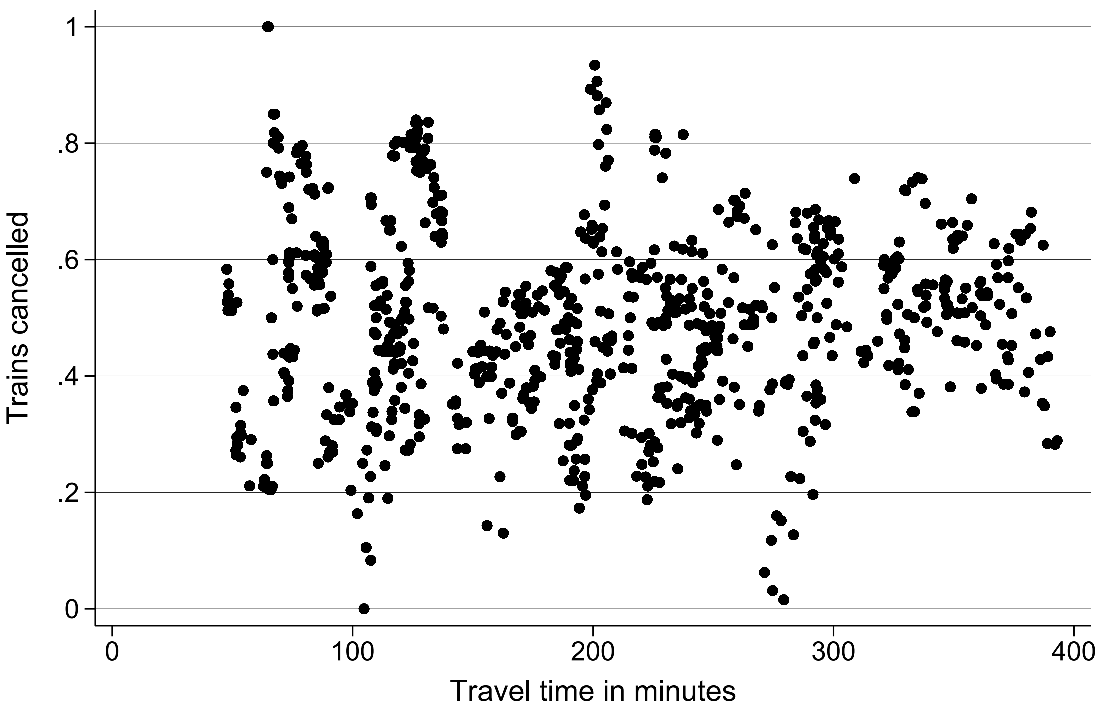
One data limitation remains: the DB emergency timetables do not include information on regional trains. We disregard connections where more than 10% of itineraries include the use of

[18]On average 30% of bus passengers are first-time customers, two-thirds of whom undertake at least one more booking within our sample period.

regional trains. DB's Inter-City and Inter-City Express trains connect all 33 cities in our sample. 81% of all connections in our sample use at least one Inter-City Express train. Nonetheless, the lack of strike data for regional trains might seriously limit our findings if regional trains were strongly affected by service cancellations or if we drop primarily short routes on which the bus may be a closer substitute for the train (we address this in Section 7).

The average train trip in our sample takes three hours. The median length of a trip is 182 minutes in pure travel time. Trips longer than six hours are uncommon in our data. The high-speed-railway trains can technically reach a speed of up to 300km per hour, yet the railway infrastructure does not permit a speed above 200km per hour on most routes. Ticket prices depend on the distance travelled. They regularly would not exceed €139 (business class: €225) for a one-way trip in 2013. DB also offers tickets at a dynamic price (Sparpreis) that varies with the expected demand, where a single economy class trip begins at €19 for an economy class trip below 250km and at €29 above. Typically, a connection between two cities in our 33-city sample uses no more than two trains and requires no more than 14 minutes of waiting time at changeovers. Of those connections that do require a changeover, 95% do not exceed a total waiting time of 53 minutes on all stops.

Figure 4: Train travel time without strike and fraction of trains cancelled during strike



Note: Data from DB itinerary and emergency timetables.

We measure each route's exposure to the rail strike by the fraction of train connections cancelled on a given route during the strikes (*trains cancelled (%)*) for each day of the week for each route. Where there are several possible connections on one route, the strike exposure is a weighted average of the connections' exposure. *Trains cancelled (%)* captures how many of the possible departures on all available connections on a route were inoperative during the strike.

Figure 4 plots the variable *trains cancelled (%)* against the rail travel time under the regular schedule. There is no visible systematic relationship between normal rail travel time and the fraction of services cancelled during the strike. Only one route-day combination maintains full service on all connections under the emergency timetable: Berlin to Hannover on Wednesday. In this case, *trains cancelled (%)* equals zero. Since the fraction is aggregated over all connections of a route, made up of up to five trains per connection, most routes are affected by the strike at least partially. Note that we can only capture the cancellations according to the emergency timetable here. Additional delays and cancellations - as are common to occur with DB services also outside the strike for all kinds of reasons - are just noise to our analysis. Our treatment variable measures strike exposure solely as the discrepancy between the regular and the strike schedule.

5 Estimation strategy

We test for the effect of a route's exposure to the rail strikes on MFB ticket sales in an estimation based on the following baseline specification:[19]

$$\ln y_{ijt} = \sum_{s}^{Ns} \beta_s (exposure_{ij} \times strike_t^s) + \mu_{ijdow} + \mu_{iw} + \mu_{jw} + \boldsymbol{X}_{it}\boldsymbol{\gamma}^{'} + \boldsymbol{X}_{jt}\boldsymbol{\delta}^{'} + \epsilon_{ijt} \qquad (15)$$

with $s \in \{1, 2, 3, post\}$, where $\ln y_{ijt}$ is the natural logarithm of the number of bus tickets sold on a route connecting origin-city i to destination-city j for a departure time t (measured in days).[20] Treatment is defined by the interaction term $(exposure_{ij} \times strike_t^s)$. $Exposure_{ij}$ captures the extent to which a route was affected by the strike, measured by the variable *trains cancelled (%)*. $Strike_t^s$ is a dummy that equals one on a strike day and zero otherwise. As we want to know whether the different strike waves affected bus travel to different extents, we include three separate dummies capturing the first, second and third wave respectively.[21] A fourth dummy, $strike_t^{post}$ identifies the post-strike period (dates from 11 November 2014).[22] The coefficient β_s

[19]We implement all OLS regressions using *reghdfe* (Correia, 2016). PPML regressions are performed using the Stata command *ppmlhdfe* (Correia et al., 2020).

[20]ln(ticket sales + 1).

[21]Note that the treatment is not staggered, as all treatment groups are treated at the same time, albeit with different intensity.

[22]As illustrated in Figure 1, rail services remained disrupted on Sunday 9 November and Monday 10 November. These two dates neither fall in the 3rd wave treatment group, nor are they captured by the post-strike dummy. They are thus part of the control group, so that $\hat{\beta}_{post}$ may underestimate the true treatment effect.

measures the extent to which higher strike exposure of affected routes impacts the number of bus bookings relative to less affected routes.

μ_{ijdow} is an interaction of route and day-of-the-week fixed effects. They capture unobserved time-invariant route-specific characteristics (such as the fact that some routes are more popular than others) that may or may not correlate with the degree of exposure to the strike. They also capture route-specific differences that vary across different days of the week. For example, some routes might be more popular during weekdays, while others may be frequented more often during weekends. As shown in Figure A.1 in the appendix, Fridays and Sundays are particularly popular travel days. μ_{ijdow} also captures such variation in ticket sales that is common over all routes.

μ_{iw} and μ_{jw} are origin-week and destination-week fixed effects, respectively. They capture variation in temporal factors common to all departures from or arrivals in each city, such as national holidays, MFB marketing campaigns, origin and destination-specific changes in ticket prices or seasonal fluctuations. Finally, the specification includes vectors of control variables for city-specific daily events, such as holidays or soccer games $\boldsymbol{X}_{it}$ and $\boldsymbol{X}_{jt}$.[23] ϵ_{ijt} is an error term. To address potential serial correlation within routes and over time, we cluster standard errors by route throughout the paper.

Identification relies on the assumption that the trend in log-linearised bus ticket sales on different routes does not vary systematically with the extent to which these routes are disrupted by strikes. Selection into strike exposure is not a threat, but must not be specific to a particular dose. We argue that the dosage of strike exposure is exogenous to the trend in bus ticket sales. DB did not strategically focus rail services on routes that were under particular threat of competition from buses. The emergency timetables were the same in all strike waves in 2014-2015, and they are almost identical to those employed by DB in the last railway strikes of 2007-2008; i.e. long before the liberalisation of the intercity bus market in 2013.

While we assume that routes follow a common trend, the levels of our dependent variable vary across routes and time. Some routes sell up to several hundred tickets daily, whereas others sell no more than two on some days. Furthermore, we know that ticket sales are responsive to major holidays. For example, Figure A.2 in the appendix shows that uncommonly many tickets were sold in the week of 3 October. 3 October is Germany's national holiday, which fell on a Friday in the year 2014, creating a long weekend off for students and many employees. On the Thursday of this week, in particular, MFB sold more tickets than usual. Further, seasonality might affect our data: the vacation period ends and travel is less frequent in the winter months. Overall, a decreasing trend is present in the data. Before the strike, MFB sold on average

[23]These are school holidays, public holidays, the day before and the last day of a long weekend, Football World Cup games, Bundesliga games, Oktoberfest, Stuttgarter Wasn, and Gamescon. Note that German holidays vary at the state level.

14,000 tickets per day. After the strike, average daily sales were at 12,500 tickets. Sales then drastically increased again for Christmas (outside of our observational period). We control for these specific events and aggregate trends using our battery of controls and fixed effects. Consequently, our key identifying assumption cannot be spoiled by such seasonality, as long as there is no difference in underlying trends across routes that coincides with our exposure measure. We put the common trend assumption to the test in an event study estimation, illustrated by Figure 5 in Section 6.2.

We identify treatment effects by relying on the variation in exposure to the strike, measured by the fraction of rail services cancelled. This strategy captures the impact of the strike itself. However, the post-strike effect cannot be exactly identified because not all individuals regularly travel on the same routes. If a route is affected by the strike and causes travellers to switch to the bus, this is captured by the respective beta coefficient. If the strike induces a person to permanently switch to bus travel after the strike, this is only captured if the individual uses the same route after the strike. To give an example, say that the route Hamburg-Munich was strongly affected during the strike, causing people to switch to the bus. If their experience convinces travellers to permanently switch to intercity buses, they will not only use them to travel from Hamburg to Munich (which is captured by β_{post}) but also to travel to other destinations such as Berlin. If Hamburg-Berlin was unaffected during the strike, this observation would fall in the control group, leading to an underestimation of the post-strike treatment effect. Our estimates for the post-strike effects should thus be seen as a lower bound of the true effect. In Section 7, we propose an alternative measure to better capture post-strike effects.

6 Results

6.1 Baseline results

Column 1 of Table 1 provides the results of our baseline estimation as specified in Equation 15. The railway strike significantly increases bus ticket sales on affected routes during all three strike waves. Specifically, the coefficient of 0.507 indicates that a one percentage point increase in the fraction of trains cancelled on a particular route during the first strike wave increases bus ticket sales on that route by 0.66%.[24] On average, about half of the possible train connections are cancelled on strike-affected routes. Our estimates suggest that moving from no cancellations to the average cancellation rate of 49% yields an increase of 32% in ticket sales - which would be around 14 additional tickets with respect to the mean of 45 tickets sold per route per day.

The coefficients of 0.366 and 0.367 for the second and third wave imply that bus ticket sales on affected routes increase by 0.44% following a one percentage point increase in the fraction of

[24] $e^{0.507} - 1 = 0.66$.

services cancelled. Perhaps most strikingly, the effect persists beyond the duration of the strike. The significantly positive post-strike coefficient of 0.155 indicates that routes which experience a one percentage point higher train cancellation rate during the strike see 0.17% higher ticket sales after the strike. This amounts to a permanent 8% increase in ticket sales on the average route. As discussed in Section 5, this estimate most likely constitutes a lower bound of the true treatment effect.

Table 1: The effect of rail strikes on bus ticket sales

	(1)	(2)	(3)	(4)	(5)
Dependent variable: ln(*tickets*)	all	first	spont.	all	planned
Trains cancelled (%) × strike 1	0.507***	0.924***	0.626***	0.474***	0.0979
	(0.0565)	(0.0855)	(0.0601)	(0.0564)	(0.0980)
Trains cancelled (%) × strike 2	0.366***	0.906***	0.633***	0.464***	-0.0797
	(0.0480)	(0.0740)	(0.0642)	(0.0480)	(0.0729)
Trains cancelled (%) × strike 3	0.367***	0.725***	0.829***	0.396***	-0.0210
	(0.0416)	(0.0587)	(0.0590)	(0.0418)	(0.0833)
Trains cancelled (%) × post-strike	0.155*	0.110	0.194***	0.0361	0.518***
	(0.0904)	(0.0898)	(0.0741)	(0.0884)	(0.152)
Trains cancelled (%) × post × weekend				0.382***	
				(0.0276)	
R^2	0.918	0.824	0.892	0.920	0.665

Note: OLS regressions with origin-week, destination-week and route-dow fixed effects as well as controls. Estimated coefficients for controls are reported in Table A.2 in the appendix. Standard errors clustered by route in parentheses. ***/**/* indicate significance at the 1%/5%/10% level. 16,336 observations.

In light of the literature on habit formation and switching costs, our results provide evidence that rail customers have under-experimented before the strike. After having been forced to experiment with alternative transport modes during the strike, some passengers continue to use buses, even after rail services have resumed. Service disruptions of incumbent firms can thus have pro-competitive effects, as rivals can permanently lure away some of the incumbent's customers.[25]

To investigate whether first-time customers drive aggregate effects, we estimate our baseline specification, using the logarithm of the number of tickets sold to first-time customers as the dependent variable. The effects of the strike are even more pronounced for first-time ticket sales, as Column (2) of Table 1 shows. A one percentage point increase in train cancellations

[25] Travellers might have booked bus tickets after the November 2014 rail strike, because they were worried about potential future strikes. The rail strikes lasted beyond the strikes in 2014, and the labour dispute was only resolved after additional strike waves in April and May 2015. However, immediately after the strike wave in November, GDL announced a temporary truce. It would refrain from industrial action until the new year.

during the first strike wave is associated with a 1.52% increase in first-time customers' ticket sales. Second and third-wave effects are also stronger for first-time customers. The estimated coefficient for the post-strike effect is not significantly different from zero. This is to be expected, as routes affected more strongly during the strike should not attract more first-time customers after the strike (only repeat customers).[26]

Potentially the best proxy for people who switch to the bus during the strike is the logarithm of spontaneous ticket sales. These are defined as all bookings made no more than three days prior to departure. Estimated coefficients for spontaneous sales are reported in Column (3). A one percentage point increase in cancellation on a given route during the first wave is associated with a 0.87% increase in spontaneous ticket sales. The number of tickets sold to passengers booking spontaneously on affected routes remains higher after the strike, as indicated by the significantly positive post-strike coefficient.

As shown in Figure A.1 in the appendix, the absolute number of ticket sales varies across days of the week. Any such variation should be absorbed by day-of-the-week fixed effects in all of our specifications. However, treatment effects may vary across different days of the week. In particular, passengers travelling over the weekend are more likely to travel for leisure than for work. They might thus be more willing to endure longer travel times using buses in return for lower ticket prices. We would thus expect the post-strike impact to be stronger for weekend trips. If treatment effects vary across different days of the week, this could also explain the relatively large standard error of the estimated post-strike coefficient (about twice as large as the standard errors of the contemporaneous strike coefficients) observed in Column (1) of Table 1. We therefore re-run our baseline regression adding another regressor, namely the interaction of our post-strike treatment variable with a dummy indicating whether the bus departs on a weekend (i.e. on Friday, Saturday, or Sunday).

Regression results including this triple interaction are presented in Column (4) of Table 1. The post-strike interaction with the strike exposure measure, *trains cancelled (%)*, turns insignificant in this specification. However, the triple interaction term is highly significant and more than twice as large as the post-strike coefficient in our baseline specification (Column 1). The results imply that the increase in ticket sales on strike-affected routes after the strike is driven by weekend sales. Bus travel thus seems a useful substitute for train travel mostly for leisure passengers, travelling on weekends (Friday to Sunday).

In Column (5) of Table 1, we estimate the effects of the strike on long-planned trips. The dependent variable is the logarithm of the number of bus tickets that were booked more than 30 days before departure day t. As strikes were announced only a few days in advance, they should not impact the number of tickets sold 30 days earlier. Indeed, estimated coefficients are

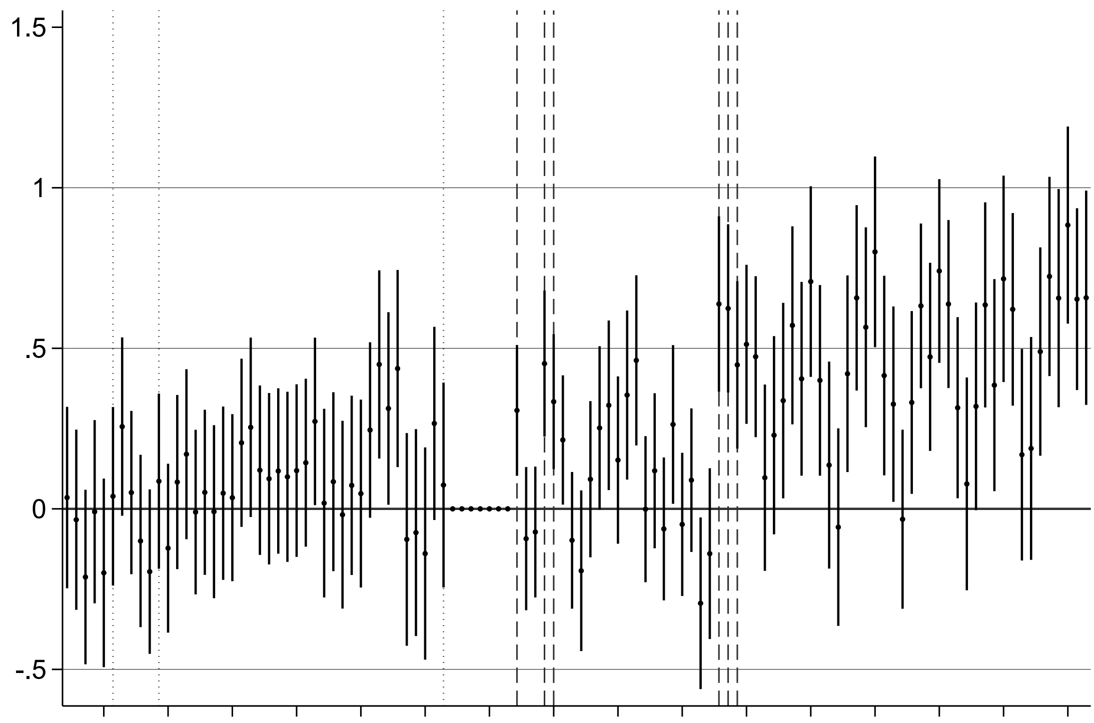
[26] We treat a ticket as a first-time ticket if it is booked using an e-mail address that has never before been registered with MFB. Note that one booking can include several tickets.

not significantly different from zero for all three strike waves. Recall that the third strike ends on 8 November, so that tickets booked more than 30 days in advance were not yet affected by the first wave, which was announced on 10 October. The post-strike period begins on 11 November - almost 30 days after the first strike was announced on 14 October. Consequently, the majority of travellers booking tickets for departure in the post-strike period have already been exposed to the strike, as indicated by the significantly positive coefficient.

6.2 Effects over time

To further illustrate the impact of the strike over time, we regress ln ticket sales on our strike exposure variable, interacted with a dummy for each day in our sample period.[27] Estimated coefficients are depicted graphically in Figure 5.

Figure 5: The effect of rail strikes on bus ticket sales, by day of departure



Note: Estimated coefficients on the vertical axis, days from 27 August to 16 December on the horizontal axis. Wednesday, 8 October, to Thursday, 14 October, are the baseline week. The dotted vertical lines indicate warning strikes, the dashed vertical lines indicate strike days. The plots show point estimates with 95% confidence intervals, indicating significant effects during and after the strikes. Ticks on the x-axis indicate Sundays.

[27]We estimate the following equation: $\ln y_{ijt} = \sum_d^D \beta_d(exposure_{ij} \times day_t^d) + \mu_{ijdow} + \mu_{iw} + \mu_{jw} + \boldsymbol{X}_{it}\boldsymbol{\gamma}' + \boldsymbol{X}_{jt}\boldsymbol{\delta}' + \epsilon_{ijt}$. day_t^d is a dummy identifying each day in the sample period. We omit the week before the beginning of the strike to interpret the coefficient relative to a baseline that includes each day of the week.

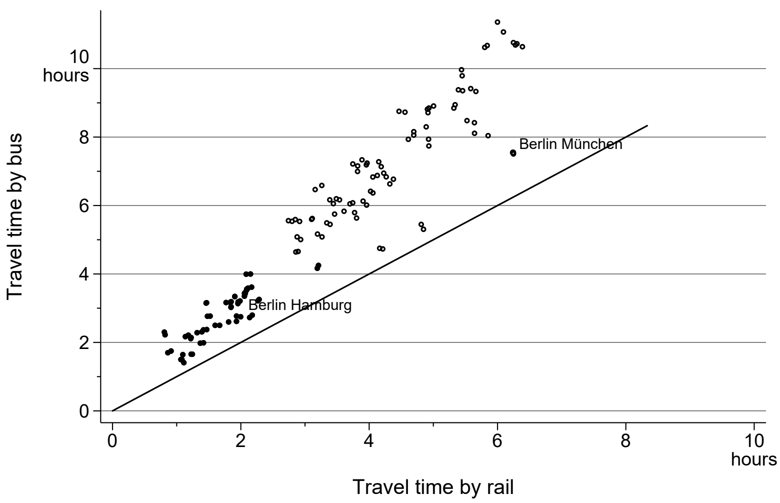
The event study serves two objectives. First, estimated coefficients are mostly insignificant before the first strike, indicating no difference in pre-treatment trends between treatment and control group. Second, the graph clearly shows that the post-strike effect is always significantly positive for Fridays, Saturdays and Sundays. It also shows significant positive effects for the two days following the third strike wave (Sunday, 9 November and Monday, 10 November). This is to be expected for two reasons: First, the strike was originally planned to last until Sunday but ended prematurely on Saturday following public pressure. Second, as indicated by Figure 1, service disruptions continued until Monday, 10 November as it took DB two days to return to its normal schedule.

7 Extensions and Robustness

7.1 Alternative treatments

Travelling by bus between cities in Germany typically takes longer than travelling by train. The relative trip duration further increases with the length of the travelled route. For each additional stop on a bus journey, the bus has to leave the highway and enter the city centre to reach the bus terminal. Figure 6 illustrates the increasing divergence in travel time. When the travel time exceeds several hours, bus travel might simply not be a good substitute for a train trip, and rail customers might have switched to travel by car or plane instead.

Figure 6: Travel time bus vs. rail



Note: Scatter of routes in duration rail and duration bus space with 45 degree line. Filled dots indicate below-median bus travel time. Routes Berlin–Munich and Berlin–Hamburg plotted as examples.

We hence introduce the duration of the bus trip as an alternative treatment variable to test the hypothesis that shorter bus routes experienced an increase in bus ticket sales during and after the strike. We define a bus ride to be bivariate relatively short if the scheduled time of travel is below the median of 265 minutes (a little over 4.5 hours). Note that shorter bus routes were not systematically more affected by the strike.[28]

Using relative trip duration as the treatment variable has another advantage compared to the fraction of services cancelled. Short routes remain relatively more attractive than long routes after the strike. As discussed in Section 5, passengers do not always travel along the same route. Customers who were affected by the strike by having travelled on a route with a high fraction of services cancelled and who decide to also travel by bus after the strike will probably do so on different (untreated) routes, too. Consequently, the estimated post-strike coefficient underestimates the treatment effect.

Relatively short bus routes, however, offer a more attractive alternative to travelling by train both during and after the strike. Consequently, one would expect post-strike bus travel to increase more strongly on shorter routes. Even during the strike, decisions by passengers to switch transport modes may partly be driven by uncertainty regarding the reliability of the emergency timetable, so passengers switched to buses even on routes less strongly affected by the strike. There is indeed some evidence for a general increase in bus use during the strike, also on less affected routes (see Table 3). Faced with this uncertainty, passengers may switch from train to bus if they perceive the bus to be a decent substitute. Finally, not having to rely on information on service cancellations means that we can include routes that are only served by regional trains (recall that for regional trains we do not have information on service cancellations). This roughly doubles the sample size.

Column (1) of Table 2 shows that the number of tickets sold indeed increases more strongly on short routes. This is true during as well as after the strike. During the first wave, ticket sales increase by 37% on short routes. In the weeks after the strike, short bus routes sell up to 24% more tickets. The post-strike coefficient remains significantly positive when including the triple-interactions (Column 2), although effects remain stronger during the weekend. All in all, results are qualitatively similar to those presented in Table 1. Given that strike-effects are indeed stronger on shorter routes and that many short routes are excluded in the baseline regression due to data limitations, the results imply that the baseline specification underestimates the true treatment effect.

The effect of service cancellations on passenger numbers may be non-linear. For example, passengers might not mind if a small fraction of rail services is cancelled as long as alternative connections are offered. However, if the fraction of services cancelled exceeds a certain level, passengers might switch to alternative modes of transport. Instead of using the fraction of services cancelled as a continuous regressor, we construct a dummy that equals one if the fractions of services cancelled on a particular route is above the median (and zero otherwise). This variable is then interacted with the four strike dummies. The results, reported in Column

[28]The correlation between the duration of the bus ride and the fraction of trains cancelled on a route is 0.06.

(3) of Table 2, are qualitatively similar to the baseline, indicating increasing passenger numbers on affected routes both during and after the strike. Specifically, routes with above median exposure to the strike experience a 9% increase in ticket sales in its aftermath.

Table 2: Alternative treatments and marketing

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dep. var.	ln(*tickets*)	ln(*tickets*)	ln(*tickets*)	ln(*price*)	ln(*tickets*)	*Voucher*	ln(*seats*)
Treat. var.	Bus ride short	Bus ride short	Cancellation above median	Trains cancelled	Trains cancelled	Trains cancelled	Trains cancelled
Treatment × strike 1	0.312*** (0.0317)	0.283*** (0.0316)	0.229*** (0.0419)	0.0446 (0.0508)	0.489*** (0.0571)	-0.0553** (0.0243)	0.0285 (0.0854)
Treatment × strike 2	0.225*** (0.0237)	0.290*** (0.0243)	0.183*** (0.0341)	0.162*** (0.0510)	0.314*** (0.0527)	-0.0186 (0.0153)	0.0630 (0.0642)
Treatment × strike 3	0.319*** (0.0221)	0.339*** (0.0223)	0.172*** (0.0316)	0.116** (0.0516)	0.280*** (0.0459)	0.00650 (0.0125)	0.0403 (0.0793)
Treatment × post-strike	0.218*** (0.0169)	0.105*** (0.0174)	0.0853** (0.0368)	0.0194 (0.0235)	0.169** (0.0831)	0.00591 (0.00620)	0.110* (0.0596)
Treatment × post-strike × weekend		0.280*** (0.0123)					
Strike 1				0.0362 (0.0267)		0.0300** (0.0146)	0.0889** (0.0421)
Strike 2				0.134*** (0.0249)		0.00948 (0.00906)	0.00824 (0.0299)
Strike 3				0.220*** (0.0268)		-0.00187 (0.00734)	0.00891 (0.0425)
Post-strike				-0.0950*** (0.0134)		-0.00574 (0.00603)	-0.105*** (0.0380)
ln(*price*)					0.137*** (0.0431)		
Observations	34,818	34,818	16,336	16,282	16,282	16,282	16,282
R^2	0.906	0.908	0.918	0.969	0.922	0.151	0.918

Note: OLS regressions with origin-week, destination-week and route-dow fixed effects. Standard errors clustered by route in parentheses. ***/**/* indicate significance at the 1%/5%/10% level.

7.2 Marketing

We argue that rising bus ticket sales are driven by an increase in demand due to the reduced availability of rail travel. However, an alternative channel could be the supply side. Specifically, bus companies could have reacted to the strike with large marketing campaigns, which may include lower prices or advertising. As argued in Section 5, potential marketing campaigns are controlled for through origin-week and destination-week fixed effects, as long as they do not vary across treated and non-treated routes. In the following robustness checks, we show that there is no evidence for higher marketing activity on routes affected by the strike.

First, we investigate ticket prices. If ticket prices at MFB were exceptionally low during the strike, this could indicate that MFB used the increased public attention during the railway strike to attract new customers with extremely competitive price offers. In this case, the estimated strike effect would be supply-side driven rather than the result of a shift in demand. We test this hypothesis by regressing the logarithm of average ticket prices at the route-day level $\ln(price_{ijt})$ on our strike exposure variables, as well as time dummies identifying the different strike waves. The results, provided by Column (4) of Table 2, indicate no such supply shock. Average ticket prices are significantly higher during the second and third strike wave. This is true for all routes, not just those affected by the strike. Prices are even higher on affected routes, a result consistent with higher demand on these routes. We are hence confident that our results do not mirror supply side effects.[29]

As an additional robustness check, we re-run our baseline regression but include average prices as an additional control (Column 5 of Table 2). The price coefficient is significantly positive, while all other coefficients remain similar to the baseline in both magnitude and significance. The post-strike effect even increases in both magnitude and statistical significance.

A second type of marketing activity that may vary across routes concerns vouchers. MFB would sometimes hand out vouchers for discounts. Our dataset includes information on whether a customer used such a voucher when booking the tickets. The average daily fraction of tickets obtained at a discount fluctuates between 2% and 4% over the sample period. Column (6) of Table 2 shows that while the use of such vouchers significantly increased during the first strike wave, this effect was not driven by strike-affected routes.

One type of marketing activity which we do not observe in our data is advertising. However, according to representatives of MFB, the company did not increase its advertising activity during the strike, especially not on strongly affected routes.

An increase in ticket sales might not directly reflect an increase in demand to an equal extent if sales were capped when MFB's offer reached short-term capacity peaks. MFB did increase the number of buses running on a route, thereby the number of seats available for booking, on departure days with high travel activity. In our data, we observe capacity increases parallel to sales increases during the strike, but also on weekends and national holidays. On average during our observation period, 0.3% of all bus connections were fully booked, meaning that there were no more tickets available for this specific connection at one specific departure time.

[29] Generally, MFB bus fares dynamically increase as capacity fills up. The significantly negative non-route specific post-strike coefficient can be explained by seasonality, as discussed in Section 5.

Occasionally, several - or even all - connections are booked out on a certain day on a certain route. During the strike, the total number of fully-booked connections increased. Yet, no route exceeded a share of 37% in fully booked connections during the strike. Within the same day on the same route, there were always options for departure at a different time. It seems that as MFB was used to adjusting capacities to demand, the strike did not present an exceptional challenge in this regard.

We re-estimate our baseline specification with the logarithm of the number of available seats per day per route as the dependent variable. As can be seen from Column (7) of Table 2, capacity increases during the strike were mostly insignificant and did not specifically affect strike-exposed routes. After the strike, at a time when overall capacities were in decline along with the seasonal trend, we observe a significant increase in capacity on strike-affected routes. This falls in line with expectations given the increase in post-strike ticket sales on these routes.

7.3 Further robustness checks

In our baseline estimation, we exploit variation across routes as well as across strike and non-strike days to estimate a treatment effect. We control for time-trends using origin-week and destination-week fixed effects. As a robustness check, we add four time-variant dummies that identify the three strike periods as well as the post-strike period and that do not vary across routes. The results are provided in Columns (1) and (2) of Table 3. Our treatment variables remain qualitatively similar to the baseline estimates, indicating an increase in the number of passengers travelling by bus on affected routes both during and after the strike.[30]

An even more conservative approach would be the additional use of day fixed effects. We choose not to do this in our baseline specification as they might absorb too much variation needed to identify treatment effects. As discussed above, estimating differential effects for weekends in the post-treatment period becomes problematic because the exposure variable does not explicitly vary in the post-treatment period any more. However, we do run our main regressions including day fixed effects as a robustness check.

The results are reported in Table 3. Estimated coefficients for our preferred strike and post-strike variables (fraction of services cancelled) remain qualitatively similar (Column 3). The post-strike effect even increases in magnitude and significance, presumably because day fixed effects better capture the overall decline in ticket sales in the post-strike period than origin- and destination-week fixed effects employed in the baseline. The weekend coefficient indeed becomes statistically insignificant, although the post-strike coefficients now turn significantly positive (Column 4). In an alternative specification, we estimate Equation 15 with PPML

[30]The significantly negative non-route specific post-strike coefficient can be explained by seasonality, as discussed in Section 5.

instead of OLS. The results, reported in Columns (5) and (6) of Table 3, are qualitatively similar to the baseline results.

Table 3: Difference-in-differences, day fixed effects and ppml

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable: ln(*tickets*)	OLS	OLS	OLS	OLS	PPML	PPML
Trains cancelled (%) × strike 1	0.250	0.205	0.243	0.236	0.393***	0.358***
	(0.155)	(0.155)	(0.156)	(0.155)	(0.0513)	(0.0502)
Trains cancelled (%) × strike 2	0.375***	0.460***	0.373***	0.388***	0.247***	0.315***
	(0.140)	(0.141)	(0.141)	(0.142)	(0.0402)	(0.0438)
Trains cancelled (%) × strike 3	0.257*	0.293**	0.261*	0.266**	0.244***	0.258***
	(0.131)	(0.132)	(0.133)	(0.134)	(0.0296)	(0.0291)
Trains cancelled (%) × post-strike	0.370***	0.209	0.328**	0.303**	0.203***	0.0442
	(0.133)	(0.130)	(0.132)	(0.131)	(0.0659)	(0.0599)
Trains cancelled (%) × post-strike × weekend		0.371***		0.0626		0.349***
		(0.0272)		(0.0951)		(0.0288)
Strike 1	0.144*	0.150*				
	(0.0808)	(0.0809)				
Strike 2	0.00333	0.00820				
	(0.0744)	(0.0746)				
Strike 3	0.0224	0.0258				
	(0.0735)	(0.0735)				
Post-strike period	-0.287***	-0.228***				
	(0.0774)	(0.0752)				
Day fixed effects	NO	NO	YES	YES	NO	NO
R^2	0.919	0.92	0.924	0.924		

Note: All regressions include origin-week, destination-week and route-dow fixed effects as well as controls. Standard errors clustered by route in parentheses. ***/**/* indicate significance at the 1%/5%/10% level. 16,336 observations.

8 Conclusion

In this study, we harness a comprehensive and unique dataset to explore the repercussions of the 2014 German railway strikes — the largest in the nation's history — on intercity bus usage. Leveraging the strikes as a quasi-natural experiment, we address the broader question of whether temporary service interruptions can encourage experimentation and induce enduring shifts in demand for competing products.

We find a route-specific effect of railway cancellations leading to more bus travel. More specifically, the number of bus tickets sold increases for departures during the strike on routes that are more strongly affected (averaging 32% during the first strike wave). Remarkably, this effect persists beyond the strike, with ticket sales on impacted routes maintaining an average 8% increase. Passengers continue embracing buses even upon train service restoration, especially weekend travellers, indicating sustained bus adoption among price-sensitive leisure passengers. Since passengers who permanently switch to buses most likely do so not only on routes that were strongly affected by the strike, our post-strike estimates provide a conservative assessment of the true treatment effect. Notably, even during the strike, our results indicate some customers divert from DB services, regardless of DB emergency timetables, emphasising route-based identification as a lower-bound contemporary strike effect estimate.

Shorter bus routes also see an increase in passenger numbers. Given increasing absolute and relative travel time disparities between buses and trains with distance, this suggests prominent switching where buses closely substitute train travel. Importantly, this measure remains unchanged post-strike, circumventing baseline estimation biases, thereby underscoring persistent mode-switch evidence. Positive price effects suggest that the increase in ticket sales stems from an increase in demand due to the disruption of rail services, not from a positive supply shock by MFB in response to the strike.

Our study unveils the affirmative and enduring influence of the DB railway strike on rival MFB's passenger counts. Such service interruptions can steer passengers towards a persistent transport mode switch — here, from rail to intercity buses. Against the backdrop of climate change, our results emphasise the need for dependable carbon-neutral transport modes to consistently attract passengers. Moreover, by recognising habit and search cost barriers to mode shift, governments should facilitate experimentation with sustainable transportation to alleviate adoption hurdles.

Beyond transportation, our conclusions underscore the pivotal role of experimentation accompanying market liberalisation. Effectively enabling customers to explore alternative options can surmount switching costs that may previously have suppressed competition. While incumbents keen on customer retention will try to avert service interruptions, consumers' welfare might be increased by encouraging experimentation. Lowering barriers to do so - even if only temporary - may enable governments to permanently foster competition and raise welfare.

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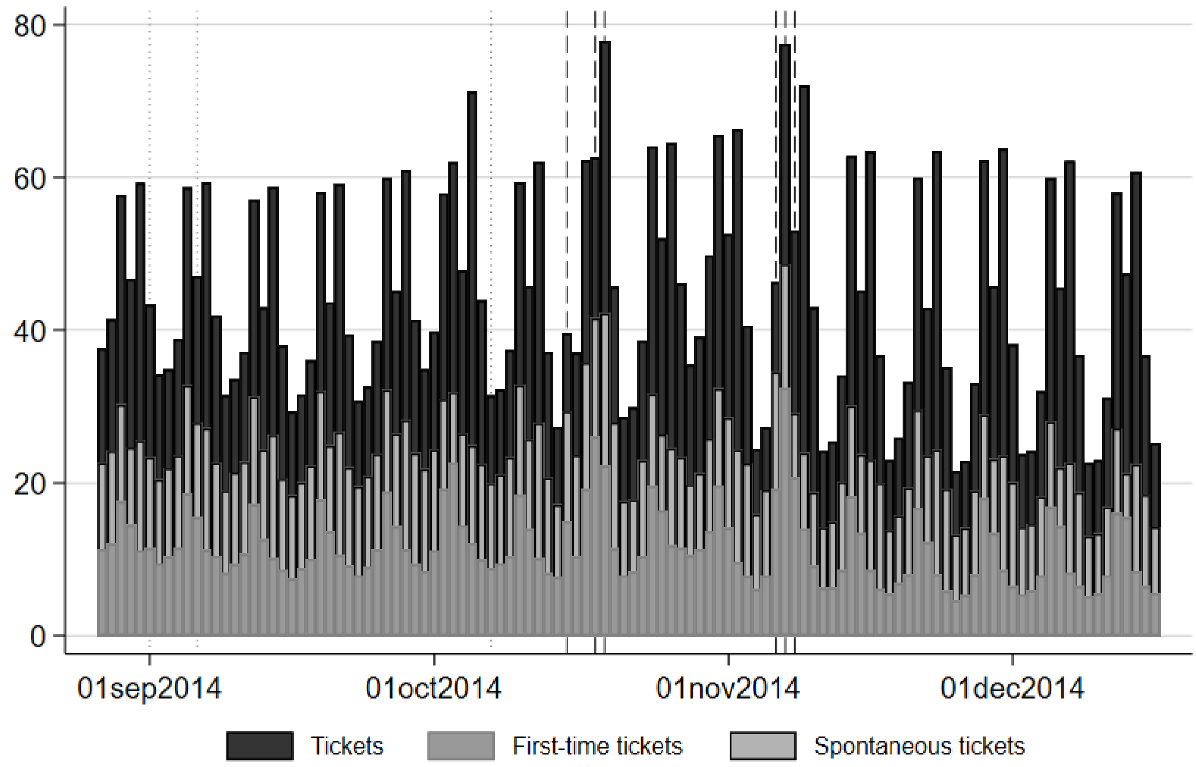
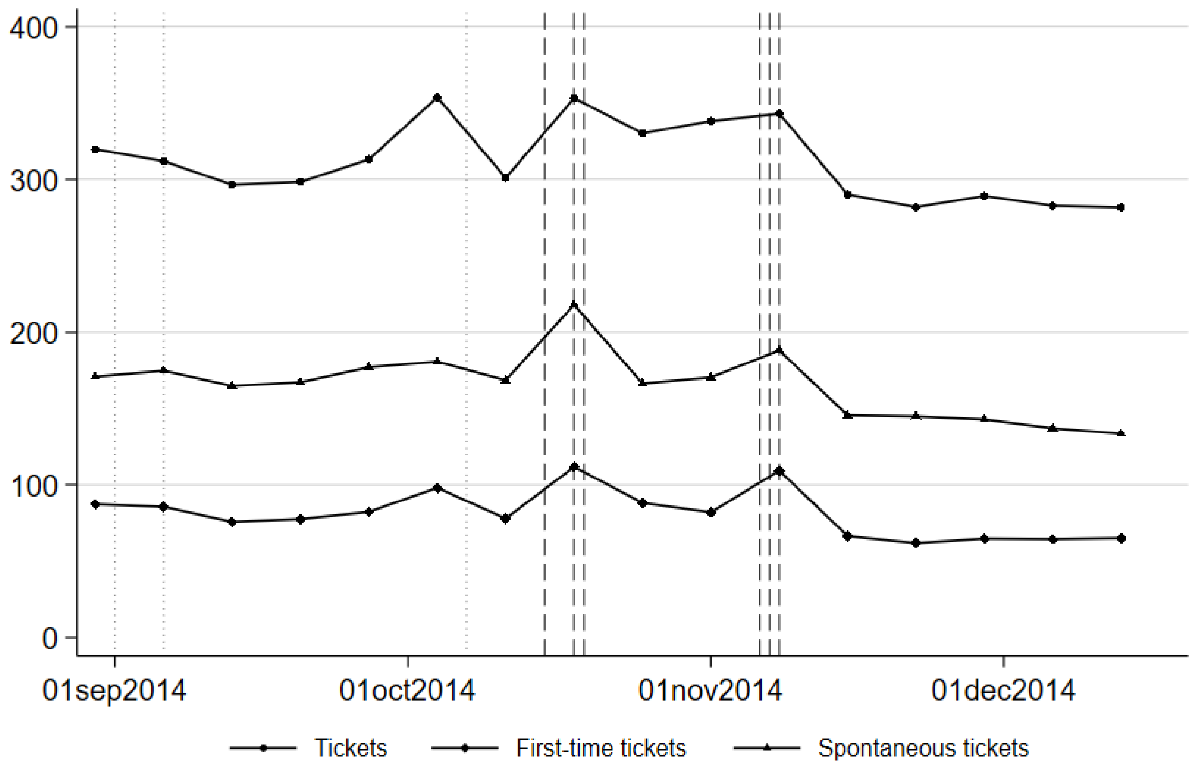
Appendix

Figure A.1: Daily mean ticket sales per route (treatment & control routes)



Note: The graph shows the average number of bus tickets sold per route, not differentiating by treatment and control groups. The bars indicate daily averages. The vertical dashed lines indicate strike days, vertical dotted lines indicate warning strikes. Overall ticket sales follow a decreasing trend, driven by seasonality. A day-of-the-week pattern is recognisable.

Figure A.2: Weekly mean ticket sales per route (treatment & control routes)



Note: The graph shows the average number of bus tickets sold per route, not differentiating by treatment and control groups. The lines show weekly averages. The vertical dashed lines indicate strike days, vertical dotted lines indicate warning strikes. Overall ticket sales follow a decreasing trend, driven by seasonality.

Table A.1: Dates and duration of railway strike waves in 2014-2015

Nr.	Strike Begin:	—	Strike End:	Duration (in hours):
1	Mon. 01/09/2014, 18:00	—	Mon. 01/09/2014, 21:00	3*
2	Sat. 06/09/2014, 06:00	—	Sat. 06/09/2014, 09:00	3*
3	Tue. 07.10.2014, 21:00	—	Wed. 08.10.2014, 06:00	9*
4	**Wed. 15/10/2014, 14:00**	—	**Thu. 16/10/2014, 04:00**	**14**
5	**Sat. 18/10/2014, 02:00**	—	**Mon. 20/10/2014, 04:00**	**50**
6	**Thu. 06/11/2014, 02:00**	—	**Sat. 08/11/2014, 18:00**	**64**
7	Wed. 22/04/2015, 02:00	—	Thu. 23/07/2015, 21:00	43
8	Tue. 05/05/2015, 02:00	—	Sun. 10/05/2015, 09:00	127
9	Wed. 20./05/2015, 02:00	—	Thu. 21./05/2015, 19:00	41

Note: Bold rows indicate waves studied in this paper. Strikes in 2015 are disregarded, because they coincide with the merger of MFB and rival competitor Flixbus in January 2015. * indicates warning strikes. Warning strikes are ignored because they only lasted a few hours and were announced with many days' advance warning.

Table A.2: The effect of rail strikes on bus ticket sales: Including controls

	(1)	(2)	(3)	(4)	(5)
Dependent variable: ln(*tickets*)	all	first	spont.	all	planned
Trains cancelled (%) × strike 1	0.507***	0.924***	0.626***	0.474***	0.0979
	(0.0565)	(0.0855)	(0.0601)	(0.0564)	(0.0980)
Trains cancelled (%) × strike 2	0.366***	0.906***	0.633***	0.464***	-0.0797
	(0.0480)	(0.0740)	(0.0642)	(0.0480)	(0.0729)
Trains cancelled (%) × strike 3	0.367***	0.725***	0.829***	0.396***	-0.0210
	(0.0416)	(0.0587)	(0.0590)	(0.0418)	(0.0833)
Trains cancelled (%) × post-strike	0.155*	0.110	0.194***	0.0361	0.518***
	(0.0904)	(0.0898)	(0.0741)	(0.0884)	(0.152)
Trains cancelled (%) × post × weekend				0.382***	
				(0.0276)	
School holiday	0.153***	0.187***	0.0761***	0.170***	0.180***
	(0.0147)	(0.0192)	(0.0164)	(0.0148)	(0.0236)
Public holiday	-0.201***	-0.294***	-0.197***	-0.149***	-0.113***
	(0.0213)	(0.0311)	(0.0265)	(0.0204)	(0.0385)
Long weekend	0.170***	0.190***	-0.0541	0.173***	0.399***
	(0.0256)	(0.0352)	(0.0384)	(0.0254)	(0.0497)
Oktoberfest (Munich)	0.234***	0.312***	0.144***	0.250***	0.182***
	(0.0325)	(0.0391)	(0.0419)	(0.0324)	(0.0642)
Cannstatter Wasen (Stuttgart)	0.172***	0.220***	0.158***	0.219***	-0.0377
	(0.0409)	(0.0598)	(0.0508)	(0.0404)	(0.0956)
1. Bundesliga match	0.168***	0.262***	0.101	0.185***	0.214**
	(0.0445)	(0.0655)	(0.0625)	(0.0440)	(0.0966)
2. Bundesliga match	0.212**	0.403***	0.123	0.206**	0.408**
	(0.0954)	(0.130)	(0.0903)	(0.0905)	(0.163)
R^2	0.918	0.824	0.892	0.920	0.665

Note: OLS regressions with origin-week, destination-week and route-dow fixed effects as well as controls. Standard errors clustered by route in parentheses. ***/**/* indicate significance at the 1%/5%/10% level. 16,336 observations.