Imperial College London

Determinants of Delay Incident Occurrence of Urban Metros

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Abstract
Train service reliability is a key metro management objective and a major part of a successful operation. The occurrence of incidents in the network is likely to cause delays to the train service, perturbing the punctuality and regularity of the metro operation, and hence its service reliability. This suggests that one way to improve train service reliability is to reduce the occurrence of incidents in urban metro systems. This paper uses statistical techniques to identify the main factors explaining the variation in the number of delay incidents across 42 metro lines (of 15 different metro systems) over the period 2005-2009. The results indicate that among the main factors explaining differences in incident performance across urban metro lines are the technology of the mode of train operation, the level of passenger demand, the service level operated during peak periods, and the practical capacity available. On the contrary, engineering, and usually fixed, metro factors such as the type of track support, the type of rail connection, the type of rolling stock wheel, do not have an effect on incident levels. The findings also suggest that metro-specific factors help explain the variation in incident performance, where such factors refer to differences in maintenance and management practices, operations management, health & safety procedures etc. [co-authors: Nigel G. Harris, Daniel J. Graham, Richard J. Anderson, Alexander Barron]

Biography
Patricia Melo is a research associate of the Railway and Transport Strategy Centre, within the Centre for Transport Studies at Imperial College London. Her research is primarily focused on the measurement of economic efficiency of metros and bus companies, and agglomeration economies. Patricia holds a PhD in transport economics from Imperial College London, and her research interests include the relationship between transport and the economy, transport economics, spatial economics, and econometrics.

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Centre for Transport Studies, December 15th 2010

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Presentation Structure

1. Railway and Transport Strategy Centre (RTSC)

Railway and Transport Strategy Centre

- Established in 1992, the Railway and Transport Strategy Centre (RTSC) at Imperial College London was set up:
  - To serve the transport industry on strategic, technology, economic and policy issues
  - As a research unit within the Centre for Transport Studies,
  - As a commercial unit within the Department of Civil and Environmental Engineering at Imperial College, supporting the academic work of the College.

- Three key research themes:
  - Public transport operations, management and strategy
  - Benchmarking & performance measurement
  - Transport economics & policy

- Activities: applied and academic research, consultancy, teaching

Imperial College London are World Leaders in the Field of Public Transport Benchmarking

Sixteen year history of benchmarking projects facilitated by Imperial College London

1994 Group of Five heavy metros formed (incl. NYCT)

1996 *Community of Metros (CoMET)* founded (9 of the world's largest 12 metros)

1998 Success of *CoMET* leads to formation of *Nova* group for medium-sized metros

2004 *International Bus Benchmarking Group* established

2005 *Nova* grows to 14 members, *CoMET* to 12

2010 *Suburban Rail Benchmarking Group* established

Significant benefits have driven continued participation:

NYCT is a member for CoMET for 16 years and the IBBG for 6 years

27 Metros Compare Performance to Identify and Share Best Practices

Thirteen Bus Benchmarking Group members

Imperial College
London

Ten members in the Suburban Rail Benchmarking Group

DSB S-Tog
(Copenhagen)

London
Rail

Metro Trains
(Melbourne)

S-Bahn
(Munich)

JR East
(Tokyo)

Metro-North
(New York)

CPTM
(Sao Paulo)

LIRR
(New York)

NSB
(Oslo)

BART
(San Francisco)

2. Background & Objectives

Background & Objectives (1)

- The occurrence of incidents often causes delays to rail service, perturbing the punctuality and regularity of the operation, and hence service reliability.

- Service reliability can be targeted through incident prevention and incident recovery. This work is concerned with the former.

- The objective is **to identify the key factors underlying the variation in the number of delay incidents across urban metros through regression analysis**.

Background & Objectives (2)

- Previous research on service reliability tends to look at travel time reliability, either by focusing on the variability or the predictability of passenger travel times.

- Some studies have looked at the consequences of incidents on service level degradation. Surprisingly, we did not find any previous evidence on the drivers of incidents.

- Since incident prevention is one way to improve service reliability it is important that metro operators have a better understanding of the factors influencing the occurrence of incidents in their systems.

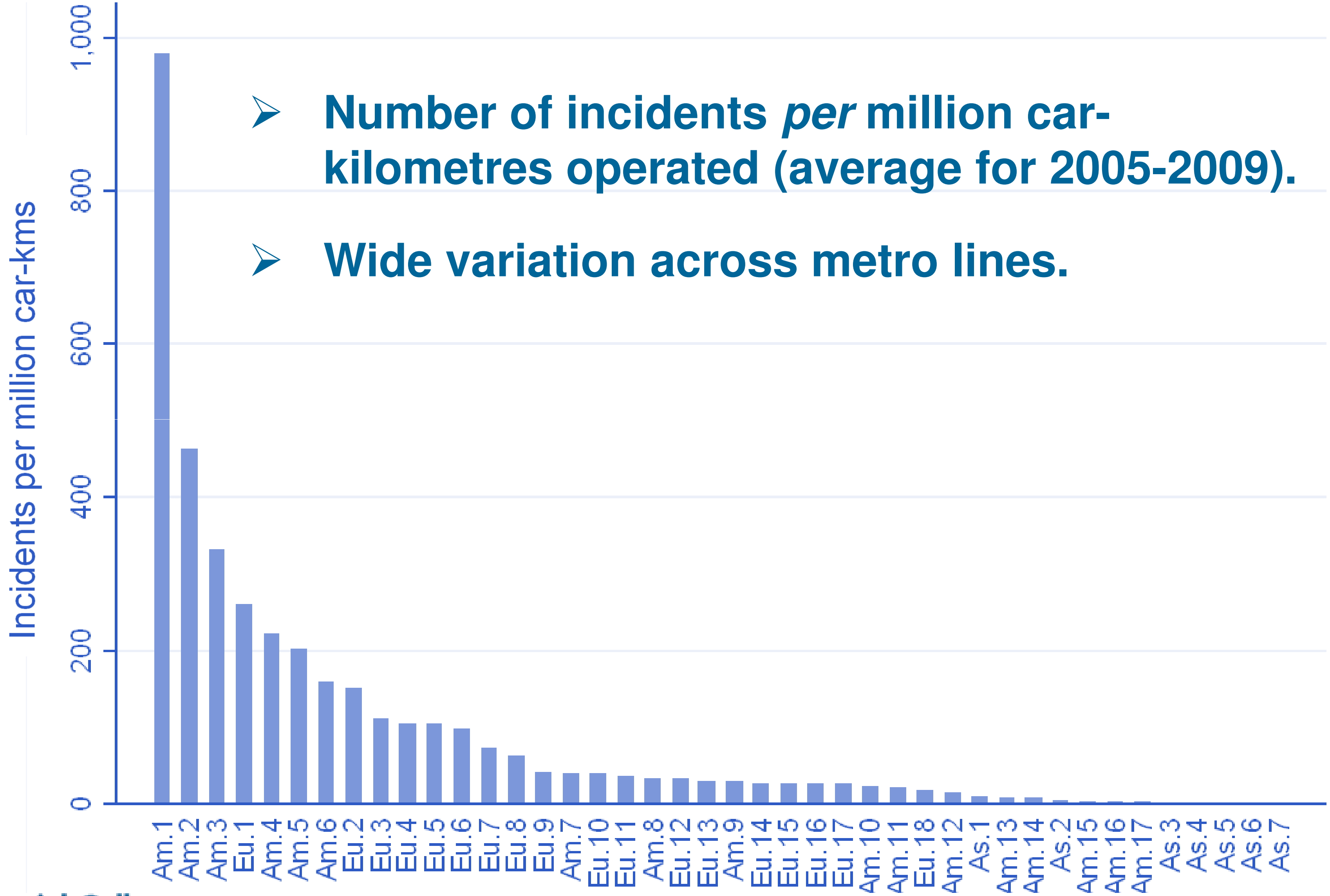
3. Data

Data (1)

- Unbalanced panel of 42 metro lines of 15 different urban metros over the period from 2005 to 2009.
  - 17 lines (6 metros) are in the Americas.
  - 18 lines (5 metros) are in Europe.
  - 7 lines (4 metros) are in Asia.

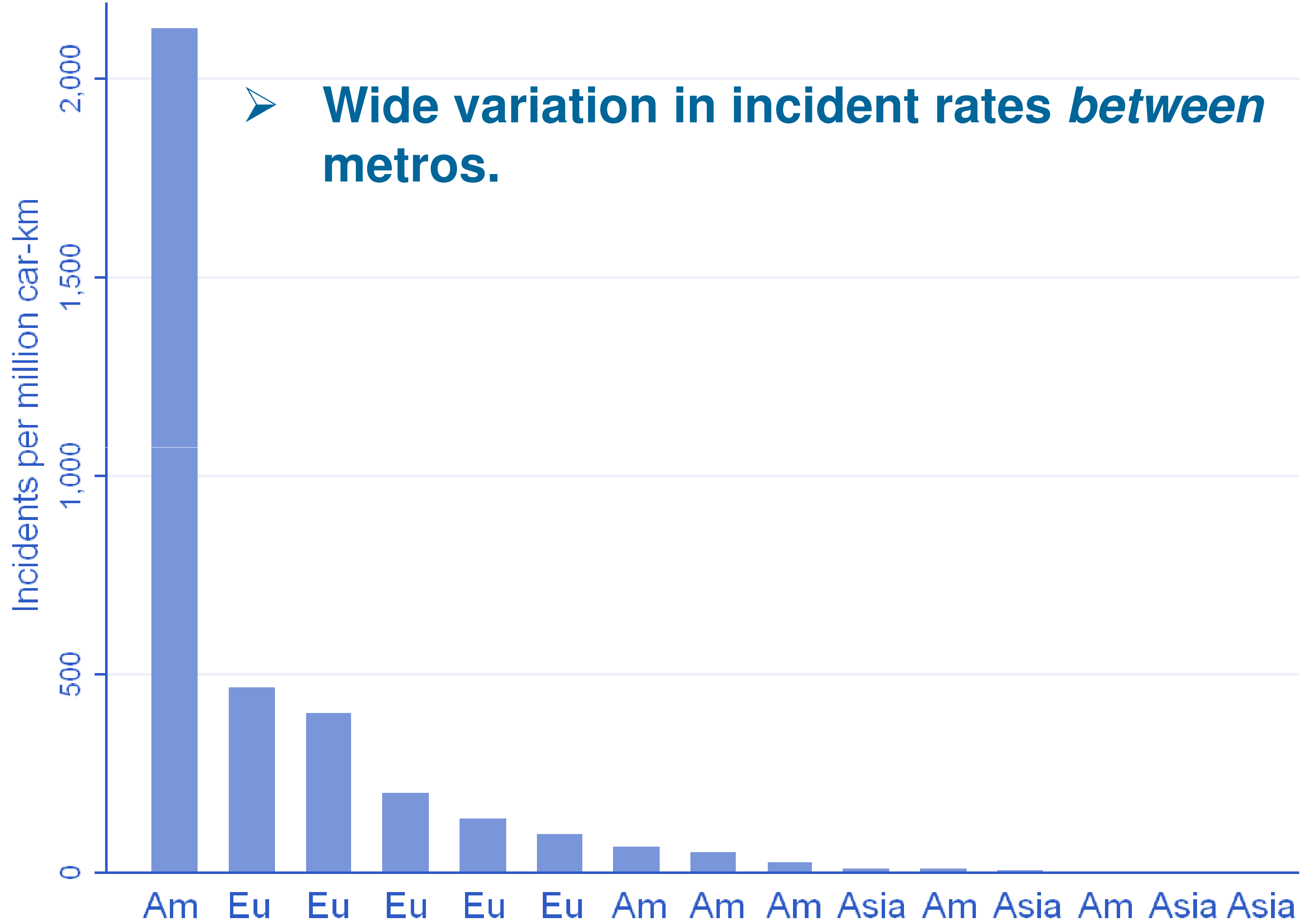
- On average, we observe each metro line 4.89 times over the 5 year period.
- The data are collected by the RTSC for their urban metro benchmarking groups CoMET and Nova through special purpose designed questionnaires.
- Data verification and validation checking tests were conducted, including regular contacts with CoMET and Nova members.

Data (2) - Distribution of Incident Rates



- Number of incidents *per* million car-kilometres operated (average for 2005-2009).
- Wide variation across metro lines.

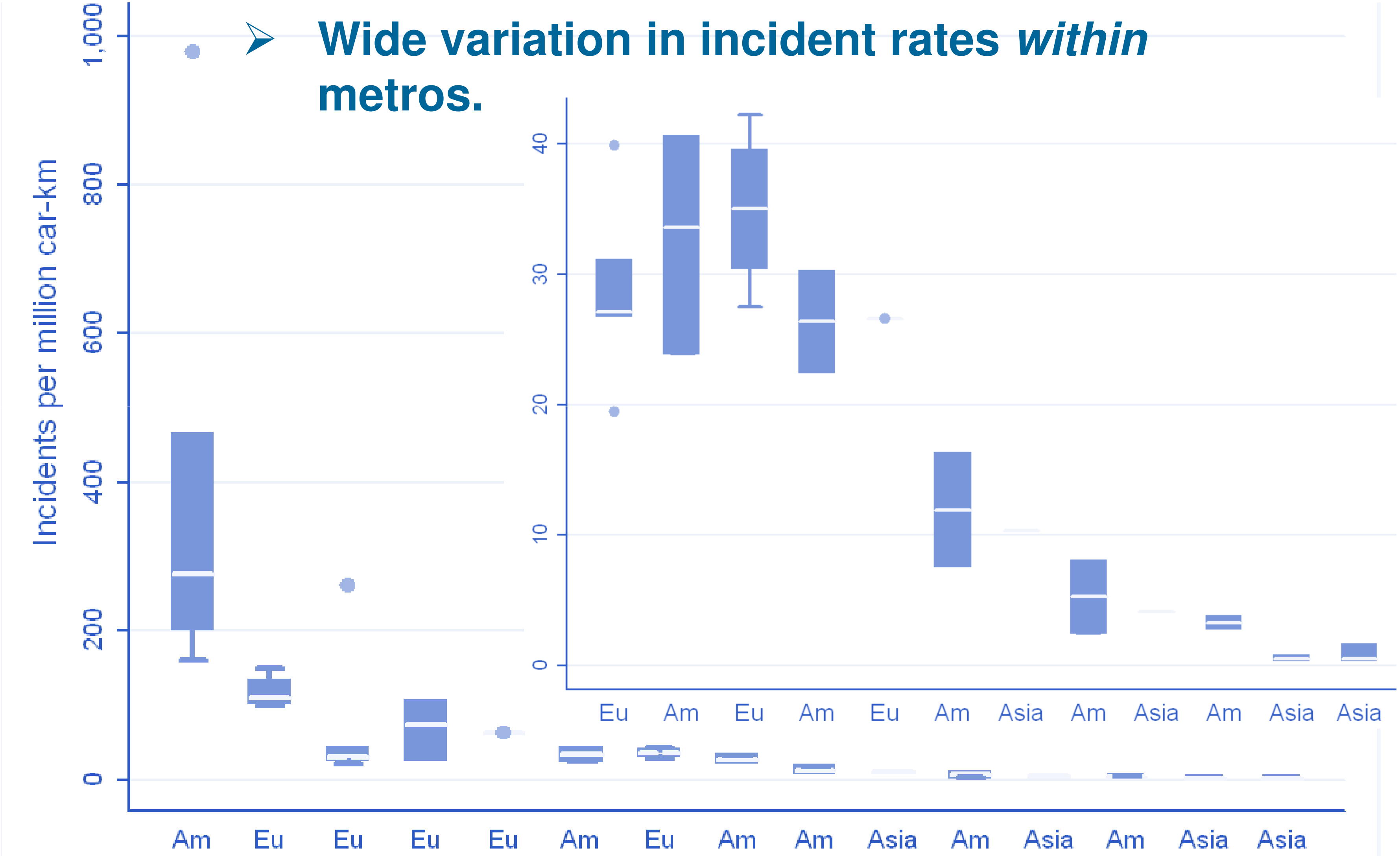
Data (3) - Between-Metro Variation



- **Wide variation in incident rates *between* metros.**

Data (4) - Within-Metro Variation

- **Wide variation in incident rates *within* metros.**



Data (5) - Incident Drivers

- **What factors explain the differences in incidents across metros?**
  - **Scale of operation**
  - **Engineering factors**
  - **Technological factors**
  - **Management & other metro specificities**

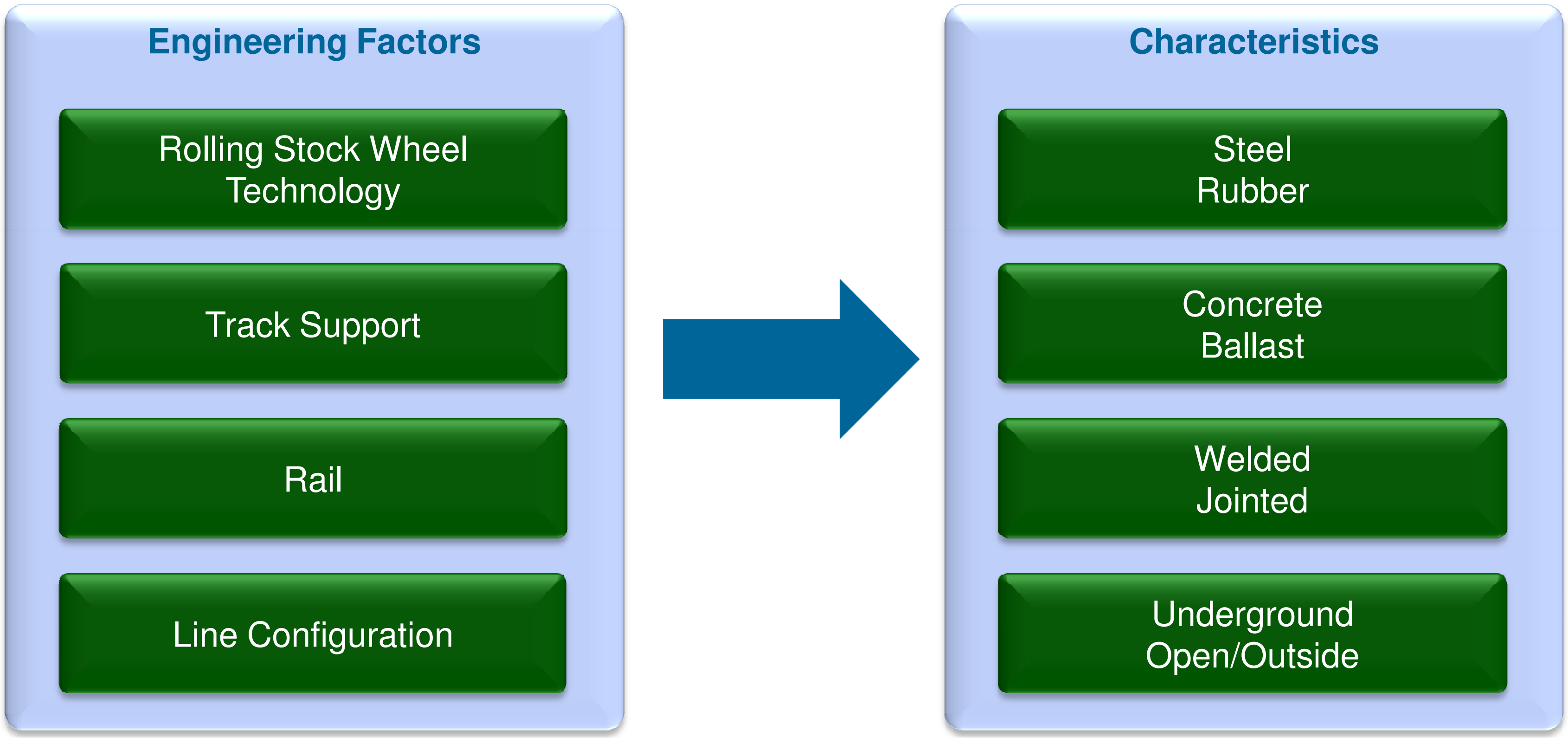
Data (6) - Scale of Operation

- **Scale of operation**: the number of incidents is determined by the size of the metro line, other factors remaining the same.
  - e.g. longer metro lines may have more incidents just because they are longer.
  - e.g. denser metro lines may have more incidents because of overcrowding, and higher pressure on resources.

- The scale of operation can be represented by various measures: route length, number of stations, level of train service operated (e.g. number of car-kilometres), and the level of demand (e.g. number of passenger-journeys).

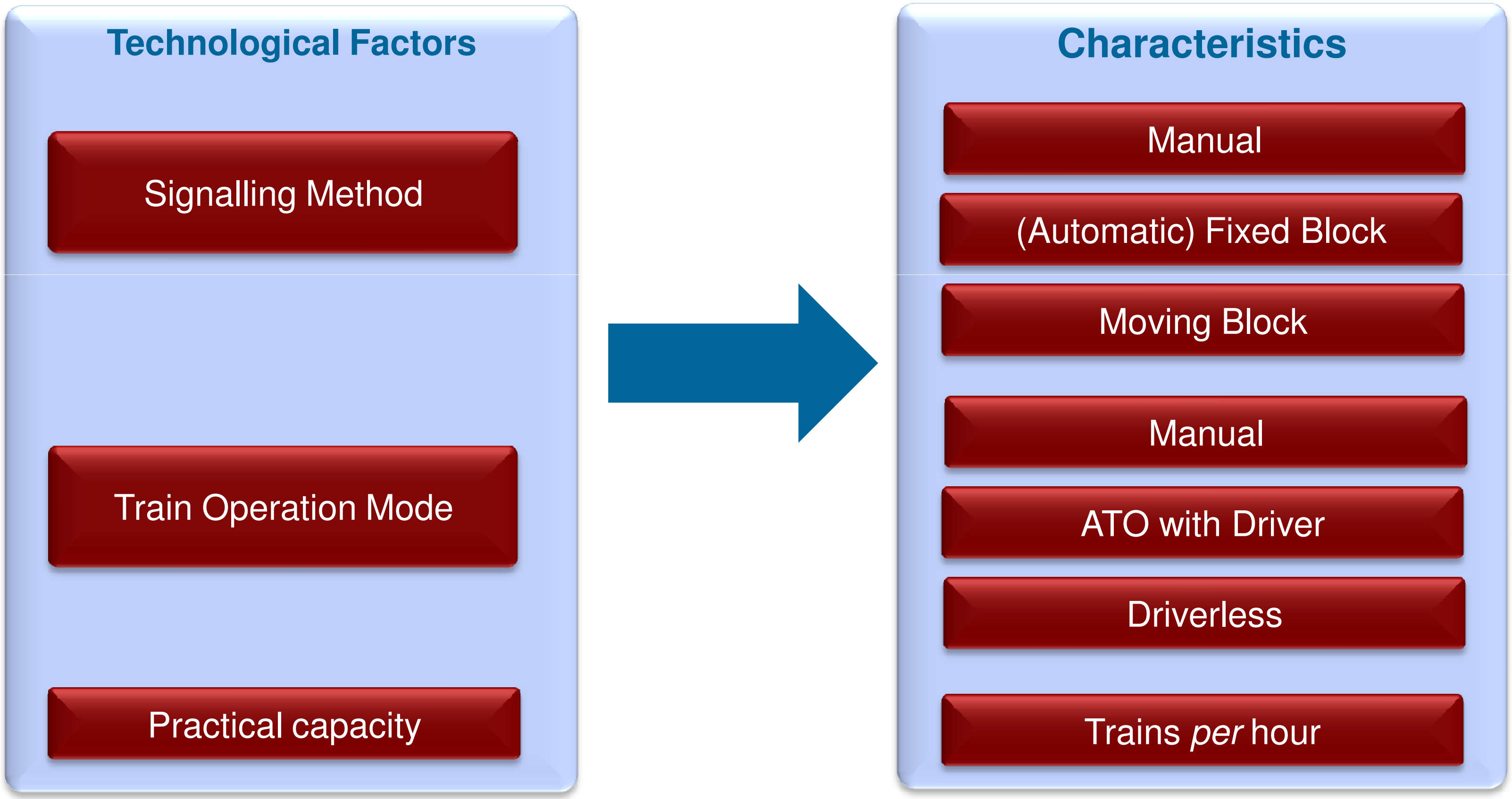
Data (7) - Engineering factors

- **Engineering factors**: type of track support (e.g. ballasted, concrete), type of rail connection (e.g. jointed, welded), rolling stock physical technology (e.g. steel wheels, rubber tyres), etc.



Data (8) – Technological factors

- **Technological factors**: technology adopted to operate the rolling stock, signalling method, etc.



Data (9) - Management & other metro factors

- **Management & other metro specificities**: other dimensions of metros that can affect incidents.
  - Observed/measured factors: peak service level (tph), age of the line, use Platform Screen Doors (PSD), use of staff for despatch purposes, maintenance effort, age of rolling stock, etc.
  - Unobserved/unmeasured factors: organizational culture, maintenance & operations management practices, training, safety legislation, etc.

4. Empirical Model

Empirical Model (1)

- The variable of interest is the number of incidents occurring in a given year and metro line. This is a discrete variable that only takes non-negative values.
- Least squares regression assumes a Normal distribution and can predict both negative and continuous values for the number of incidents, which is not appropriate.
- Standard approach to model count data is to use a use a Poisson regression model (PRM) or a Negative Binomial regression Model (NBRM).
- According to the PRM, the probability that of a metro line *i* at time period *t* receiving y_{it} incidents is

$$Pr(Y = y_{it}) = \frac{e^{-\mu_{it}} \mu_{it}^{y_{it}}}{y_{it}!}, \qquad y_{it} = 0, 1, 2, \ldots, n$$

Empirical Model (2)

- The PRM is estimated by specifying the expected value of the response variable (i.e. number of incidents) as a function of a series of explanatory variables [X].

$$\mu_{it} = E[y_{it}|X_{it}] = e^{(\beta X_{it})}, \qquad i = 1, 2, 3, \ldots, n; \; t = 1, 2, 3, \ldots, T$$

  - Y_{it}: number of incidents reported for metro line *i* in year *t*.
  - β: vector of model parameters.
  - X_{it} : vector of the explanatory variables included in the regression model.
  - PRM assumes equidispersion between the conditional mean and variance of y_{it}. This equality is often violated, commonly the variance is greater than the mean [overdispersion]. PRM unbiased but inefficient.

Empirical Model (3)

- Common alternative to the PRM is the Negative Binomial regression model (NBRM), which allows for overdispersion by adding an error that can capture unobserved cross-sectional heterogeneity:

$$E[y_{it}|X_{it}] = \mu_{it} v_{it} = e^{(\beta X_{it} + \varepsilon_{it})}, \qquad i = 1, 2, 3, \ldots, n; t = 1, 2, 3, \ldots, T$$

  - $v_{it} = e(\varepsilon_{it})$ adds random variation in the model due to unobserved heterogeneity.
  - The most commonly used version of the NBRM is known as NB2. It has conditional mean μ_{it} and the variance is a quadratic function of the mean and the overdispersion parameter α: $\mu_{it}(1+ \alpha \mu_{it})$. [Cameron and Trivedi, 2005]

- In addition to the NBRM, we also estimate a random effects PRM/NBRM, which allow for metro-specific heterogeneity.

Empirical Model (4)

- Models estimated:
  - **Negative Binomial Regression Model (NBRM)** which allows for overdispersion in the data.
  - To allow for metro-specific heterogeneity we also estimated:

  (i) **Random effect PRM**: allows for a metro-specific random intercept.

  (ii) **Random effect NBRM**: allows the dispersion parameter to vary randomly between metros.

  - Random effect models help explain part of the variation in incident levels without creating identification issues due to collinearity between some of the covariates and the metro-specific dummy variables.

5. Results

Results (1)

- Key data & estimation issues:
  - Missing data (e.g. maintenance)
  - Multicollinearity (e.g. fixed engineering factors)
  - Simultaneity (e.g. PSD, use of staff for despatch)

- Overdispersion test rejects null of overdispersion, so NBRM should be preferred to the PRM.

- Metro-specific heterogeneity helps to explain the differences in incident levels across metro lines, as reflected by the improvement in the goodness of fit of the models allowing for metro specific variation.

- Goodness of fit statistics [AIC and BIC indices] further indicate that the NBRM with random metro-specific variation is the best model.

Results (2) - Detailed Table

	Negative Binomial Model (NBRM)			PRM, with random metro variation			**NBRM, with random metro variation**		
	b	SS	b/SE	b	SS	b/SE	**b**	**SS**	**b/SE**
Line age (years)	0.0051		-0.85	0.0065	***	-16.25	**0.0067**	**	**-2.31**
Route length (km)	0.0337	***	-2.72	-0.0012		1.20	**0.0088**		**-1.11**
Rolling stock age (years)	0.0015		-0.15	0.0163	***	-20.38	**0.0025**		**-0.32**
Peak frequency (tph)	0.1365	***	-4.27	0.1112	***	-46.33	**0.0431**	**	**-2.22**
Practical capacity (tph)	0.0281		-0.84	-0.0460	***	17.04	**-0.037**	**	**2.23**
Log of Passenger journeys	-0.4074	**	2.44	0.1787	***	-12.95	**0.2884**	***	**-3.10**
Train operation is ATO driver or driverless (vs. Manual)	-1.5218	***	6.20	-0.5223	***	36.02	**-0.4031**	***	**2.87**
Rubber-tyred trains (vs. steel trains)	1.9063	***	-4.01	2.4189		-1.19	**-1.0850**		**1.29**
Overhead (vs. third rail)	0.9876	***	-2.75	0.7420	***	-24.01	**0.1178**		**-0.53**
Proportion of concreted track (vs. ballasted)	-0.6091	*	1.75	0.1634	***	-4.29	**0.1358**		**-0.51**
Proportion of jointed track connection (vs. welded)	0.3829		-1.00	9.4787	***	-9.56	**-0.2424**		**0.29**
Proportion of track in open area (vs. underground)	-0.8558		1.31	0.6639	***	-12.89	**0.5812**		**-1.41**
+dummy for years (2005 reference)	0.83			381.91	***		**3.14**		
Observations	106			106			**106**		
LR/Wald chi2	113.16***			10761.7***			**168.72*** **		
LL (model)				-2,649			**-687**		
Number groups (metros)	11			11			**11**		
Likelihood-ratio test of no overdispersion (H0:alpha=0)	16,129***			-			**12,333*** **		
Hausman test (FE versus RE)				2,069***			**1.57**		
McFadden's *pseudo* R^2	0.070			0.882			**0.491**		
AIC	1,538			5,334			**1,411**		
BIC	1,586			5,382			**1,462**		

Results (3) - Summary Table

- Based on the results from the preferred model we calculated elasticity values to evaluate the importance of the different factors.

Explanatory factors	Elasticity
Line age (years)	0.26
Route length (km)	-
Rolling stock age (years)	-
Peak frequency (trains per hour)	0.92
Practical capacity (trains per hour)	-0.93
Log of Passenger journeys	0.29
Train operation is ATO driver or driverless (vs. manual)*	-0.33
Rubber-tyred trains (vs. steel trains)	-
Overhead (vs. third rail)	-
Proportion of concreted track (vs. ballasted)	-
Proportion of jointed track connection (vs. welded)	-
Proportion of track in open area (vs. underground)	-

Only statistically significant results are shown.*Pseudo elasticity since the covariate is a binary variable.

Results (4) - Factors that help reduce incidents

Moving from manual to automatic train operation

-33% Incidents

+1 tph practical capacity

-3.7% Incidents

Results (5) - Factors that can increase incidents

+1 year line age

+ 0.67% Incidents

+1 peak tph

+ 4.31% Incidents

+10% pax journeys

+ 2.9% Incidents

Results (6) - Factors that do not affect incidents

- Evidence suggests that engineering and fixed metro attributes do not determine incidents:

Factors not relevant to incidents

- Rail connection (welded vs. jointed)
- Rolling stock steel wheels vs. rubber tyres
- Track support (concrete vs. ballast)
- Proportion of track in open area

6. Conclusions

Conclusions (1)

- One of the key results is that **moving from manual to some form of automatic train operation can reduce incidents substantially**.

- It is important to distinguish the effects of different types of automatic train operation (ATO with driver vs. fully driverless); this was not possible due to insufficient data for fully automatic train operation.

- **Increasing levels of demand** (passenger journeys) and **peak train service frequencies** can increase incidents, especially if there is no alleviation of the pressure placed on the fixed resources available through additional practical capacity.

Conclusions (2)

- **Engineering and fixed metro factors do not explain the differences in the number of incidents across metro lines.**This is good news to metro companies, because changing these attributes would not only be very costly but essentially impractical.

- **Metro-specific heterogeneity helps to explain the differences in incident levels across metro lines.** Examples include maintenance and management practices, operations management, health & safety procedures, etc. But it is difficult to test for these factors because they are very difficult or impossible to measure.

Thank you for your attention

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Results (5) - Factors that can increase incidents

- Increasing passenger-journeys by 10% is associated with an increase in incidents of 3%, all other factors remaining constant.

- Increasing service levels during peak periods without increasing the available practical capacity can also increase incidents. The elasticity of incidents with respect to peak trains per hour suggests that a 10% increase in service levels is associated with an increase in incidents of 9.2%.

- A 10% increase in line age is associated with an increase in incidents of 2.6%, reflecting the wearing of fixed infrastructure and assets over time. To counter this effect on incident occurrence metros need to invest in the maintenance and upgrading of the various components of the network.

Results (4) - Factors that help reduce incidents

- Moving from manual to some form of automatic train operation is associated with a reduction in incidents of 33%. This suggests to metro companies that automatic train operation modes are more reliable than manual operation modes.

- Increasing practical capacity by 10% is associated with a reduction in incidents of about 9.3%.

- Metro-specific heterogeneity helps to explain the differences in incident levels across metro lines. These differences relate to procedures implemented by the different metros to achieve incident reduction, but are difficult to measure.