



The impact of optimal rail access charges on frequencies and fares

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ABSTRACT

Sweden has been a front runner in vertical separation. We use data from the business long-distance corridor in Sweden to calibrate and define a demand and supply model. We simulate how the profit, welfare, fares, frequencies, modal shares and train size depend on the level of the track charges. We simulate the welfare optimal track charges, given different levels of congestion on the track, hence using the charges as a pricing instrument to allocate the train slots efficiently. We find that increases in charges have a limited impact on fares but larger impacts on the frequency. When the length of the trains can be extended and when the crowding penalty is high, the impact of higher track charges on the frequencies is larger. Higher track charges increase the length of the trains if possible. The intermodal competition from road and air has a significant impact on rail fares.

1. Introduction

Over the past decades, the European Commission has promoted vertical separation on the railway market, where rail operators are separated from the public infrastructure manager (IM). The aim is to encourage competition by opening access to commercial operators, even if real on-track competition is still uncommon in Europe. With vertical separation, rail access, or track charges are indispensable for welfare-efficient allocation of capacity, because the public IMs do not have full information regarding demand and operation costs (Ait Ali, 2020). Yet, both Sweden and the UK apply charges below the marginal social cost (Nash et al., 2018). One contributing factor to the low track charges could be the notion that higher track charges would increase fares.¹ In this paper, we therefore model how track charges impact frequencies and fares set by a profit-optimizing monopolist rail operator in a vertically separated corridor with publicly owned rail tracks, applying a demand and supply model. The model includes two user groups (business and private) and four competing modes (train, car, bus, air) since intramodal competition will determine the operator's monopoly power.

We include congestion on the tracks, other externalities, and crowding in the trains, making the problem too complex to solve analytically. We therefore solve the model numerically by calibrating the model for the busiest corridor connecting the two largest cities

(Stockholm and Goteborg) of Sweden. One reason for choosing this corridor is that there exists a calculation of the external congestion cost (Ait Ali et al., 2020) and other externalities (Nilsson and Haraldsson, 2018). Data on travel volumes by all modes and ticket prices are also available. Moreover, Sweden was the first country to introduce vertical separation in 1988 with publicly owned infrastructure, allowing a mixture of regional, commuting, freight and commercial long-distance train operators. Since vertical separation with publicly owned infrastructure is promoted by the commissions' railway packages, and since track charges are so important for the allocation of scarce capacity in such setting, our findings for the Stockholm and Goteborg corridor are deemed relevant for many European countries.

The extensive literature on optimal pricing and frequency for scheduled services (for instance, Parry and Small, 2009; Basso and Silva, 2014; Tirachini et al., 2014 and Börjesson et al., 2017) has so far focused on urban transit corridors that are heavily subsidized. No previous study has explored how fares depend on the track charges on a vertically separated rail corridor. Sánchez-Borrás et al. (2010) and Ljungberg (2013) analyse the effects of track charges but assume that increases in charges are directly passed on to the consumers through higher fares. Broman and Eliasson (2019) study the impact of higher track charges assuming duopoly competition (see future section 2).

Allocation of track capacity is different from the allocation of road

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¹ The EU legislation permits lower track charges if road transport is not charged full marginal social cost. However, for passenger transport this is not the case since passenger cars in general pay the full marginal social cost. Stockholm and Gothenburg both have time-of-day varying congestion charges, and the congestion on the motorways in between is limited.

capacity, which is simply queuing, when capacity is scarce. Track capacity must be planned by solving scheduling conflicts. However, a given capacity can be allocated in many ways (number of and mix of train types with different speeds (Eliasson and Börjesson, 2014)), and the scheduled travel times and delays also tend to rise with higher capacity utilization. Higher capacity utilization implies that trains must wait more often for other trains to pass. If one train is held up and runs behind schedule, this will often in turn force other trains to wait. Hence a primary delay will tend to spread more quickly in the form of reactionary delays or cancellations in a network with higher capacity utilization (Arup, 2013).

If the commercial transport markets are perfect, the welfare optimal track charge equals the total external cost, including the marginal opportunity cost of capacity. If the commercial train operator has monopoly power, this might not be the case. In this paper, we use the assessment of the total external cost, including congestion and other costs, to calculate the optimal reservation price for the slot allocation. Only if the long-distance train operator is willing to pay the reservation price, will the slot be allocated to its trains. An allocation based on a cost-benefit exercise would be just as efficient as a price-based allocation if the IM has full information of demand and operation costs, but for commercial operators this is almost never the case.

The complicated nature of congestion on tracks implies that cost calculations of congestions are scarce. But Ait Ali et al. (2020) calculate the external congestion cost of commercial long-distance trains on the same tracks that we study, under the assumption that the baseline supply of commuting trains operating on the same track is given. The baseline supply of commuting trains is determined by the regional public authority aiming at optimizing welfare and also, for good reasons, subsidizing the commuting trains heavily. Ait Ali et al. calculate the marginal external congestion cost of a long-distance train by removing or rescheduling the commuter trains. The result is that waiting time, crowding and the number of transfers may increase for commuters, or that the travel time increases because the commuting train must wait for the long-distance train to pass. The social loss is calculated as the sum of the change in consumer surplus and the producer surplus in the commuting train market. Johnson and Nash (2008) developed a similar method.

This type of allocation problem is not unique to the rail sector, but practical solutions are relatively immature compared to other network industries facing them, such as the electricity, telecommunication, and aviation industries (Peña Alcaraz, 2015). General experiences from other network industries are that price-based allocation is equivalent to capacity-based allocation if perfect information and full certainty is assumed (Czerny, 2010; Weitzman, 1974). In capacity-based allocation, the IM instead let the operators bid for the capacity in an auction, revealing its valuation (Affuso, 2003; Perennes, 2014). Such auctions have not yet been implemented in the rail industry.

A further conclusion from other network industries is that the IM can recover fixed infrastructure costs if applying marginal cost pricing, if investments are not lumpy, and if there is perfect information, full certainty, and if the operators lack market power (Besanko and Cui, 2019; Peña Alcaraz, 2015). However, such circumstances do rarely occur in the rail sector, where fixed infrastructure and maintenance costs are very high and indivisible. Smith and Nash (2018) assess that the marginal cost is only 25–35 percent of the total maintenance and renewals cost. For this reason, EU legislation allows track charges to be higher than the marginal social cost to achieve cost recovery (Nash et al., 2018). Besanko and Cui (2019) compare the scenarios where track charges in a vertically separated market can be regulated or and when they are negotiated between the company owning and managing the infrastructure and the commercial train operators. They find that negotiation would produce higher welfare, if the infrastructure company were allowed to price discriminate. Nash (2003) notes, however, that negotiation-based charges in the rail sector are time consuming, and often lacks transparency and flexibility over time. Moreover, Besanko

and Cui conclude that both regulated and negotiated prices would resemble Ramsey prices where there are large, fixed costs to cover. But Ramsey pricing would in many cases significantly reduce social welfare by increasing distortions in the transport market. This is one reason why we assume that the public IM strives at maximizing welfare without considering coverage of fixed costs.

The trade-off between distortions in the transport market and cost coverage is demonstrated by the NEC corridor, abandoning negotiation-based prices in 2015 since the revenues did not even cover basic maintenance of the tracks (Gardner, 2013; Peña Alcaraz, 2015). In Europe, the outcome of this trade-off varies between countries. In the UK, the track charges correspond to the short run marginal cost, demanding large subsidies from the government to cover the fixed infrastructure costs (Nash et al., 2018). Germany and France, on the other hand, are aiming for full cost coverage (except for investments in Germany), resulting in some form of Ramsey pricing, with the result that the track charges make up 40 percent of the ticket price (Crozet, 2016).

In the corridor under study, the track charges cover roughly the marginal cost except congestion. This will imply that the taxpayers must cover most of the large, fixed cost of maintenance and investment in the rail infrastructure. On one hand, our assumption can be questioned because welfare is not optimized whilst considering that the public funds covering the subsidies are costly. On the other hand, it is a political decision to publicly invest and maintain the railway, taken while also considering the cost of public funds. It seems to be taken because many governments are simply not willing to allow competition from other modes to determine the market outcome (Nash and Smith, 2021). If cost coverage is desired, Ramsey pricing or pricing proportional to the use is preferable (Crozet, 2004; Monchambert and Proost, 2019; Nash, 2005). But with Ramsey pricing, evidence suggest that it is difficult to attract commercial operators. Crozet (2016) reports that to achieve competition on the Italian HSR, the track charges had to be reduced by 35%.

To increase the transferability of our results to other corridors, we simulate the welfare optimal rail track charges assuming different levels of congestion on the tracks. We then simulate the profit-maximizing fares and frequencies for a wide range of track charges. We study how the train frequencies and fares change in response to changes in the competition from other modes, due to lower supply of air traffic and more competition from autonomous electric vehicles. The paper is organized as follows. Section 2 describes the market structure of the corridor. In Section 3 we derive an aggregate model. We define the disaggregate demand and supply model in Section 4. The model calibration and scenario assumptions are presented in Section 5 while Section 6 reports the results. Section 7 concludes.

2. The competition in the corridor

In the past, railways were often owned and operated by private monopolies, and regulations of these monopolies were common (Nash and Smith, 2021). Such regulations were gradually lifted as competition from road transport weakened the monopoly power. In European countries, the rail infrastructure and operators ended up as publicly owned monopolies receiving large subsidies. But the productivity of the public monopolies was low; for freight the modal share for rail halved between 1970 and 1990 and also fell for passenger transport, even though subsidies increased (Nash and Smith, 2021). To address this issue, in the 90s the EU started to promote competition on the publicly owned tracks, by encouraging private train operators.

Real on-track competition among long-distance passenger trains is, however, not common. It exists in the Swedish corridor under study, on the Italian HSR, in Austria and in the Czech Republic (Crozet, 2016). Competition among rail operators can also be organized as competitive tendering for franchises. In the UK, a passenger service is operated by the winner of a franchise competition (Smith, 2016). One reason why competition is unusual may be that it seems to work best on tracks with spare capacity, high passenger demand and low track charges (Nash

et al., 2018), which are rather unusual circumstances. Another reason is that the incumbent can relatively cheaply employ the entry deterrence strategy by increasing frequencies above what is optimal for the monopoly. Moreover, simulating on-track competition Broman and Eliasson (2019) find that if operators can cooperate, the monopoly situation will return. Where one-track competitions exist in the form of a duopoly, they also find that it is weakened by (i) train operators taking into account the fares set by the competitor, (ii) competitors not being permitted to run trains at the same track slot so that each operator has a local monopoly, and (iii) the regulator being able to influence the timetable and thereby the frequencies of the operators.

Up until 2015, the incumbent state-owned company SJ AB operated a commercial monopoly in the corridor under study. This corridor is their core service and runs at a large profit (Nilsson, 2018). In 2015 MTR Express entered the market as the first competitor in the corridor. The MTR trains are slightly slower than the SJ trains. On the entry of MTR, the SJ ticket fares fell on average by 13 percent, but mostly on tickets booked more than ten days in advance. MTR has lower fares than SJ and runs at a deficit (according to their 2018 annual report). Vigren (2017) finds indications that the price decline is an effect of the increased supply of train seats rather than price competition. Moreover, SJ has denied MTR access to their ticket sales website (Fröidh and Nelldal, 2015), implying that large groups of travellers are unaware of MTR operating trains in Sweden. MTR had no first-class tickets for sale. Hence, their available data suggests that MTR specifically targets informed and price-sensitive travellers. Evidence suggests that many of these travellers were previously buying cheap tickets booked far in advance from SJ, implying that more seats became available, and prices fell for these tickets.

In this paper, we refrain from modelling two identical competitors and solving for a representative competitor. We do this for two reasons. First, the market is not yet in equilibrium; the incumbent operator makes a profit while the newcomer makes a deficit. Second, the two operators primarily target different market segments, and there are no strong indications of price competition. Third, the competition is weak in the sense that many travellers only have the incumbent and former stated-owned and well-known operator SJ in mind when booking tickets.

We will, however, use the results by Broman and Eliasson to gain insights into how the impact of track charges would change if we assumed a duopoly in equilibrium instead of a monopoly. Moreover, when calibrating the demand model to match present input data, i.e. to passenger volumes, transport supply such as travel times and frequencies, and fares, it does not matter whether there is a monopoly or two competing operators. The calibration only determines the behavioural response to the present supply in terms of mode choice constants. Treating the operator as a monopolist in the scenario analysis will also help streamline the most important competition coming from other modes.

3. The aggregate model

Assume that there is one rail track linking two cities. Section 3.1 analytically derives the optimal fares and frequencies assuming aggregated demand and a profit-maximizing operator. Section 3.2 derives the welfare optimal track charge under some restrictive assumptions. Section 5 defines a more realistic, less restrictive model, not demanding zero marginal cost of train operations, and, for instance, allowing for crowding. But on the other hand, that model is too complex to solve analytically.

3.1. Profit maximization

We first assume that all consumers have identical preferences. A profit-maximizing rail operator with monopoly power will set the fare and the frequency to optimize producer surplus

$$PS = Dp(D) - C(D), \quad (1)$$

where $p(D)$ is the inverse demand function and $C(D)$ is the production cost of rail trips. Optimizing PS while keeping train frequency constant implies $p(D) + Dp'(D) - C'(D) = 0$. Rearranging this equation, we get the monopoly pricing formula

$$\frac{p(D) - C'(D)}{p(D)} = -\frac{D}{p(D)}p'(D) = -\frac{1}{\varepsilon}, \quad (2)$$

where ε is the price elasticity of demand. This is the Lerner index measuring monopoly power, ranging between 0 and 1. In a perfectly competitive market, the price equals the marginal production cost $p(D) = C'(D)$. A price higher than the marginal production cost $p(D) > C'(D)$ indicates monopoly power (an example is when the incumbent operator can produce at a lower cost than potential competitors, preventing market entry). (2) shows that a monopolist will serve along the elastic part of the demand function where $|\varepsilon| > 1$.

Assume now that $C(D) = kf(D)$, where k is the operation cost per train service including the track charges, i.e. $k = \tau + \nu$, where τ is the track charge and ν other operation costs. If k is independent of D (and frequency is fixed), marginal production cost is zero and the fare is $-Dp'(D)$, such that elasticity will be -1 . The track charges τ would then not impact the fares. However, if k is proportional to D (or frequency is not fixed), so that $\partial(kf)/\partial D$ is not zero but constant, an increase in the track charges is only absorbed for 50 percent by the monopolist (assuming a linear demand function). The other 50 percent would be paid by the travellers through higher fares. In the main analysis of this paper we will not, however, assume that the track charge depends on the number of travellers per train and we will not assume that f is fixed.

Next, we optimize PS with respect to frequencies, keeping the fare constant. Let the demand depend not only on fare p but on the generalized user cost $V = p + c$, such that $D(c + p)$. The user cost c is the sum of schedule delay and waiting cost, and a set of other variables Γ , including in-vehicle time, crowding, and access time, such that $c = \frac{\gamma}{f} + \Gamma$, where γ is the value of headway representing the waiting and schedule delay cost. Optimizing $PS = D(V)p - kf$ with respect to frequency keeping fare constant implies

$$pD'(V)V'(f) - k = 0. \quad (3)$$

Since $V'(f) = -\frac{\gamma}{f^2} + \Gamma'(f)$, the optimal frequency is

$$\hat{f} = \sqrt{\frac{-\gamma p D'(V)}{k - \Gamma'(f)p D'(V)}}. \quad (4)$$

Assuming that $\Gamma'(f) = 0$ and $C'(D) = 0$ (i.e. no crowding and the length of the train can be extended at zero cost) and that $p = -Dp'(D)$, the optimal frequency is

$$\hat{f} = \sqrt{\frac{\gamma D}{k}}. \quad (5)$$

This formula shows that optimal frequency increases proportionally with the square root of the value of schedule delay, the square root of demand, and the inverse of the square root of the operating cost per vehicle k .

If $C'(D) > 0$ and/or $\Gamma'(f) < 0$, i.e. if the trains are crowded, the optimal frequency is higher, but then the optimal fare is also higher due to crowding (increasing $C'(D)$).² Moreover, it might, however, be rational for a monopolist to have higher frequency in peak to deter market entry by newcomers. It is well known that an incumbent monopoly bus operator may set higher-than-profit-optimal frequencies to

² This is the same formula as in the welfare optimal case in appendix C, but in that case the optimal fare is lower implying higher demand D .

deter market entry by competitors by not leaving gaps in the schedule (Evans, 1987; Van Der Veer, 2002).

This heavily simplified derivation disregards that frequencies and fares are actually optimized simultaneously, and it also makes the extreme assumption of zero marginal cost, i.e. no crowding or capacity constraints. We also made the assumption that the utility function is additive and that the scheduling delay cost is inversely proportional to frequency. Hence, the results only hold under very specific conditions. Still, the derivation gives the useful baseline indication, that we can expect a larger impact on the frequency than the fares when track charges are increased, if the track charges and other operation costs per train are relatively independent of the number of passengers per train and if the crowding is reasonably small. Under these conditions the simultaneous optimization has less impact on the results, since the optimal fare only depends on the elasticity. Including crowding in the model, and also adding the possibility of extending the length of the trains, requires a simultaneous optimization of fares and frequencies (and the length of the train), which demand that we solve the model numerically, which is done in sections 4 to 6.

3.2. Optimal track charges

We proceed by exploring how a welfare-maximizing railway authority, disregarding cost recovery and thus the fact that public funding is costly, will set track charges for the reasons discussed in the introduction (if cost recovery is needed, some form of Ramsey pricing would be more appropriate). We assume that the track charge per train is independent of the number of passengers in the train and that $k = \nu + \tau$. The welfare-optimal track charges cannot easily be computed analytically, and we will therefore simulate the welfare-optimal track charges as explained in section 6.1. However, under the assumptions that the fares stay constant and that there are no crowding or seat capacity constraints on the trains, we can analytically derive the welfare optimal track charges. From (4) we have

$$k = \hat{p}D'(V)V'(f) \quad (6)$$

Assume that the welfare function is

$$\Omega = \int_0^D V(s)ds - cD - kf + \tau f - ef - gf,$$

where e is the marginal external cost of maintenance and g is the marginal external cost of congestion on the tracks, accidents, and noise. To find optimal track charges we take the derivative of Ω with respect to the frequency

$$VD'(V)V'(f) - cD'(V)V'(f) - c'(f)D - k + \tau - e - g = 0$$

Plugging in (11) we get

$$\tau = e + g + c'(f)D.$$

In the absence of crowding we have $c'(f) = -\gamma/f^2$. The optimal track charge is thus the sum of externalities minus the marginal schedule delay cost increase for the travellers

$$\tau = g + e - \frac{\gamma D}{f^2} \quad (7)$$

In the absence of externalities g and e , the optimal charge is negative: operators should be paid for running more trains. This corrects for the results from above: that profit-optimizing operators implement lower frequencies than are welfare-optimal. Note, however, that the EU directive 2012/34/EU does not permit charges below direct marginal costs. Still, there is very little empirical evidence on the congestion cost g , so it is difficult to charge for it. Moreover, if all transport markets were perfect (i.e. not a monopoly market), then optimal price would equal the marginal cost $g + e$.

4. The disaggregate model

As shown above, the impact of changed track charges on fares and frequencies will depend on several factors, including the demand elasticity, which in turn depends on competition from other modes. We therefore define a stylized demand and supply model, including all competing modes, of one intercity corridor linking two cities. We assume that trips can go in either direction. The model assumes that passengers from different user groups can choose to travel by train, car, bus or air, in either the peak or in the off-peak period. The model will be calibrated for the Stockholm and Gothenburg corridor.

4.1. Demand

The demand model includes the four competing modes $m \in \{\text{rail} = r, \text{bus} = b, \text{air} = a, \text{car} = c\}$. Travellers are distinguished into two user groups $j \in \{\text{private} = P, \text{business} = B\}$. Preferences differ by user group – business travellers have higher value of travel and waiting/scheduling times. The model covers weekdays 5 a.m.-9 pm. Travellers choose between travelling in the peak or off-peak time period, $q \in \{p = \text{peak}, o = \text{off-peak}\}$. However, we take the trip frequency as given. Peak services depart within the period 5–9 am and 3–6 pm and off-peak services depart within the remaining hours.

Fig. 1 illustrates the nested logit model structure with time of day choice on the upper level and mode choice on the lower level. The structure assumes that the random errors in the utility functions of the mode alternatives in the same time period are more correlated than mode alternatives in different time periods. We assume this structure for two reasons. First, most attributes we have added to the utility functions explain the mode choice, e.g. travel cost and time, while at the departure time level, only an alternative specific constant is included. This will probably imply larger correlation of the error terms (i.e. the unobserved attributes) of the utility functions of different modes under a given time period. Second, Börjesson (2009) finds that departure time shifts of more than 45–90 min are less sensitive than mode switching, i.e. that there are then more unobserved attributes varying between the time periods than between modes. Daly et al. (2005) found mostly the same, that for departure time shifts with the peak, departure time choice is more sensitive than mode shifts, but suggest that for larger departure time shifts, mode choice is more sensitive. Since we model large departure time shifts, between peak and off-peak, we deem the departure time shifts to be less sensitive and thus on the upper level. It is not realistic to assume that there is no induced traffic as the generalized cost of travelling changes, but we still use the simplification to be able to evaluate the effect on changes of the generalized cost of all competing modes.

The utility of travelling in period q by mode m for user group j is

$$U_{qm}^j = V_{qm}^j + \varepsilon, \quad (8)$$

where ε is a Gumble distributed random error. The observed part of the utility function is

$$V_{qm}^j = \mu^j \left(\theta_{qm}^j + p_{qm}^j + \beta_{qm}^j t_{qm}^j + \gamma_{qm}^j h_{qm}^j \right) \quad (9)$$

where μ^j is the marginal utility of money, θ_{qm}^j is the alternative-specific constant and p_{qm}^j is the monetary cost of the trip for user group j for travelling by mode m in time period q . The variables t_{qm}^j and h_{qm}^j , and represent the in-vehicle travel time and headway, and the parameters β_{qm}^j and γ_{qm}^j represent the travellers' valuations of the corresponding variables. The demand is then

$$D_{qm}^j = Y^j \frac{\exp(A_q^j)}{\sum_q \exp(A_q^j)}, \quad (10)$$

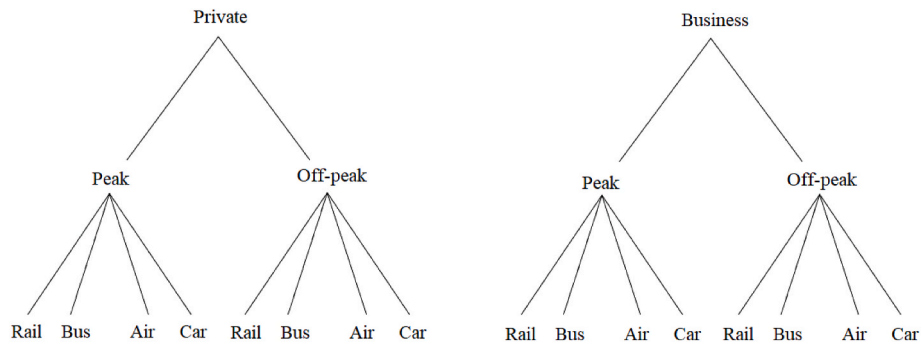


Fig. 1. The nested logit model structure.

where Y^j is the total number of trips made by group j and A_q^j is the logsum

$$A_q^j = \lambda^j \log \left(\sum_m \exp(V_{qm}^j) \right). \quad (11)$$

λ^j is a unitless scale parameter representing the substitutability between peak and off-peak.

4.2. Generalized travel costs

We assume that all trips start and end at the central stations of the two cities. Effectively this means that the access/egress times and costs to the central stations are assumed to be constant within modes and user groups and reflected in the mode choice constants determined in the calibration.

For rail and bus, p_{qm}^j includes only the fare. For car, it includes expenses for fuel and vehicle wear cost, divided by the average car occupancy, differentiated for private and business trips. For air, the monetary cost includes the flight and access/egress fares between the airport and the central stations of the cities.

For car, we assume that travel time is 1.2 times longer in peak periods than in off-peak periods due to congestion (assessed by using Google maps). For other modes, we assume that the travel time is equal in the two time periods. For air, the in-vehicle travel time is assumed to include time spent at the airport (assumed to be 60 min before departure and 15 min upon arrival). For air, we also include the connection time to and from the airport to the central stations of the cities in the in-vehicle time. We assume that business travellers use the more expensive mode train, while private travellers use bus.

For train, bus, and air we take headway to be

$$h_{qm} = \frac{1}{(f_{qm}/s_q)}, \quad (12)$$

where f_{qm} is the total number of services and s_q is the number of hours in the time period q .

We assume that the crowding cost increases with occupancy level, even if the number of travellers does not exceed maximum seat capacity. Hence, the generalized cost of in-vehicle travel time is

$$\beta_{qm=rail}^j = \beta_{m=rail}^j \psi^{\frac{\sum_j p_{q,m=r}^j}{\sigma_{sq}}} \quad (13)$$

The parameter ψ shows the proportionate increase in the value of in-vehicle travel time if all the seats in the train are occupied compared to the situation where the train is empty. A meta study by [Wardman and Whelan \(2011\)](#) indicates a seated crowding multiplier of 1.05–1.26, but the variability between studies is large, where some studies report multipliers of up to 1.8 for seated travellers. Moreover, the studies of crowding multipliers focus almost exclusively on regional or local public

transport. So the crowding multiplier for a 3-h rail trip is uncertain. In our model, the crowding multiplier can also represent other effects than discomfort. For instance, it might not be possible to choose a specific train within the peak-or off-peak, when demand is high relative to supply, unless the ticket is booked early in advance. Since we are not modelling the demand for individual departures but only for the aggregate number of trains within a time period, this will be captured by a crowding cost even if it is a scheduling cost. Moreover, the more crowded the train is, the longer in advance the traveller will need to book the ticket, which also increases the generalized cost and thus can be captured by the crowding cost. Hence, the crowding multiplier will probably be lower if the yield management system is better, managing to better fill up the trains. To test the sensitivity of the crowding multiplier we will try $\psi = 1.1$ and $\psi = 1.6$. We will find that $\psi = 1.6$, retrieves the current occupancy rate best, and so is probably the most accurate estimate. This relatively high multiplier suggests that the crowding multiplier indeed captures scheduling costs etc.

4.3. Operating costs and capacity constraints for rail

The operating cost per service includes a component proportional to journey time and a component proportional to travel distance making up the total cost v_q for a train in the corridor. The cost proportional to distance reflects fuel cost. The cost proportional to journey time represents personnel costs, daily maintenance, cleaning costs and capital cost of vehicles. The operating cost differs between time periods because the capital cost is assigned to the peak only v_q . The operating cost k_q also includes track charges, differing between time periods.

In the first analysis we assume that the train size is fixed, and that operation cost is independent of the number of travellers

$$k_q = v_q + \tau_q. \quad (14)$$

We then constrain the number of travellers to maximum seat capacity $\hat{\sigma}$. In a second analysis we assume that the length of the train can be extended, and that the operator optimizes the size of the train. We assume no crowding multiplier in this scenario and assume that the number of seats in the train always matches the number of passengers. However, we used the cost functions applied by the [Swedish Transport Administration \(2018\)](#) and assume that the operation cost increases with train size such that³

$$k_q(\sigma) = v_q(\sigma) + \tau_q \quad (15)$$

³ One alternative specification could be a step function representing another coach to the train if the existing coaches are filled up. The reason we do not adopt this is that the size of a train coach is not really that fixed, but it varies even within each train type.

4.4. Optimization problem

We base the model on the assumption that the operator is a monopolist, although there have been two competing companies operating in the corridor since 2015 for the reasons stated in the introduction. To find the optimal fares and frequencies of the monopolist train operator, we maximize producer surplus

$$PS = \sum_{jq} D_q^j p_q^j - \sum_q k_q f_q. \tag{16}$$

Decision variables are rail fares p_q^j (four variables) and train frequencies f_q (two variables). The train frequency variables are constrained to take only integer values.

As discussed in 2.2, we cannot analytically determine the track charges that maximize the welfare under which the operator remains profitable. For this reason, we will derive these welfare optimal track charges by numerical optimization. We do this by defining the social welfare function

$$\Omega = \sum_j Y^j B^j + \sum_{jq} D_q^j p_q^j - \sum_q k_q f_q + \sum_q \tau_q f_q - \sum_q e f_q - \sum_q g_q f_q \tag{17}$$

The first term represents consumer surplus equalling the upper level logsum $B^j = \frac{1}{\mu} \ln \sum_q \exp(A_q^j)$ summed over business and private trips. The sum of the second and third term is the producer surplus. The fourth term is the government’s revenue from the track charges. The fifth term reflects the marginal cost of the wear and tear on the tracks, noise and accidents. It consists of two parts: $e = m + n$, where m is the marginal cost of wear and tear on the tracks, and n is the marginal cost of noise and accidents. The final term is the marginal congestion cost on the tracks. We assume here that the marginal congestion cost per train is independent of the frequency of the long-distance trains in the corridor since they are few compared to the number of commuter trains.

We search for the optimal track charges in the peak and off-peak by stepwise assuming different track charges within the range of possible charges. The peak and off-peak charges are varied independently to span up a two-dimensional grid. For each pair of assumed peak and off-peak charges, we derive the profit-optimizing fares and frequencies. Given these fares and frequencies, we compute the welfare that they would generate. The pair of peak and off-peak charges that give the operators incentives to set the frequencies and fares (by optimizing PS in (21)) that generate the highest welfare Ω is the optimal track charges.

5. Model scenarios and calibration

In section 5.1 we produce a baseline scenario by calibrating the model for the Stockholm-Gothenburg corridor, using current demand, fares, frequencies and track charges. The calibration and the optimization of the model are summarized in Appendix A. Section 5.2 describes the externalities including congestion on the tracks and Section 5.3 the scenarios that we apply.

5.1. Calibration of baseline scenario

We first calibrate the mode choice constants θ_{qm}^j such that the current user equilibrium is retrieved given the current demand and fares. The travel demand by mode is obtained from the Swedish Transportation Administration. Table 1 shows number of trips by mode in a day for outgoing (weekdays) trips from Stockholm, mode shares and fares (we assume that demand is symmetric in the two directions).⁴ Rail and car have the largest market share, closely followed by air.

The traffic supply in the baseline is given in Table 2. The fare data is

Table 1 Demand and fares per mode in one direction.

			# trips/weekday D	Mode share	Fare (€/trip) p
Rail	Private	Peak	1992	56%	40.3
		Off-peak	1707	53%	37.8
		peak			
	Business	Peak	892	56%	95
		Off-peak	99	83%	95
		peak			
Bus	Private	Peak	33	1%	25
		Off-peak	232	7%	18
		peak			
	Business	Peak	1	0%	25
		Off-peak	0	0%	25
		peak			
Air	Private	Peak	778	22%	176
		Off-peak	722	23%	42.1
		peak			
	Business	Peak	578	36%	176
		Off-peak	6	5%	176
		peak			
Car	Private	Peak	774	22%	42.2
		Off-peak	538	17%	42.2
		peak			
	Business	Peak	126	8%	84.4
		Off-peak	14	12%	84.4
		peak			
Total	Private	Peak	3 577	100%	
		Off-peak	3 199	100%	
		peak			
	Business	Peak	1 597	100%	
		Off-peak	119	100%	
		peak			
Total		8 492	100%		

Source: Vigen (2017), Swedish Transport Agency (2015) and Swedish Transport Administration (2016).

obtained from several sources. For private trips, peak and off-peak rail fares are taken from Vigen (2017), who produces a unique dataset collected from operators’ online booking sites.⁵ For business trips, we assume first-class fares obtained from the Swedish Transport Agency (2015). Air and bus fares are obtained from the Swedish Transport Administration (2016). The cost of car trips is calculated based on average fuel consumption and fuel prices. The cost for a car trip is then divided by the average car occupancy, which is two passengers for private trips and one passenger for business trips according to the travel survey (Transport Analysis, 2020).

Rail operator costs are based on data from the official Swedish CBA guidelines (Swedish Transport Administration, 2018). In the first analysis we assume a fixed train size and 278 seats per train, which was the average number of seats on the trains in the corridor in 2016 (eqn. (14)). In the second analysis we assume variable train size, where the operation cost depends on the number of trains (eqn. (15)) according to Table 2.

Table 3 shows the values of time by mode and user group. The applied value of headway is much lower than half the value of waiting time for local public transport, since we model a long-distance service with headway up to 1 h modelled. We assume marginal utility of income $\mu^{j=P} = 0.005$ for private and $\mu^{j=B} = 0.01$ for business trips based on estimation of the Swedish long-distance model (WSP, 2011). The value if λ^j is based on the same report.

⁵ A web crawler was used to find the lowest price on the booking sites sj.se and mtexpress.se. The data we use is the observed average over 2014–2016. (Vigen, 2017).

⁴ In this paper we use the conversion rate 1 SEK = 0.1 Eur.

Table 2

Traffic supply variables in the baseline, operating costs, and track charges in the Stockholm-Gothenburg corridor. Frequency and travel time from 2019 timetable. Operating cost and track charges from the [Swedish Transport Administration \(2018\)](#).

	Rail		Bus		Air		Car	
	Peak	Off-peak	Peak	Off-peak	Peak	Off-peak	Peak	Off-peak
Frequency, departure/day, f	14	12	1	7	14	13	–	–
Travel time, h/trip, t	3	3	7	7	1	1	6	5
Operating cost, main analysis, €/departure, v_q	4 001	2 209	837	837	1 803	1 803	–	–
Operating cost, sensitivity analysis, €/departure, $v_q(\sigma)$	$4\,001 + 140 \cdot (\sigma - \hat{\sigma})$	$2\,209 + 84 \cdot (\sigma - \hat{\sigma})$						
Monetary travel cost per trip private €/trip	40	38	25	18	1 76	42	42	42
Monetary travel cost per trip business €/trip	95	95	25	25	1 76	1 76	84	84

Table 3

Values of time by mode and user group in price level 2019 ([Swedish Transport Administration, 2018](#)).

	Rail		Bus		Air		Car	
	Private	Business	Private	Business	Private	Business	Private	Business
Value of in-vehicle time, €/h, β	7.8	26.5	4.2	31.2	11.6	31.2	11.6	31.2
Value of headway, €/h	2.1	11	0.55	8.4	3.0	24	–	–
Value of access time, €/h, δ	–	–	–	–	15.8	31.2	–	–

Source: [Börjesson \(2012\)](#) and [Börjesson and Eliasson \(2014\)](#).

5.2. External costs and scenarios

In Sweden, the external costs of bus and car travel are covered by the fuel tax and congestion charges in Stockholm and Gothenburg ([Börjesson et al., 2018](#); [Börjesson and Kristoffersson, 2018](#); [Nilsson and Haraldsson, 2018](#)). For domestic air traffic, airport charges and the EU Emissions Trading System (EU ETS) internalize the external costs ([Nilsson and Haraldsson, 2018](#)). The external cost of producing electric power used to fuel the trains is also assumed to be internalized by EU ETS (and in addition, the electricity production in Sweden emits virtually no carbon emissions since it relies on hydro- and nuclear power). We also assume that the impact of the passenger volumes on the average operation costs for air and bus is zero (i.e. that there are no economies of scale for these modes).

To compute the welfare Ω , thereby deriving the optimal track charges, we need to know the external costs e and g . The external cost e includes the cost of wear and tear on the tracks, accidents and noise. According to [Table 4](#) in [appendix C](#), e equals 536 €/train for the train corridor under study, in the peak and in the off-peak.⁶ The baseline track charge is very close to this external cost (excluding congestion), which is not a coincidence. The EU legislation stipulates that the track charges must at least correspond to the short-term marginal cost. However, the cost of congestion has not been fully considered.

Calculating g on the rail is complicated and requires a sophisticated analysis by solving capacity conflicts arising when one more commercial train is added. This is done by [Ait Ali \(2020\)](#), for the long-distance trains reaching the Stockholm Central during three different time periods (morning peak, afternoon peak, and mid-day). The tracks to and from the Stockholm Central Station are shared by commuter trains and commercial long-distance passenger trains. The signalling system allows for 28 trains per hour, but a few are currently not allocated but saved as a buffer. By applying the simulation tool RailSys ([Radtke and Bendfeldt, 2001](#)), Ait Ali et al. calculate the marginal external congestion cost of a long-distance train by assessing the social cost of removing or rescheduling the commuter trains in order to solve the capacity conflict that arises. That is, the congestion cost equals the social opportunity cost of

⁶ [Odolinski and Boysen \(2019\)](#) show that a higher capacity utilization of the tracks in the peak implies a higher marginal cost for wear and tear (much of the work has to be undertaken at night for instance). We disregard such differences here and assume the same marginal cost for wear and tear in the two periods.

the capacity. This cost accrues exclusively to the operator and passengers of the commuter trains in the form of waiting, crowding, transfer, and travel time cost for travellers and operation costs for the commuter trains.

The baseline supply of commuting trains is taken as given because it is determined by the regional public authority aiming at optimizing welfare. Hence, it seems reasonable to assume that the commuter train schedule is close to welfare optimum, even without optimal track charges. The price-based allocation is also less important for commuting train since information on demand and operation costs is readily available for the IM. Moreover, commuting trains are currently receiving large subsidies.

Ait Ali et al. estimate that this marginal social external congestion cost for long-distance trains travelling into the Stockholm central station in the peak lies in the span 900–10 500 €/train. In the off-peak, the marginal external cost is 500–3 000 €/train. The external cost is highest if the capacity conflict is solved by removing a commuter train altogether, and lower if the departure time is shifted or the commuter is train held up at some stations to let the long-distance train pass. If the number of trains that can be allocated has reached its maximum, for some technical reason, this implies that the commuting train must be cancelled in order to add another long-distance train. Then the social opportunity cost and thereby the reservation price will be at the higher end of the span, implying that the optimal track charges are higher, reducing the demand for more long-distance trains.

There are further congestion costs at the Gothenburg end, but the size of these is unknown. Since the congestion costs can vary and are also uncertain, we set up four scenarios, differing with respect to the congestion costs in the peak and in the off-peak. For each assumed congestion cost (i.e. for each scenario), we will first simulate the optimal track charge in the peak and in the off-peak. Given this optimal track charge, we will model the resulting fares and frequencies. Hence, we will find out how the fares and frequencies depend on the level of the track charges (which in turn depend on the congestion costs).

In the scenarios where we have assumed the highest congestion cost, in the upper level of the span found by Ait Ali et al. we have implicitly assumed that the maximum number of trains is reached so that a commuting train must be cancelled to allow for one more long-distance train. In these scenarios we also find that the number of long-distance trains is lower than in the baseline.

Table 4

Profit-optimal results for the welfare-optimal track charge given different congestion levels. Crowding multiplier $\psi = 1.1$, $\psi = 1.6$ and the possibility to extend the length of the trains.

		P1	P2	P3	P4
Congestion peak g €		1 500	2 500	6 000	9 000
Congestion off-peak g €		1 500	1 500	3 000	4 500
Optimal τ peak €	$\psi = 1.1$	500	1 300	1 250	4 500
	$\psi = 1.6$	500	750	3 800	5 500
	Longer train	500	1 400	4 500	8 000
Optimal τ off-peak €	$\psi = 1.1$	600	0	0	250
	$\psi = 1.6$	600	450	1 600	2 000
	Longer train	600	1 400	2 750	3 000
Fare Private peak €	$\psi = 1.1$	37	39	39	45
	$\psi = 1.6$	41	42	46	48
	Longer train	37	39	38	38
Fare Private off-peak €	$\psi = 1.1$	31	30	30	30
	$\psi = 1.6$	34	33	33	33
	Longer train	33	33	32	32
Fare Business Peak €	$\psi = 1.1$	78	79	79	81
	$\psi = 1.6$	86	85	81	79
	Longer train	80	80	75	72
Fare Business off-peak €	$\psi = 1.1$	81	79	79	74
	$\psi = 1.6$	85	83	76	73
	Longer train	85	81	76	74
Freq peak €	$\psi = 1.1$	12	11	11	8
	$\psi = 1.6$	17	15	10	8
	Longer train	13	9	5	4
Freq off-peak €	$\psi = 1.1$	8	9	9	10
	$\psi = 1.6$	10	11	9	8
	Longer train	8	6	4	4
PS €	$\psi = 1.1$	150 963	139 392	87 392	55 548
	$\psi = 1.6$	148 831	146 994	99 771	81 777
	Longer train	153 492	148 109	123 474	105 887
Change in CS relative to baseline €	$\psi = 1.1$	28 494	28 330	28 330	13 713
	$\psi = 1.6$	16 971	14 300	-3 622	-13 289
	Longer train	29 793	21 543	16 742	14 889
Government revenue-maintenance costs €	$\psi = 1.1$	22 760	33 760	85 760	110 484
	$\psi = 1.6$	4 726	6 788	45 522	54 208
	Longer train	23 898	26 070	38 742	51 104
Welfare €	$\psi = 1.1$	187 937	168 002	168 002	149 613
	$\psi = 1.6$	125 330	109 558	51 365	7 912
	Longer train	172 029	161 611	135 392	116 488
Rail mode share Priv Peak	$\psi = 1.1$	62%	57%	57%	40%
	$\psi = 1.6$	56%	52%	38%	30%
	Longer train	63%	57%	56%	55%
Rail mode share Priv off-peak	$\psi = 1.1$	62%	66%	66%	67%
	$\psi = 1.6$	54%	56%	52%	48%
	Longer train	60%	60%	58%	58%
Rail mode share Business Peak	$\psi = 1.1$	73%	72%	72%	66%
	$\psi = 1.6$	73%	72%	65%	61%
	Longer train	74%	72%	70%	68%
Rail mode share Priv off-peak	$\psi = 1.1$	87%	89%	89%	92%
	$\psi = 1.6$	83%	86%	85%	84%
	Longer train	87%	86%	85%	86%

6. Results

The result section 6.1 describes the optimal track charge. Section 6.2 describes the impact of the track charges and section 6.3 the effect on changes in competing modes.

6.1. Optimal track charges

The congestion cost g in the peak and off-peak assumed in our four scenarios are shown in the top row of Table 4. For each scenario we simulate the optimal track charges. The optimization procedure of the social welfare as a function of peak and off-peak charge produces a

surface as shown in Fig. 2. The objective functions (social welfare) are fairly flat over large areas, for two reasons. First, the train frequency is defined as a discrete number and the optimal frequency will therefore not vary for track charges within a certain range. Second, the track charges primarily impact the frequency (and not the fare).

For the resulting optimal track charge by scenario, the profit-optimizing outcomes are presented in Table 4, in terms of fares, frequencies, producer surplus, government surplus, welfare and modal shares. All scenarios are presented in three versions, assuming crowding cost parameters $\psi = 1.1$, $\psi = 1.6$ and the possibility of extending the length of the trains (assuming $\psi = 1.0$).

In the first profit-maximizing scenario (P1) assuming $g = 1 500$

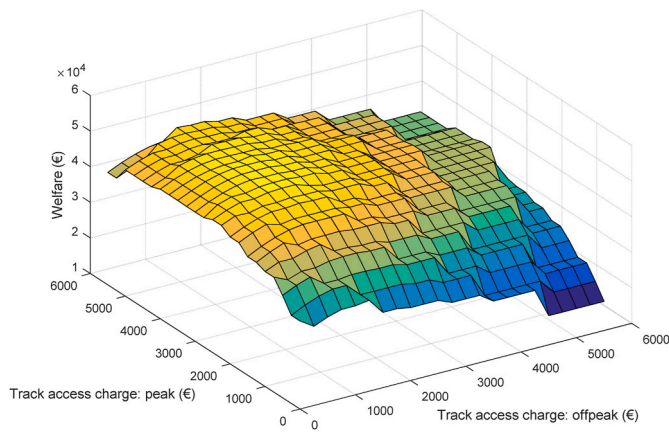


Fig. 2. Total welfare as function of track charge in the peak and in the off-peak. Congestion cost of 6 000 and 3 000 is assumed while ψ is assumed to be 1.6 in this figure. The welfare optimal track charge is 3 800 € per train in the peak and 1 600 € per train in the off-peak.

€/train for the peak and in the off-peak, the optimal track charge is slightly higher in the off-peak than in the peak. This is because the cost of longer headway is higher in the peak due to higher peak demand, in particular for business travellers with high value of headway. In the following scenarios, we make the more realistic assumption that the

congestion cost is higher in the peak than in the off-peak.

The optimal track charge increases as expected with higher peak congestion. This is most pronounced in the case where the length of the trains can be extended, because higher charges then reduce frequency more, without reducing the consumer surplus more than in the other versions (because crowding cost does not increase). Higher charges encourage the operators to take on more passengers per train implying that frequency can be reduced without missing out on too much ticket revenue. This effect is largest when the length of the trains can be extended, and weakest with low congestion penalty ($\psi = 1.1$). In the case of $\psi = 1.1$, the trains are more filled even with low track charges, so there are fewer possibilities of increasing occupancy as track charges increase. Moreover, when the crowding parameter is high, and when operators cannot extend the length of the trains, the fares are higher in the baseline, because it is then more costly to increase profit by increasing the number of passengers.

Note the track charge is considerably lower than the congestion cost, as predicted in section 2, in particular when the length of the trains cannot be extended. In all cases, the off-peak track charge is less sensitive to higher congestion, because as the peak congestion cost increases, it is welfare-increasing to move trains to the off-peak.

6.2. The impact of track charges on fares and frequencies

The crowding parameter resulting in a scenario corresponding most closely to what we observe in terms of the traveller's behaviour

Table 5

Profit-optimal scenarios (P1–P4) for the welfare-optimal track charge given different congestion levels. Crowding cost $\psi = 1$. Welfare optimal scenarios (W1–W2) for the same marginal congestion cost g.

	Baseline	Profit Optimal Baseline	P1	P2	P3	P4	W1	W3
Congest. g peak			1 500	2 500	6 000	9 500	1 500	6 000
g off-peak			1 500	1 500	3 000	4 500	1 500	3 000
Optimal τ peak	696	696	500	750	3 800	5 500	–	–
Optimal τ off-peak	609	609	600	450	1 600	2000	–	–
Fare private peak €	40	42	41	42	46	48	25	31
Rail fare private off-peak €	38	33	34	33	33	33	15	17
Rail fare business peak €	95	85	86	85	81	79	25	31
Rail fare business off-peak €	95	94	85	83	76	73	15	17
Rail frequency peak (trains/day)	14	15	17	15	10	8	19	14
Rail frequency off-peak (trains/day)	12	10	10	11	9	8	14	13
CS change (€/day)	0	11 660	16 971	14 300	–3 622	–13 289	179 759	124 087
Ticket revenues (€/day)	238 947	245 521	253 435	247 505	212 060	191 455	157 400	171 676
Operating cost (€/day)	82 519	82 103	90 104	84 311	59 889	49 678	106 942	84 728
Track charges (€/day)	17 049	16 527	14 500	16 200	52 400	60 000	0	0
PS (€/day)	139 379	146 892	148 831	146 994	99 771	81 777	50 458	86 948
Noise (€/day)	3 068	2 950	3 186	3 068	2 242	1 888	3 894	3 186
Accidents (€/day)	1 456	1 400	1 512	1 456	1 064	896	1 848	1 512
Wear & tear (€/day)	9 412	9 050	9 774	9 412	6 878	5 792	11 946	9 774
Total welfare - congestion cost (€/day)	142 492	161 678	165 830	163 558	138 365	119 912	212 529	196 563
Government (€/day)	7 637	7 477	4 726	6 788	45 522	54 208	–11 946	–9 774
Congestion cost (€/day)			40 500	54 000	87 000	112 000	49 500	12 3 000
Welfare (€/day)			125 330	109 558	51 365	7 912	163 029	73 563
Share of trips								
Rail private peak	55%	52%	56%	52%	38%	30%	84%	69%
Bus private peak	2%	2%	2%	2%	2%	2%	1%	1%
Air private peak	22%	23%	21%	23%	30%	34%	8%	15%
Car private peak	22%	23%	21%	23%	30%	34%	8%	15%
Rail private off-peak	51%	55%	54%	56%	52%	48%	87%	82%
Bus private off-peak	12%	11%	11%	10%	11%	12%	3%	4%
Air private off-peak	22%	20%	20%	19%	21%	23%	6%	8%
Car private off-peak	16%	15%	15%	14%	16%	17%	4%	6%
Rail business peak	56%	71%	73%	72%	65%	61%	98%	96%
Bus business peak	0%	0%	0%	0%	0%	0%	0%	0%
Air business peak	36%	23%	22%	23%	28%	32%	1%	3%
Car business peak	8%	5%	5%	5%	6%	7%	0%	1%
Rail business off-peak	83%	100%	83%	86%	85%	84%	99.49%	99%
Bus business off-peak	1%	0%	1%	1%	1%	1%	0.02%	0%
Air business off-peak	5%	0%	5%	4%	4%	4%	0.14%	0%
Car business off-peak	12%	0%	11%	10%	10%	10%	0.35%	1%
Train occ. Peak %	74%	71%	67%	70%	83%	88%	83%	93%
Train occ. Off-peak %	54%	71%	70%	68%	79%	85%	84%	92%

(occupancy rate) is $\psi = 1.6$. Such a high cost of crowding is not surprising, since some of the crowding cost includes a possible scheduling cost as discussed in section 4.2. Table 5 presents the resulting profit-optimizing scenarios for $\psi = 1.6$ in greater detail than in Table 4, for different assumptions of the congestion costs and resulting optimal track charge. For comparison it also includes the welfare-optimal scenarios for the given congestion costs.

The first columns of the table show the baseline scenario and the scenario with optimizing profit assuming present track charges. The assumed congestion cost is zero in these two scenarios, since the baseline track charges are close to this external cost excluding congestion as discussed in section 5.2. The two columns show that the baseline frequencies and fares are close to the profit-optimizing frequencies. The main difference is that the optimal off-peak frequencies and fares are lower than the observed. Differences in fares and frequencies are related because when the frequency increases the scheduling cost reduces, allowing the fares to increase for a given generalized cost. A possible reason is that peak and off-peak trips are sometimes complements, and not always substitutes as we have assumed in our model.

Turning to scenarios P1–P4 of Table 5, the fares still remain relatively stable in spite of substantial increases in track charges. The change in frequency is more substantial than the change in fares. These findings are consistent with the simple model in section 3, even if the latter disregards crowding and the fact that fares and frequencies are optimized simultaneously.

The fare even reduces slightly for business peak trips when the crowding penalty is 1.6 (but not when for $\psi = 1.1$), which is explained by the larger decline in frequency, leading to higher generalized travel cost. The fares are lowered to compensate for the reduction in frequency, so that the business trips would not switch mode. Hence, the increased marginal cost for the operators is partly absorbed by the travellers in terms of lower frequencies rather than higher fares. The consumer surplus and the producer surplus (PS) both decline with higher track charges. For travellers, this is mainly because frequency reduces. For operators, the lower operation costs due to reduced frequency cannot fully compensate for the higher track charges and lower ticket revenues. The table shows the total welfare for a given congestion cost per train g . The welfare can only be compared across columns, since it always increases with higher congestion cost g .

Broman and Eliasson (2019) give an indication of how our results might change if we assumed on-track competition. They model on-track competition between two initially identical operators. They find that in the Nash equilibrium, one operator has higher frequency and fares than the other. Their model shows, like ours, that in the monopoly case, fares remain fairly unchanged while frequency reduces more in response to higher track charges. However, their model shows that in the case of duopoly in equilibrium, fares increase slightly more (10% as track charges increase 50%), but then the initial fares are also lower. They find that frequencies are impacted in a similar way in the monopoly and duopoly case. However, Broman and Eliasson assume infinite capacity in the trains and from Table 4 we know that higher crowding costs and capacity constraints increase the impact on frequencies, which in turn reduces the effect on the fares. Hence, the lower effect on fares in our model could be an effect of the capacity constraint on the trains, implying a large effect on the frequency since it is higher than the baseline. Moreover, the optimal track charges would be higher for a given external cost in the duopoly case. Then there is less need for reducing the charge to account for the monopoly setting a frequency that is lower than welfare optimal (as shown by (7)).

The net revenue for the government (revenue from track charges minus the maintenance cost) is positive in all scenarios and increases with higher congestion cost. This revenue can be used to cover parts of the fixed cost for railways.

Modal shares are shown further down in the table. Since the total demand is fixed, the modal shares are proportional to the total number of trips. The share of rail trips reduces most for private peak trips,

reducing from 56 to 30 percent for the scenario with the highest track charge. These trips are moved to car and air. The peak business trips reduce less, from 73 to 60 percent. Almost all business trips that switch from rail are moved to air. The modal share for rail in the off-peak remains relatively stable (as do the off-peak frequencies).

To summarize, as track charges increase, the producer surplus and frequencies decline. However, the fares remain fairly unchanged and the number of travellers reduces less than frequency due to increased occupancy rates. The main reason for the small impact on the fares as track charges increase is that the competition from other modes discourages the rail operator from increasing the generalized cost too much. The operator gains more from increasing generalized cost by reducing the frequency than by increasing the fares when track charges increase. Hence, although the higher marginal cost is partly absorbed by the travellers (as basic theory yields) this is primarily done in terms of lower frequencies rather than higher fares.

Moving on to the social welfare optimization in scenarios W1 and W3 in the rightmost columns of Table 5, a comparison with the scenarios assuming the same congestion cost, P1 and P3, reveals that welfare-maximizing fares are lower than profit-maximizing fares, in line with the theory of Section 2. The difference between profit-optimizing and welfare-optimizing fares is largest for business trips, since their lower price elasticity implies that the profit-maximizing operator can charge them higher fares.

There are higher train frequencies in the welfare-optimal scenarios W1 and W3 than in the corresponding profit-optimal scenarios P1 and P3. Still, the difference is lower in terms of frequencies than in terms of fares. This is in line with the results of Monchambert and Proost (2019), who find that frequencies do not differ greatly between a revenue-raising monopoly and a welfare-optimizing operator.

Since there are no track charges involved in the welfare-optimal scenarios, the government revenue is negative. However, adding the PS to the government's loss, the net revenue for the government is positive and higher in W3 because the higher congestion on the tracks implies a lower train frequency. Hence, there is no need to subsidize the operating costs of the trains. Still, the taxpayers must cover the lion's share of the fixed investment and maintenance cost of the tracks.

6.3. Intermodal competition

Since we assume no competition on the tracks, only the other modes provide the competition. Hence, if the competition from other modes changes, so will the profit-optimizing fares and frequencies. To study this effect, we construct two scenarios in which the intermodal competition changes considerably. In the scenario NoAir, we assume that domestic air traffic in the corridor is eliminated, for instance due to taxes or environmental regulations and restrictions.

In the scenario Auto-Electric Car, we assume that autonomous and electric vehicles reduce the generalized travel cost for cars. To what extent autonomous and electric vehicles would reduce generalized cost, which might take several decades if car ever become fully autonomous, is largely unknown. This scenario should thus be interpreted as an example rather than a forecast.⁷ We first reduce the pecuniary distance cost ($p_{q,m=c}^j$) by 50 (because electric cars are more fuel-efficient). We also assume that the value of in-vehicle time for cars reduces to the same level as for rail ($\beta_{q,m=c}^j = \beta_{q,m=r}^j$), because in an autonomous car the travel time can be used for other activities than driving, as in a train. On one hand, electric vehicles might not be as comfortable as a train trip, but on

⁷ A key factor is presently the driving range. However, some cars already have a driving range exceeding the distances between Stockholm and Gothenburg (500 km), and over time the driving range will gradually also increase for other EVs. In addition, ultrafast charging takes less than 20 min (European Court of Auditors, 2021).

Table 6
Profit maximization scenarios.

	Profit Optimal Baseline ^a	P3	NoAir	NoAir3	Auto-Electric Car	Auto-Electric Car 3
Optimal τ peak	696	3 800	696	3 800	696	3 800
Optimal τ off-peak	609	1 600	609	1 600	609	1 600
Rail fare private peak (€/trip)	42	46	46	49	34	39
Rail fare private off-peak (€/trip)	33	33	37	36	21	22
Rail fare business peak (€/trip)	85	81	107	103	60	58
Rail fare business off-peak (€/trip)	94	76	97	93	44	43
Rail frequency peak (train/day)	15	10	16	11	7	4
Rail frequency off-peak (train/day)	10	9	11	14	3	4
CS change (€/day)	11 660	-3 622	-32 424	-40 425	284 523	277 286
Ticket revenues (€/day)	245 521	212 060	314 422	292 550	70 167	53 804
Operating cost (€/day)	82 103	59 889	88 312	74 935	34 633	24 839
Track charges (€/day)	16 527	52 400	17 831	44 463	6 697	15 712
PS (€/day)	146 892	99 771	208 278	173 152	28 837	13 253
Noise (€/day)	2 950	2 242	3 186	2 950	1 180	944
Accident (€/day)	1 400	1 064	1 512	1 400	560	448
Wear and tear (€/day)	9 050	6 878	9 774	9 050	3 620	2 896
Government (track charge revenue – maintenance cost) (€/day)	7 477	45 522	4 826	55 150	1 680	18 704
Modal shares						
Rail private peak	52%	38%	58%	45%	7%	3%
Bus private peak	2%	2%	3%	4%	0%	0%
Air private peak	23%	30%	0%	0%	1%	1%
Car private peak	23%	30%	39%	52%	92%	96%
Rail private off-peak	55%	52%	60%	64%	15%	17%
Bus private off-peak	11%	11%	17%	15%	1%	1%
Air private off-peak	20%	21%	0%	0%	2%	2%
Car private off-peak	15%	16%	23%	21%	82%	80%
Rail business peak	71%	65%	79%	76%	52%	38%
Bus business peak	0%	0%	0%	0%	0%	0%
Air business peak	23%	28%	0%	0%	4%	5%
Car business peak	5%	6%	20%	24%	44%	57%
Rail business off-peak	83%	85%	100%	100%	100%	100%
Bus business off-peak	1%	1%	0%	0%	0%	0%
Air business off-peak	5%	4%	0%	0%	0%	0%

Table 6 (continued)

	Profit Optimal Baseline ^a	P3	NoAir	NoAir3	Auto-Electric Car	Auto-Electric Car 3
Car business off-peak	12%	10%	0%	0%	0%	0%
Train occupancy Peak (%)	71%	83%	73%	83%	57%	64%
Train occupancy Off-peak (%)	71%	79%	73%	68%	57%	53%

^a Current track charges and supply for other modes than rail.

the other hand car travellers have the advantage of privacy in the car. We assume that the congestion levels on the road remain the same as in our main analysis, because there is currently very limited congestion on the Swedish motorways. In both cities, the traffic is presently also subject to congestion tax.

Table 6 includes results. As expected, wiping out the competition from air allows the rail operator to increase the fares. Fares increase more for business travellers, relative to the corresponding profit-optimal scenario with current track charges and supply for other modes that rail (the Profit-Optimal Baseline scenario in Table 5), because air is currently a stronger competitor for rail for business travellers. The optimal frequency increases slightly in NoAir, because demand for rail trips increases, despite the higher fares. Still, the demand for rail trips increases less than the demand for car and bus trips, because of higher rail fares and because of rail congestion and crowding. Due to the increased number of passengers and higher fares, the profit of the rail operator increases. The consumer surplus reduces because the air alternative vanishes. The results are fairly similar comparing Profit-Optimal Baseline/NoAir and P3/NoAir3, hence results are not sensitive to the level of the track charges or the external congestion cost of the track.

Optimal fares and frequencies both decrease in the autonomous electric car scenario. The number of car trips increases substantially, and the number of rail trips reduces. Still, the rail operator makes a profit. The government's revenue reduces and covers a smaller share of the fixed maintenance cost. Hence, it seems that the largest threat to the rail industry is cheap electric and autonomous car trips.

7. Conclusion

In the public debate, there is a notion that increases in track charges will be passed on to rail users in the form of higher fares. This study has therefore set out to analyse the impact of rail fares and frequencies on increased (and optimal) track charges. The welfare-optimal track charge is defined as the track charge that maximizes welfare, given that the monopolist rail operator will optimize profit. The optimal level of the track charge depends crucially on the marginal external congestion cost of the tracks. Since the congestion cost is largely unknown, we make assumptions and perform a sensitivity analysis. We assume different levels of congestion on the tracks and then simulate the optimal track charges.

We show that as track charges increase, the producer surplus and frequencies decline. However, the fares remain fairly unchanged, in particular if there are crowding costs and it is possible for the operator to extend the length of the train. The frequency reduces, but the number of travellers reduces less than the frequency. Hence, the occupancy rate increases. It might be surprising that fares do not increase, since standard economics yields that only half of the increase in the marginal cost is absorbed by the monopolist and the rest is transferred to consumers (assuming a linear demand function). The main reason for the small impact on the fares as the track charges increase is that the competition from other modes discourages the rail operator from increasing the generalized cost too much. The operator gains more from increasing

generalized cost by reducing the frequency than by increasing the fares. Hence, although the higher marginal cost is partly absorbed by the travellers (as basic theory yields) this is primarily done in terms of lower frequencies rather than higher fares. We find that the resulting reductions in demand for rail trips is moderate compared to the findings of Sánchez-Borràs et al. (2010), suggesting that demand would increase between 20 and 60 percent if track charges were decreased.

The net revenue for the government (revenue from track charges minus the maintenance cost) is positive in all scenarios and increases as expected with higher congestion cost. We find that fares are lower, and frequency is higher when optimizing welfare instead of the operator's profit. However, welfare-optimal fares and frequencies would mean that taxpayers must cover a larger deficit.

Vertical separation with public owned infrastructure and commercial operators has largely been promoted to increase competition on the track. However, competition has been difficult to accomplish, which is one reason for assuming a monopolist in this paper. However, if accomplished such that a duopoly reaches equilibrium, evidence suggests that fares are impacted slightly more by increased track charges. But in that case, the fares are also lower than in the monopoly case in the first place. We show that in the monopoly case, the optimal track charge is lower than the external congestion cost, because the monopoly will otherwise run a lower frequency than is socially optimal.

Optimal track charge is higher when the length of the trains can be extended (train size can be optimized) and when the crowding penalty is high. Higher track charges then more strongly encourage the train operators to increase the number of travellers per train instead of increasing the number of departures. With more crowding and possibility to extend the length of the trains, the impact on the fares of higher track charges is also lower. This shows that there are large efficiency gains from increasing track charges when the space on the tracks is scarce.

Since we assume no competition on the tracks, other modes provide

the only competition. To demonstrate this, we show that if intermodal competition reduces or increases, the monopolist train operator will change the fares. If electric and autonomous cars become a reality, lowering the generalized travel cost of driving, this could become a severe threat to the competitiveness of long-distance rail trips (at least in countries like Sweden where the congestion on the motorways is limited outside the urban areas). If, on the other hand, air traffic in the corridor is eliminated, for instance due to taxes or environmental regulations, this would reduce the intermodal competition substantially. The results would be higher rail fares. These results indicate that competition from other modes plays a significant role in how the operator sets its key variables.

To conclude, charging for rail congestion seems to be an efficient allocation instrument for scarce space on the tracks, without inducing large increases in fares faced by the consumers. Higher charges would also give operators more appropriate incentives to utilize their vehicles more efficiently.

Author statement

Maria Börjesson designed the model and the computational framework and analysed the data. Chengxi Liu and Ajsuna R. Rushid carried out the implementation. Maria Börjesson and Ajsuna R. Rushid wrote the manuscript with input from Chengxi Liu and Maria Börjesson conceived the study and were in charge of overall direction and planning.

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APPENDIX A. MODEL CALIBRATION AND OPTIMIZATION

The model calibration and optimization are set up and solved by the standard constrained nonlinear optimization solver, fmincon, provided by the optimization toolbox in Matlab r2016. The default algorithm 'interior-point' is used. The detailed convergence criteria are:

Objective function value tolerance: 'TolFun' = 1e-6, Decision variable tolerance: 'TolX' = 1e-6, Maximum number of objective function evaluation: 'MaxFunEvals' = 10 000, Maximum number of iteration: 'MaxIter' = 3 000.

The specific documentation of the used optimization solver can be found at: <https://se.mathworks.com/help/optim/ug/fmincon.html>. It is, however, important to note that frequency as the decision variables in this optimization problem are integer variables. Given that there is no standard optimization solver that solves non-linear mixed integer optimization problems, a grid search is performed. This involves the following steps:

1. Allowing frequency variables to be non-integers and use fmincon to solve the "non-integer" version of the optimization problem.
2. The non-integer frequency values are obtained from step 1 and grid search candidates can be determined. For example, if the optimal non-integer peak frequency is 11.5 and optimal non-integer off-peak frequency is 7.3, all combinations of integer peak frequency [10,11,12,13] and integer off-peak frequency [6,7,8,9] near the optimal non-integer values (so in total 4*4 = 16 combinations) will be considered as candidates.
3. For each frequency candidate from step 2, solve a reduced optimization problem where frequency variables are no longer decision variables but are fixed, thus in total solving 16 reduced optimization problems.
4. Compare the objective function values obtained from step 3 and select the frequency candidate with the highest objective function value.

In this paper, only four numbers are searched in the grid search for each frequency variable. We conjecture this is sufficient as the objective function surface is not very non-linear to the frequency variables.

APPENDIX B. MARGINAL COSTS

Table 4

External cost of X2000 trains Stockholm-Gothenburg. Source: (Nilsson and Haraldsson, 2018). Marginal cost of wear and tear are based on Andersson (2007).

	Marginal external cost	Marginal external cost
Distance	456	km/train
Weight train	315	ton/train

(continued on next page)

Table 4 (continued)

	Marginal external cost		Marginal external cost	
Maintenance	0.00087	€/tonkm	125	€/train
Re-investments tracks and electric infrastructure	0.00148	€/tonkm	213	€/train
Re-investments signal system etc.	0.05372	€/km	24	€/train
Accidents	0.123	€/km	56	€/train
Noise	0.259	€/km	118	€/train
Sum external cost wear and tear on the tracks, accidents and noise $e = r^e$			536	€/train

APPENDIX C. SOCIAL WELFARE MAXIMIZATION

Assume instead that the fares and frequencies are set by a public welfare-maximizing operator. Let the inverse demand function be $V(D)$. The consumer surplus is $CS = \int_0^D V(s)ds - (p + c)D$. In the absence of external cost, the total welfare is

$$\Omega = CS + PS = \int_0^D V(s)ds - cD - C = \int_{-\infty}^V D(s)ds + pD - C.$$

Maximizing social welfare holding frequency-fixed yields

$$\hat{p} = Dc'(D) + C'(D).$$

Hence, the optimal fare is the marginal production cost of one more traveller $C'(D)$ plus the crowding cost $Dc'(D)$. In the absence of crowding and with zero marginal production cost, the optimal fare is zero (not taking into account the marginal cost of public funds). Keeping the fare fixed at p and optimizing welfare Ω with respect to frequency f , yields

$$-DV'(f) - C'(f) = 0.$$

Using that $V(f) = -\frac{\gamma}{f^2} + \Gamma(f)$ and that $C'(f) = k$ we have

$$\hat{f} = \sqrt{\frac{\gamma D}{(k + D\Gamma'(f))}}.$$

If there is no crowding ($\Gamma'(f) = 0$), the optimal frequency is $\hat{f} = \sqrt{\frac{\gamma D}{k}}$ (hence in the presence of crowding, the optimal frequency is higher). This formula coincides with the optimal frequency for the profit-maximizing operator (in the absence of crowding). However, since the latter will set higher fares, the demand D will be lower, implying that the optimal frequency is also lower for the monopolist.

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