# DO PASSENGERS RESPOND TO FARE CHANGES? DOES INFLATION MATTER?

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## 1. INTRODUCTION

The production of accurate forecasts of passenger rail demand is important for a wide range of organisations, including train operators, infrastructure managers and government departments. In Great Britain, there is a well-established framework used to produce forecasts of passenger rail demand (the Passenger Demand Forecasting Handbook), based on many research papers.

To the best of our knowledge, all of these papers share an important assumption: that passengers (actual and potential) respond to changes in *real* fares and incomes (i.e. fares after inflation has been accounted for). For example, if inflation were 2% and the cash price of tickets were to increase by 2%, there would be no response from passengers because the *real* price of the tickets is unchanged. This is consistent with standard economic theory, where consumer preferences are assumed to be well behaved.

However, there are two problems here. First, from a forecasting perspective, the PDFH is generally held to be underperforming (for example, it struggles to explain high passenger growth in the north of England). Second, recent developments in behavioural economics are challenging standard economic theory and suggesting that passengers may respond to changes in *nominal*, not real, prices and incomes.

Since forecasts of passenger demand underpin the spending of billions of euros on railway schemes every year, it is important that they are as accurate as possible. In this paper, we explain in more detail why passengers may respond to changes in *nominal* (i.e. money of the day) as opposed to real monetary variables (section 2). We then present an empirical investigation into whether a real or nominal forecasting framework performs better (sections 3 and 4), before concluding with some policy implications (section 5). A Technical Appendix provides more details on the econometric analysis.

## 2. BEHAVIOURAL ECONOMICS AND THE CONCEPT OF MONEY ILLUSION

### 2.1 Behavioural economics

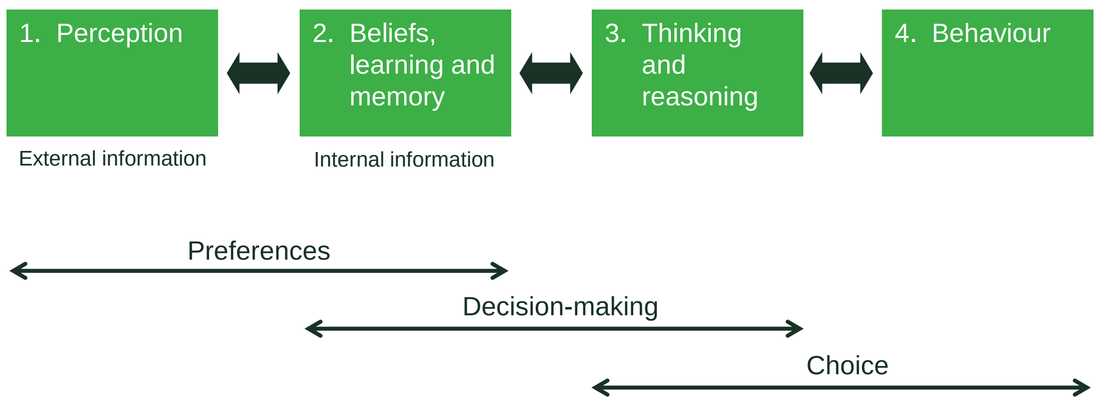
Behavioural economics has captured the attention of policymakers and regulators across all sectors. Policymakers are increasingly looking for lessons from behavioural economics to help them improve policy and find more cost-effective ways to improve consumer outcomes. Behavioural economics can also improve the application of economics by better capturing human behaviour.

Behavioural economics uses insights from psychology to explain the effects of cognitive and behavioural processes on consumer behaviour and market outcomes. It provides insights into individual behaviour that go beyond the 'fully rational choice' approach of standard economics.

## 2.2 Behavioural vs traditional economics

The differences between behavioural and traditional economics can be highlighted by placing side by side the key decision-making process as explained by psychology and economics. The top half of Figure 2.1 displays processes that are familiar to psychologists: how people perceive information presented to them; how they draw on their internal information, such as beliefs, goals, and experience; how they then think about and weigh up the best course of action; and lastly, how they subsequently behave. The bottom half of the figure matches these to concepts that are familiar to economists: consumer preferences; their decision-making process; and the choices they make in practice.

**Figure 2.1 Stylised representation of cognitive and behavioural processes involved in making choices**




Source: Niels, G., Van Dijk, R. and Fields, L. (2013), Behavioural economics and its impact on competition policy: A practical assessment, *Competition Law Journal*, **12**(3), pp. 374–84; and Oxera (2013), Behavioural economics and its impact on competition policy: a practical assessment with illustrative examples from financial services, prepared for the Netherlands Authority for Consumers and Markets, May.

There are three key insights from behavioural economics:

- **preferences depend on context**. People's preferences may be influenced by how the information is presented or framed. For example, one would expect a higher demand for a burger that's 90% non-fat compared with one that is 10% fat;
- **decision-making involves taking shortcuts**. Conscious, fully rational deliberation of every single decision would be exhausting to apply to all day-to-day tasks. Instead, some decisions are made purely subconsciously and

automatically, given what consumers have learned, without much thinking at all. These shortcuts are called ‘heuristics’;

- **choices over time can be time-inconsistent**. Consumers can face a conflict between their short-term urges and what would be best for them in the long term. In economics terminology, their preferences can be ‘present-biased’ or ‘time-inconsistent’ relative to what traditional economics would predict.

The next subsection focuses on a particular aspect of behavioural economics called ‘money illusion’, which could be particularly relevant to rail passenger demand.

### 2.3 Money illusion

Money illusion is consumers’ tendency to think in terms of nominal rather than real monetary values. In other words, if the price of a good (or service) increases, the consumer will not take into account the rate of inflation when deciding how much of that good to consume.

While the term ‘money illusion’ has been familiar to economists for a long time,[1] it cannot be fully explained by rational economic models.[2] By incorporating insights from cognitive psychology, behavioural economics sheds light on both the causes and consequences of money illusion.

As mentioned above, a key insight of behavioural economics is that context matters. In particular, alternative representations of the same situation may elicit different responses from consumers. In behavioural economics, this is known as ‘framing’. For example, consider a worker who has received a wage rise of 1% in a zero inflation environment with another worker who has received a 2% raise when inflation is 1%. Who would you say is happier with their pay rise?

The frame on which people rely will be the one that is most salient, simple or intuitive. The nominal representation of price changes is more appealing to people; after all, most economic transactions are represented in nominal terms. People are generally aware of inflation and the difference between nominal and real prices;[3] however, at a single point in time, the nominal representation of prices is more salient and easier to understand. Consequently, the evaluation of price changes will often be the result of nominal and real assessments, giving rise to money illusion.

Another key insight of behavioural economics is that consumers’ preferences, and hence their appraisal of different available options, are affected by what is presented as an initial reference point or ‘anchor’. Anchoring can influence consumer perceptions even when the initial anchor is arbitrary or irrelevant. For example, if a bottle of wine is initially priced at €10 and then reduced to €5, consumers may perceive that they are getting a better deal than if the wine were offered at €5 in the first instance.

In situations where there are changes in prices, the anchor is often the last price the consumers paid for that good. For example, consider two passengers who are considering purchasing train tickets. The tickets currently cost €30. The last time the first passenger bought a ticket, the cost was €25, while the second passenger previously bought the ticket for €35. The decision to buy the ticket for the two passengers will tend be different because they will anchor their decision on the point at which they last bought the ticket. Hence, the second passenger might be more willing to buy than the first. The rest of this paper empirically tests for evidence of money illusion in the GB rail passenger market.

## 3. APPROACH TO TESTING FOR MONEY ILLUSION

### 3.1 Outline of approach

This section sets out the econometric approach that will be used to investigate the extent to which the money illusion phenomenon, as understood in behavioural economics, is present in the rail industry. Results from this analysis may have implications regarding how rail demand might be forecast more accurately.

First, the dataset that will be used to perform this empirical investigation is presented, followed by an explanation of three central econometric challenges involved when modelling with time-series data, before developing the overall econometric model opted for: a single equation error correction model (ECM).

The main advantage of the selected ECM is that it permits relatively straightforward econometric modelling of our data in both real and nominal terms, allowing the money illusion hypothesis to be empirically tested in a moderately simple way with commitment to relatively few assumptions. In particular, this modelling approach allows direct comparison of forecast performance between the nominal and real models, centrally connecting with our issue of determining whether consumers rely on—and therefore can have their behaviour best predicted by—nominal as opposed to real prices and income.

### 3.2 The data

We use a dataset of quarterly time-series data from 1998Q1 to 2015Q1. The analysis focuses on the long-distance rail sector in Great Britain, such that the data for i) the number of passenger journeys, ii) ticket prices (proxied by yield, total revenue divided by passenger numbers), and iii) a measure of train performance are all specific to the long-distance rail sector. All of the data used in this paper is available from public sources (see Table 3.1 below).

## Table 3.1 Description of dataset

| Variable | Definition | Source |
|---|---|---|
| Passenger journeys | Number of long-distance passenger journeys in Great Britain | Office of Rail and Road |
| Fare price | Revenue from all long-distance journeys in Great Britain divided by passenger journeys | Office of Rail and Road |
| Population | Population of the United Kingdom | Datastream[1] |
| GDP | United Kingdom Gross Domestic Product | Office for National Statistics |
| Cost of motoring | Motoring index | Office for National Statistics |
| Performance | Measured using the Public Performance Measure (PPM), which is the percentage of trains that arrive at their destination within ten minutes of scheduled arrival time | Office of Rail and Road |
| Retail Price Index[2] | Measure of UK inflation | Office for National Statistics |

Note: [1] Office for National Statistics data for the full population was not available, therefore an alternative source, based on Oxford Economics data, was used. The robustness of the series was confirmed by a cross-check with additional Eurostat population data. [2] The following regression analysis was also separately conducted with Office for National Statistics consumer prices index data to cross-check our analysis, acknowledging some differences between the series. The results were not found to change substantively.

Source: Oxera.

The key summary statistics for these variables are presented in Table 3.2.

## Table 3.2 Summary statistics

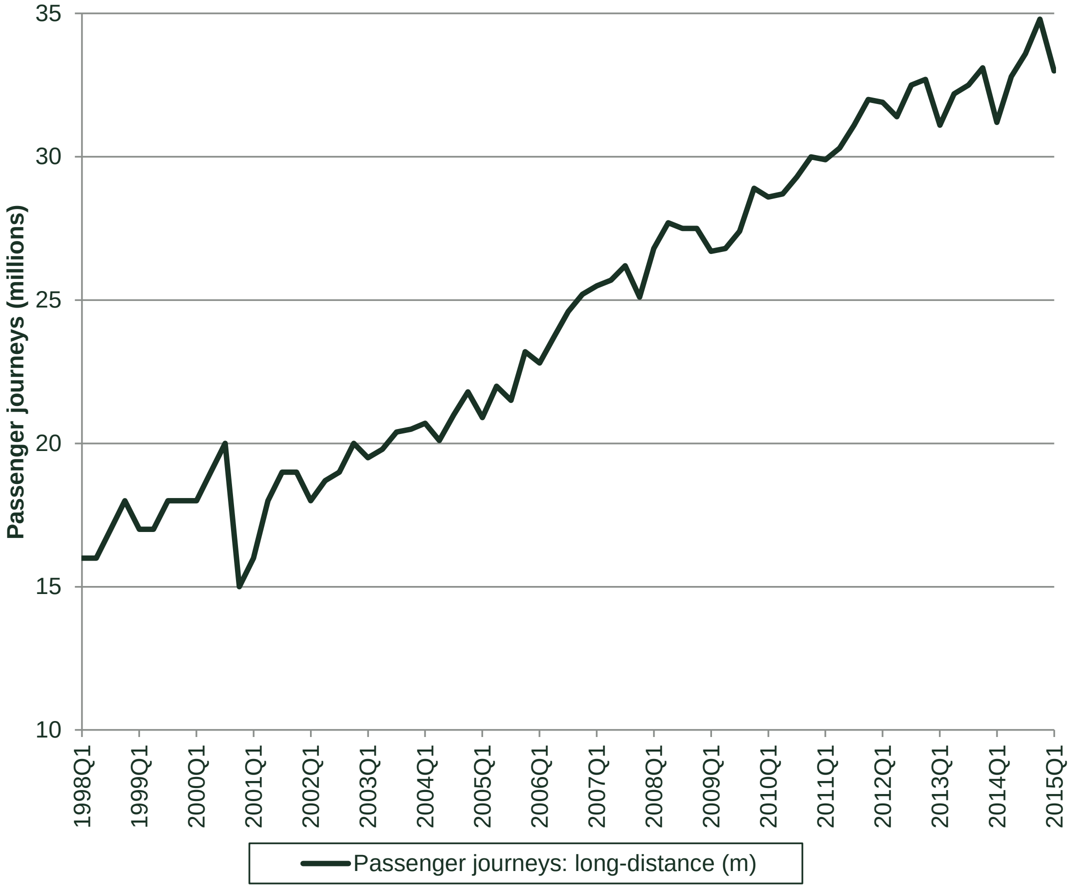
| Variable | Number of observations | Mean | Standard deviation | Min. | Max. |
|---|---|---|---|---|---|
| Long distance passenger journeys (m) | 69 | 24.5 | 5.8 | 15.0 | 34.8 |
| Fare price (£, nominal prices) | 69 | 18.5 | 2.1 | 14.2 | 22.8 |
| Population (m) | 69 | 61.2 | 2.0 | 58.4 | 65.0 |
| GDP (£m, nominal prices) | 69 | 341,180 | 68,347 | 227,449 | 458,039 |
| Cost of motoring (index, 1987=100)[1] | 69 | 198.9 | 25.2 | 168.8 | 242.5 |
| Performance (%, PPM) | 69 | 82.0 | 8.2 | 49.1 | 91.0 |

Note: [1] Cost of motoring is retained in RPI index format (with base year 1987) for both nominal and real specifications because computing a cost of motoring measure that reflects overall inflation will lead to issues of circularity (since the cost of motoring is itself an input into the overall price level index). This then leads to issues of multicollinearity—a form of model mis-specification—in the ECM.

Source: Oxera.

Figure 3.1 reports the time-series plot of passenger demand for rail over the sample period 1998Q1 to 2015Q1.

**Figure 3.1 Demand in the long-distance rail sector**

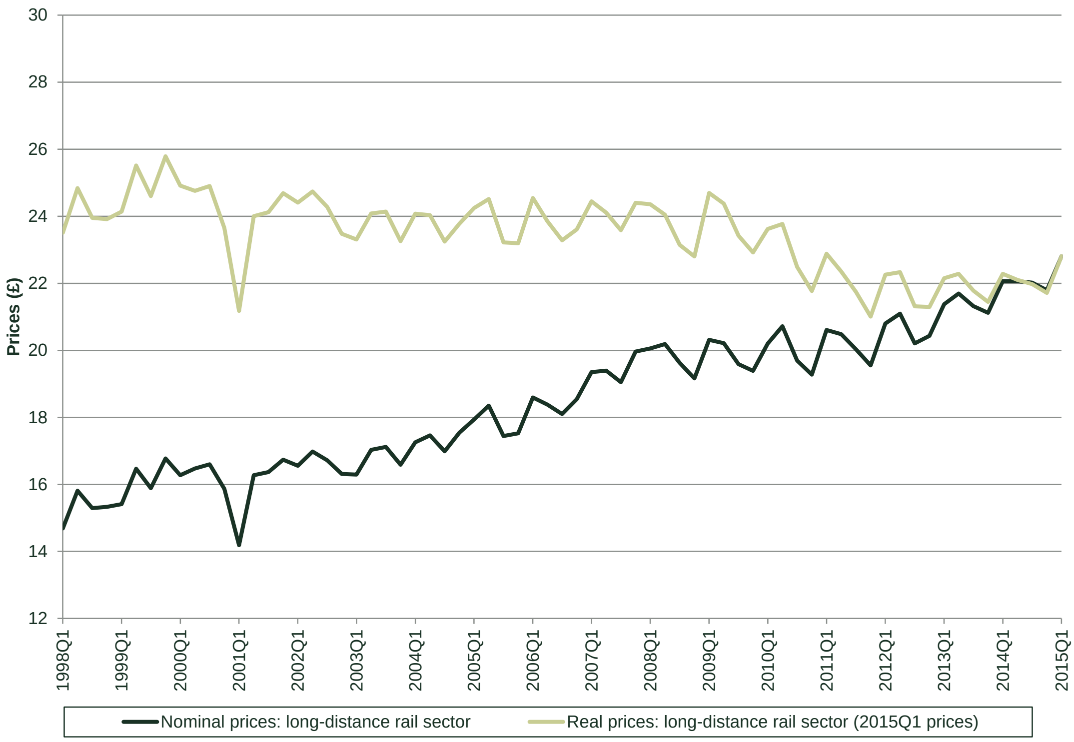



Source: Oxera, and Office of Rail and Road.

One immediate observation from Figure 3.1 is that there is a sharp drop in demand for 2001Q1. This is the result of the Hatfield rail accident in October 2000 (a train derailment resulting in four fatalities).[4] A second observation is that total demand grows considerably, doubling over the 17-year sample period.

Plots of a nominal and real price series are presented in Figure 3.2 below. These price series are computed by taking publicly available data on aggregate revenues for long-distance rail travel and dividing by the number of long-distance rail journeys, and therefore are most accurately described as nominal and real average yield.

**Figure 3.2 Nominal and real long-distance fares**




Source: Oxera, and Office of Rail and Road.

While nominal fares rise over the period, real fares appear to fall slightly, due to inflationary pressure. Again, the effects of the Hatfield accident are observed in 2001Q1. Further plots of the other variables of interest can be found in Technical Appendix [1]–[4]. We estimate a model using the natural logarithm (a transformation) of our key variables—this makes the data series smoother, and is standard practice in econometric modelling. It also makes the interpretation of coefficient estimates easier, as interpretation can now be made in percentage rather than unit terms, but it does not change the underlying relationships.

### 3.2 Three econometric issues

This section reviews three central econometric issues faced when using time-series data, both with respect to our dataset and in general, and presents the solutions opted for in our modelling approach.

#### 3.2.1 Non-stationarity

The first econometric issue concerns trending series. From an econometric viewpoint, one particularly important feature of some of these graphs is that they display series which contain trends: the mean average of the series does not appear constant through time. In more technical language, these trending series are likely to be 'non-stationary'. If non-stationary data is not handled properly, it can present significant issues when estimating econometric models. In particular, failing to control for non-stationary data can result in the spurious regression problem.[5] Regressing one non-stationary variable on another results in a number of issues, not least that the standard significance tests on variables—assessing whether one variable (an independent variable) has a significant effect on another (the dependent variable)—become invalid.[6] Spurious regression can lead to nonsensical conclusions, such as those explored in Hendry (1980), which demonstrated that cumulative rainfall in the UK can better explain certain price-level movements than money supply, when rainfall is clearly unrelated to price.[7]

It is therefore vital to test whether our data series are non-stationary, and if so, take the appropriate action to avoid these problems. The results of these non-stationary tests—an Augmented Dickey–Fuller test and Augmented Phillips–Perron test—are reported in Technical Appendix [5]. We find that all variables used in our analysis are non-stationary in levels, as suspected from their trending plots, but that through application of one solution to this issue—first differencing, taking the value of the difference between the series in time (t) and time (t+1)—the series become stationary as desired.[8] This means that even if we have data that is non-stationary in levels, in first differences the data can be used in econometric analysis.

### 3.2.2 Structural breaks

A second issue faced in developing an econometric model for rail demand concerns the possible existence of structural breaks. With time-series data, a structural break[9] occurs where a series suddenly changes at a particular point in time. In an econometric model, a structural break means that a coefficient estimate is significantly different before the break as compared with after the break. This may occur, for instance, in a GDP time series following an economic policy to boost economic growth or following the discovery of valuable natural resources (an exogenous shock).

Therefore, before arriving at our specification for a model to investigate the money illusion hypothesis, the data series are tested for structural breaks. The Zivot and Andrews test is one such test for structural breaks.[10] It is performed on each of the series, and the results are reported in the Technical Appendix. With this dataset, the Hatfield accident is not identified as a structural break by the Zivot and Andrews test. Structural breaks are identified, however, in 2006Q2 in long-distance passenger journeys, 2003Q4 in the PPM variable and 2008Q4 in nominal GDP per capita. Owing to the magnitude and economic implications of the recession in 2008, coupled with this result, we opt for a dummy variable to account for the structural break that the recession involved to explicitly quantify its impact.[11]

### 3.2.3 Cointegration

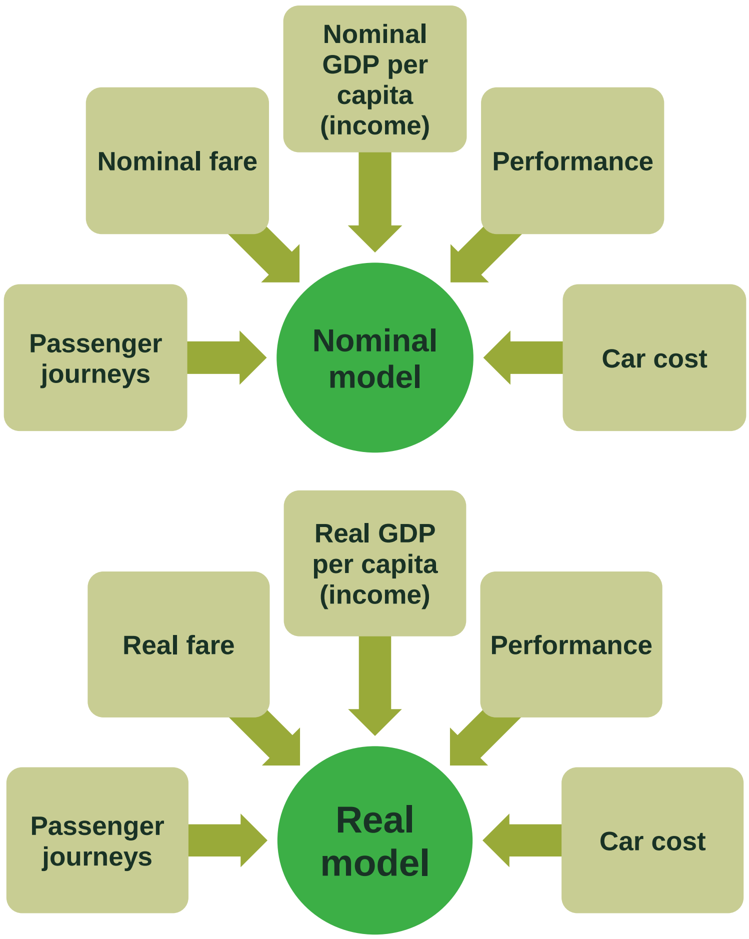
A third issue that can be considered while attempting to establish a robust econometric model is whether the data series might happen to jointly feature a statistical relationship known as 'cointegration'. Cointegration occurs when two non-stationary series happen to share the same stochastic—that is, random—trend; while individually the series are trending, there happens to be a linear relationship between them.[12] Out of the possible scenarios in which we might expect to find cointegration, one is in a situation where two non-stationary series, when regressed on each other, yield an error term that is itself stationary. For example, if a regression of Y on X in the form:

$$Y_i = X_i + \varepsilon_i$$

yields an error term $\varepsilon_i$ which is stationary, then Y and X can be said to be cointegrated. This is relevant in this case because if our data series do jointly cointegrate, we can argue that the series share a long-run equilibrium. That is, in the long-run coefficient estimates exist that are able to capture the long-run effect of a percentage increase in, for example, nominal GDP per capita on demand for rail services. If we can identify such a long-run equilibrium between our variables, then it will be possible to use a powerful ECM to model our data.

In order to build an econometric specification suitable to illustrate whether money illusion is a feature of our rail dataset, cointegration is tested for separately for nominal and real variables (in conjunction with the other relevant variables). This is because in order to estimate separate nominal and real models it must be ensured that a cointegration relationship holds between the two sets of variables independently. Figure 3.3 below shows the clusters of variables that are tested for cointegration in both the real and nominal cases; the models are differentiated by their fare price and income input variables.

**Figure 3.3 Cointegrating relationships**




Source: Oxera.

The two groups of variables are tested for cointegration. The first group uses only nominal data: nominal rail fares and nominal GDP per capita as a proxy for income. The second group uses only real variables: real rail fares (inflated to 2015Q1 prices) and real GDP per capita (inflated identically).

To test for the existence of a long-run equilibrium between the variables of interest, the Johansen test for cointegration is used.[13] The results are reported in Technical Appendix [7]–[8]. Overall, it is found that that there is indeed a single cointegrating relationship between variables of interest, in both the real and nominal specifications.

### 3.3 The ECM framework

The cointegrating relationship found above provides theoretical grounds to use models of the error correction form. However, the technical legitimacy of the approach is a necessary but secondary consideration for the use of such an ECM. It is important that the econometric model to be used is based on a conceptual framework that explains how rail demand is determined, drawing on both rail industry-specific knowledge and that of economic theory. In addition, previous work by Oxera,[14] which utilised a general-to-specific modelling approach[15] on a similar dataset, established this specification as a good model, at the aggregate level, for rail demand. Some studies[16] also indicate the salient variables for rail demand, which we take primarily to be price, income (proxied here by GDP per capita), performance of the rail service and the cost of alternative modes of transport (e.g. cars). This industry understanding, in combination with the Johansen cointegration tests of section 3.2.3, together indicate that the following pair of ECMs can be employed (all variables in natural logs).

**Real ECM**

$$\begin{aligned}\Delta\text{passenger journeys}_t &= \alpha + \beta_1\Delta\textbf{real}\text{ price}_t + \beta_2\Delta\textbf{real}\text{ gdp per capita}_t + \beta_3\Delta\text{car cost}_t \\ &+ \beta_4\Delta\text{performance}_t - \emptyset(\text{passenger journeys}_{t-1} - \delta_1\textbf{real}\text{ price}_{t-1} \\ &- \delta_2\textbf{real}\text{ gdp per capita}_{t-1} - \delta_3\text{car cost}_{\text{t}-1} - \delta_4\text{performance}_{t-1} \\ &- \delta_5\text{recession}_{t-1})\end{aligned}$$

**Nominal ECM**

$$\begin{aligned}\Delta\text{passenger journeys}_t &= \alpha + \beta_1\Delta\textbf{nominal price}_t + \beta_2\Delta\textbf{nominal}\text{ gdp per capita}_t \\ &+ \beta_3\Delta\text{car cost}_t + \beta_4\Delta\text{performance}_t - \emptyset(\text{passenger journeys}_{t-1} \\ &- \delta_1\textbf{nominal}\text{ price}_{t-1} - \delta_2\textbf{nominal}\text{ gdp per capita}_{t-1} \\ &- \delta_3\text{car cost}_{\text{t}-1} - \delta_4\text{performance}_{t-1} - \delta_5\text{recession}_{t-1})\end{aligned}$$

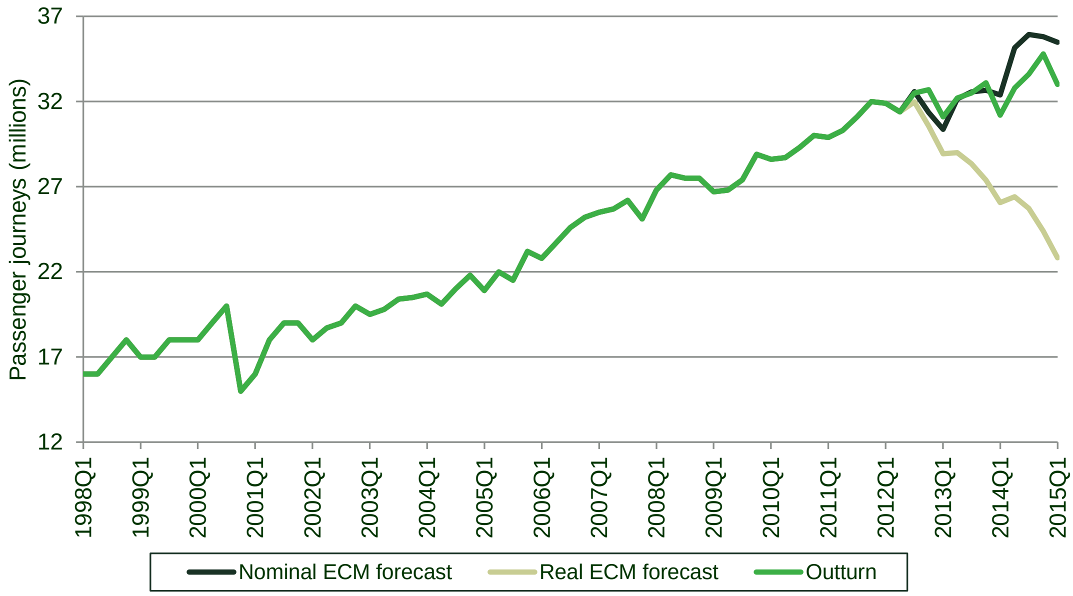
In these models, $\alpha$ is a constant term, $\beta_{1-4}$ are the coefficients on the short-run variables, $\delta_{1-4}$ are the coefficients on the long-run variables, and ∅ is the adjustment speed coefficient which captures the rate at which the model returns to long-run equilibrium following a disturbance. It must be highlighted that these are simple, stylised models and are likely to omit some important factors in the determination of rail demand. The results yielded by these models are presented in section 4.

## 4. RESULTS FROM ECONOMETRIC MODELLING

### 4.1 Results

The headline result of this paper is that we find a significant difference between the performance of a model specified in nominal money as opposed to real money terms, broadly in line with the predictions of money illusion (see Figure 4.1).

**Figure 4.1 Nominal vs real forecasts**




Source: Oxera.

Prominent differences emerge between the forecasting abilities of the nominal as opposed to the real model. Forecasting rail demand using nominal as opposed to real demand drivers results in a forecast that performs considerably better when compared with the actual passenger journey outturn data. While the nominal forecast tracks outturn passenger journeys quite closely until 2014Q1, the real forecast is considerably below the outturn value. At the end of the sample period, while the outturn number of passenger journeys is 33m, the real model predicts 22.8m, while the nominal predicts 35.4m: clearly, the nominal model performs better. In terms of average percentage error, the nominal model is incorrect by 0.53% on average; and the real by 2.54% on average.

These forecast results are based on the models as estimated below in Table 4.1.

## Table 4.1 Error correction model estimation

| | Nominal ECM | Real ECM |
|---|---|---|
| | **D.lpax_long** | **D.lpax_long** |
| **D.ln(nominal price)** | -0.0641 | |
| | (-0.47) | |
| **D.ln(real price)** | | -0.3 |
| | | (-1.69) |
| **D.ln(nominal GDP per capita)** | 1.591* | |
| | (2.56) | |
| **D.ln(real GDP per capita)** | | 1.588** |
| | | (3.12) |
| **D.ln(performance)** | 0.243 | 0.278 |
| | (1.68) | (1.71) |
| **D.ln(car cost)** | -0.325 | 0.00437 |
| | (-1.53) | (0.02) |
| **L.ln(passenger journeys)** | -0.884*** | -0.651*** |
| | (-7.11) | (-5.27) |
| **L.ln(nominal price)** | -0.157 | |
| | (-0.85) | |
| **L.ln(real price)** | | -0.578* |
| | | (-2.23) |
| **L.ln(nominal GDP per capita)** | 0.795*** | |
| | (5.49) | |
| **L.ln(real GDP per capita)** | | 0.910*** |
| | | (4.37) |
| **L.ln(performance)** | 0.371*** | 0.413** |
| | (3.52) | (3.44) |
| **L.ln(car cost)** | 0.294*** | 0.450** |
| | (4.22) | (2.79) |
| **L.recession** | 0.0788*** | 0.0769** |
| | (3.67) | (3.46) |
| **_cons** | -5.094*** | -6.485* |
| | (-6.33) | (-2.62) |
| **N** | 68 | 68 |
| | | |
| **(t-statistics in parentheses)** | | |
| *** p<0.05, ** p<0.01, *** p<0.001** | | |

Notes: (1) D.ln() is the first difference of the variable;
(2) L.ln() is the first lag of the variable;
(3) ln() refers to the natural logarithm of a variable.

Source: Oxera.

### 4.1.2 Robustness checks

Following the estimation of an econometric model and prior to interpreting the results, it is important to perform some robustness checks to ensure we can have a good degree of confidence in the coefficient estimates. Both models pass key tests for mis-specification, as follows.

- There is no significant evidence of serially correlated residuals through time (which would lead to inefficient and incorrect standard errors).[17]
- Plots of the residuals appear approximately normally distributed (see Technical Appendix [9]–[10]), enabling more accurate testing of hypotheses about the data.
- While there is some evidence of errors that vary in their spread through time (heteroscedasticity), this is controlled for as far as possible using an estimation procedure that is robust to heteroscedastic errors.

In addition, a further robustness check is performed by removing the quarter 2001Q1, which corresponds to the impact of the Hatfield accident—to inspect whether this makes a different to the econometric results. Excluding the data is found to make very little difference to the long-run relationships.

## 4.2 Interpretation of results

From Table 4.1 a number of important points emerge about the determinants of rail demand.[18] The only statistically significant short-run coefficients found with both specifications above are for nominal and real GDP per capita. With either model, a 1% change in GDP per capita leads to a 1.59% change in passenger journeys (rail demand).[19] Otherwise, our short-run coefficients are not statistically significant from zero at the 5% significance level.

More important for our purposes, since we are seeking to understand the long-run behaviour of passenger demand, is the interpretation of the long-run coefficients, given by the lagged variables—e.g. L.ln(passenger journeys) divided by the adjustment speed coefficient $\emptyset$. This yields a set of long-run elasticity estimates, which are presented in Table 4.2 below.

## Table 4.2 Short- and long-run elasticities

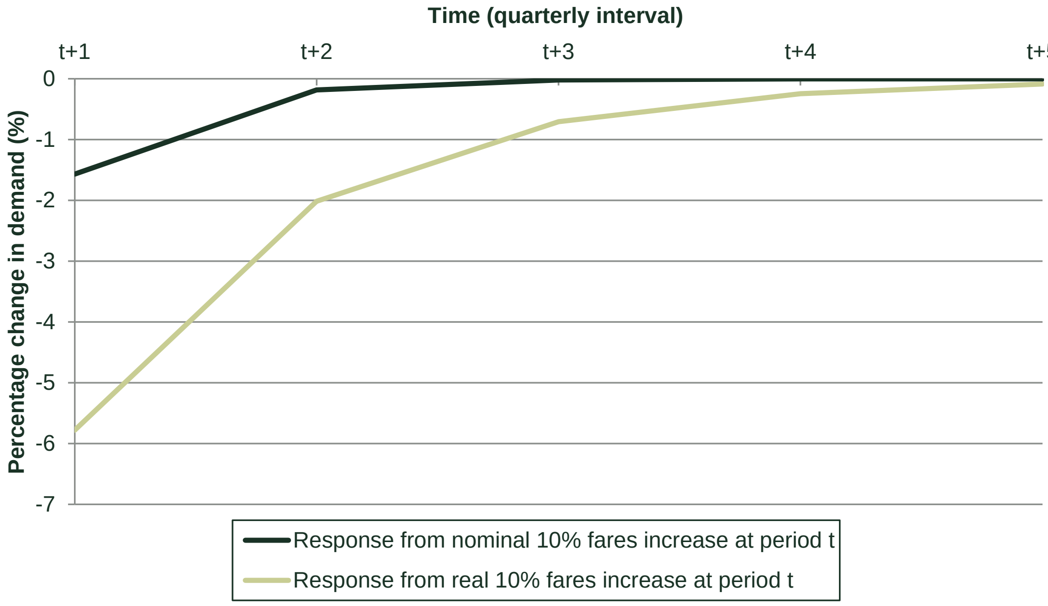
| Real ECM | | |
|---|---|---|
| | **Short-run coefficient** | **Long-run coefficient** |
| **ln(realyield)** | -0.300 | -0.888 |
| **ln(real gdp per capita)** | 1.588 | 1.398 |
| **ln(performance)** | 0.278 | 0.634 |
| **ln(car cost)** | 0.004 | 0.691 |
| | | |
| **Adjustment speed** | -0.651 | |
| | | |
| **Nominal ECM** | | |
| | **Short-run coefficient** | **Long-run coefficient** |
| **ln(nominalyield)** | -0.064 | -0.178 |
| **ln(gdp per capita)** | 1.591 | 0.899 |
| **ln(performance)** | 0.243 | 0.420 |
| **ln(car cost)** | -0.325 | 0.333 |
| | | |
| **Adjustment speed** | -0.884 | |

Source: Oxera.

In the long run, it is found that fares, income (GDP per capita), performance of the rail services and the cost of alternative modes of transport are key drivers of rail demand. As expected, increases in fares result in a decrease in passenger journeys, holding all else constant.[20] Increases in income, or GDP per capita, result in an increase in rail demand, whether in nominal or real terms. However, while we can know the sign of the increase, it is not possible to directly compare these long-run elasticities.[21] Increase in rail performance and the cost of alternative modes of transport similarly lead to an increase in rail demand.

The above models also provide adjustment speeds for each specification—that is, the speed at which each model reverts back to its estimated long-run equilibrium (in a sense where the relationship between the different variables in the system is in balance and there are no further sudden shocks). In the nominal case, the adjustment speed (0.88) is larger in absolute terms than the adjustment speed in the real case (0.65), indicating a faster return to long-run equilibrium when using nominally specified variables. For clarity, these adjustment speeds are illustrated in Figure 4.2.

## Figure 4.2 Adjustment speeds to long-run equilibrium




Source: Oxera.

Figure 4.2 illustrates that when using nominal rather than real data, passenger journey demand is quicker to respond to shocks, returning faster to its 'stable' relationship. With the nominal fares increase the demand effect quickly falls close to zero at (t+2); with a real fares increase such a return to zero does not occur until (t+4).

In the present context, the fact that adjustment is faster (larger in absolute terms) when in nominal rather than real terms may provide grounds to believe that consumers are themselves faster to respond to changes in nominal rather than real variables. Consumers may not be taking into account all relevant information, and in particular the rate of inflation, when deciding how much of the good (i.e. rail journeys) to consume. In turn, this may indicate the presence of a behavioural bias in consumer response to rail fare increases, where the anchor of past nominal prices is more salient for the consumer than the real price taking inflation into account.

### 4.3 Forecast performance: is money illusion responsible?

The estimates of the two ECMs, one in nominal and one in real terms, can be used to compute sample forecasts, in turn enabling us to consider the relative performance of the two models with respect to actual outturn data. The forecasts are computed by estimating the econometric models over the same subset of the data, and then using these estimates to predict passenger journeys until the end of the sample period (see Figure 4.1).

## 5. CONCLUSIONS

The poor forecast performance of the real model can be seen to mirror real GDP per capita in Technical Appendix [3], which begins to fall following the recession. However, this can only offer part of the explanation for the poor performance of the model, as some datapoints following the recession in 2008Q4 are included in the estimation of the in-sample coefficient estimates. The superior performance of forecasts using nominal as opposed to real incomes might suggest that, from the consumer's viewpoint, nominal rather than real incomes are used in consumers' decision-making processes. In turn, this suggests more generally that nominal rather than real values are more important when it comes to consumer decision making regarding rail travel. Nominal prices and incomes are most salient and easier to process than real prices and incomes, and as such consumers do not appear to consider fully the effects of inflation on their consumption decisions.

These results come with the caveat that the performance of particular forecasts is contingent on the forecast period and the data sample used. Further work is needed on a disaggregated, rail line-specific basis. This would permit stronger conclusions to be drawn above the stylised example presented here. Nonetheless, the approach employed above, and the contrast that emerges between forecast powers when using nominal as opposed to real prices, makes it seem probable that a more detailed study would reveal that behavioural economics' money illusion phenomenon is in play in the rail industry.

## 6. NOTES

[1] See Fisher, I. (1928), *The Money Illusion*, Adelphi Company, New York.
[2] In fact, the notion has been undermined by some economists. James Tobin said that 'an economic theorist can, of course, commit no greater crime than to assume money illusion'. See Tobin, J. (1972), Inflation and unemployment, *American Economic Review*, **62**(1), pp. 1–18.
[3] Shafir, E., Diamond, P. and Tversky, A. (1997), Money illusion, *The Quarterly Journal of Economics*, **112**(2), pp. 341–74.
[4] A final report by the Independent Investigation Board is available at: Office of Rail Regulation (2006), Train Derailment at Hatfield: A Final Report by the Independent Investigation Board, July, http://webarchive.nationalarchives.gov.uk/20131001175041/http://www.rail-reg.gov.uk/upload/pdf/297.pdf.
[5] See Verbeek, M. (2008), *A Guide to Modern Econometrics*, John Wiley & Sons, Ltd, Chichester, p. 327.
[6] See Granger, C. and Newbold, P. (1973), Spurious Regressions in Econometrics, *Journal of Econometrics*, **2**, pp. 111–20.
[7] See Hendry, D. (1980), Econometrics – Alchemy or Science?, *Economica New Series*, **47**(188), pp. 387–406.
[8] As stationary series, the first differenced series have a constant mean, a finite variance and the covariance between two sample points only depends on the distance between the points (known as covariance stationarity).
[9] See Greene, W.H. (2012), *Econometric Analysis*, Pearson Education Ltd, Harlow, p. 208.
[10] See Zivot, E. and Andrews, K. (1992), Further Evidence on the Great Crash, the Oil-Price Shock, and the Unit-Root Hypothesis, *Journal of Business & Economic Statistics*, **10**(3), pp. 251–70.
[11] Additional sensitivity and robustness checks were carried out by including a full set of dummies corresponding to the periods indicated by the structural breaks and including a dummy variable for 2000Q4, as visual indication suggests that it may be an unusually large deviation from equilibrium (the result of the Hatfield accident). This model results in a broadly similar difference in forecast performance between the nominal and real models, and is reported in Technical Appendix [11].
[12] See Verbeek, M. (2008), *A Guide to Modern Econometrics*, John Wiley & Sons, Ltd, Chichester, p. 328.
[13] Johansen, S. (1991), Estimation and Hypothesis Testing of Cointegration Vectors in Gaussian Vector Autoregressive Models, *Econometrica*, **59**(6), pp. 1551–80.
[14] Oxera (2013), Responding Slowly to Change? Passenger Rail Demand in Great Britain, *European Transport Conference*.
[15] General-to-specific modelling involves first specifying a general model that includes variables believed to be of significance and then refining the model (making it specific) by removing variables that are not found to significantly influence the dependent variable.
[16] Department for Transport (2012), Revisiting the elasticity based framework: rail trends report, April, https://www.gov.uk/government/publications/revisiting-the-elasticity-based-framework-rail-trends-report.
[17] Serial correlation is tested for using a Breusch–Godfrey test. In the nominal model, we are unable to reject a hypothesis of serial correlation with a p-value of 0.7458. In the real model, the corresponding p-value is 0.6376, again providing no evidence of serially correlated errors.
[18] At the outset, it is important to note that direct interpretation of the coefficients is only possible for the short-run variables; the long-run coefficients must be computed by dividing by the adjustment factor and cannot be immediately read from the regression output.
[19] The first differenced variables (e.g. D.ln(passenger journeys)) refer to the short-run adjustment speeds.
[20] 'Holding all else constant', or ceteris paribus, is an important qualifier when interpreting results from regressions, and will be assumed during discussion of the effects of different variables.
[21] This is due to difficulties in directly comparing real and nominal price increases. A 5% nominal price increase may be constituted 3% by inflation and 2% by a real price increase. Yet, we do not observe pure nominal price increases or pure real price increases: while we can decompose a nominal price increase, it is not straightforward to back out comparable elasticities for nominal and real price increases, as we only observe a single demand response from consumers in the data.

## BIBLIOGRAPHY

Department for Transport (2012), Revisiting the elasticity based framework: rail trends report, April.

Fisher, I. (1928), *The Money Illusion*, Adelphi Company, New York.

Granger, C. and Newbold, P. (1973), Spurious Regressions in Econometrics, *Journal of Econometrics*, **2**, pp. 111–20.

Greene, W.H. (2012), *Econometric Analysis*, Pearson Education Ltd, Harlow.

Hendry, D. (1980), Econometrics – Alchemy or Science?, *Economica New Series*, **47**(188), pp. 387–406.

Johansen, S. (1991), Estimation and Hypothesis Testing of Cointegration Vectors in Gaussian Vector Autoregressive Models, *Econometrica*, **59**(6), pp. 1551–80.

Niels, G., Van Dijk, R. and Fields, L. (2013), Behavioural economics and its impact on competition policy: A practical assessment, *Competition Law Journal*, **12**(3), pp. 374–84.

Office of Rail Regulation (2006), Train Derailment at Hatfield: A Final Report by the Independent Investigation Board, July.

Oxera (2013), Behavioural economics and its impact on competition policy: a practical assessment with illustrative examples from financial services, May.

Oxera (2013), Responding Slowly to Change? Passenger Rail Demand in Great Britain, *European Transport Conference*.

Shafir, E., Diamond, P. and Tversky, A. (1997), Money illusion, *The Quarterly Journal of Economics*, **112**(2), pp. 341–74.

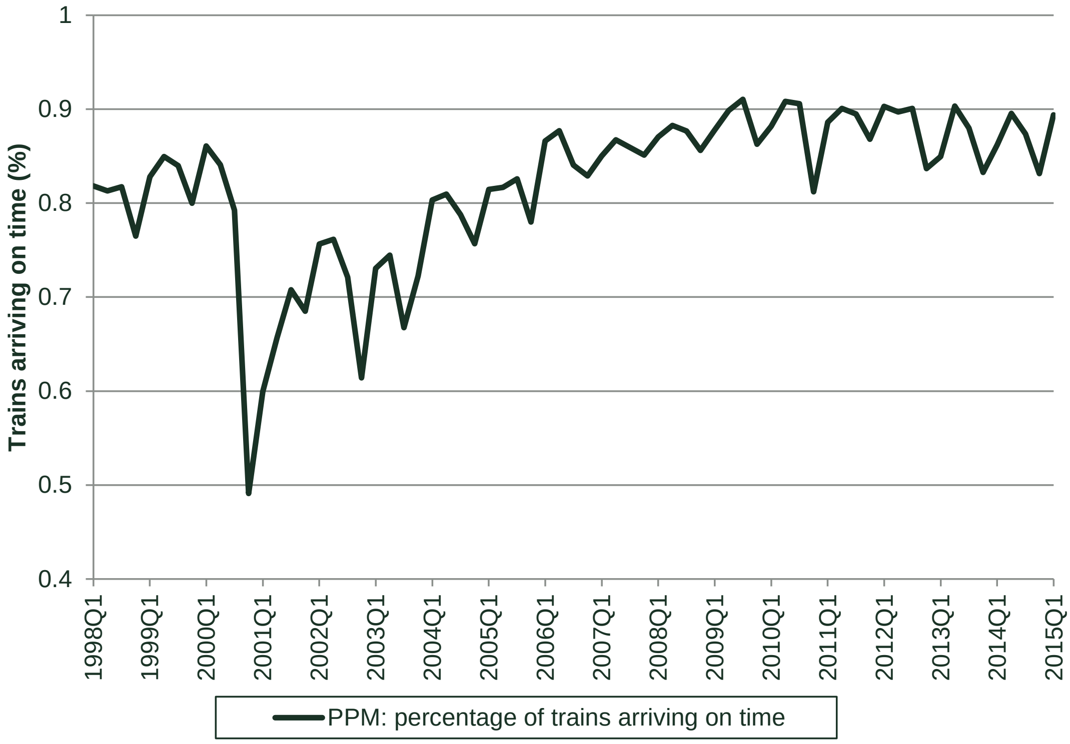
Tobin, J. (1972), Inflation and unemployment, *American Economic Review*, **62**(1), pp. 1–18.

Verbeek, M. (2008), *A Guide to Modern Econometrics*, John Wiley & Sons, Ltd, Chichester.

Zivot, E. and Andrews, K. (1992), Further Evidence on the Great Crash, the Oil-Price Shock, and the Unit-Root Hypothesis, *Journal of Business & Economic Statistics*, **10**(3), pp. 251–70.

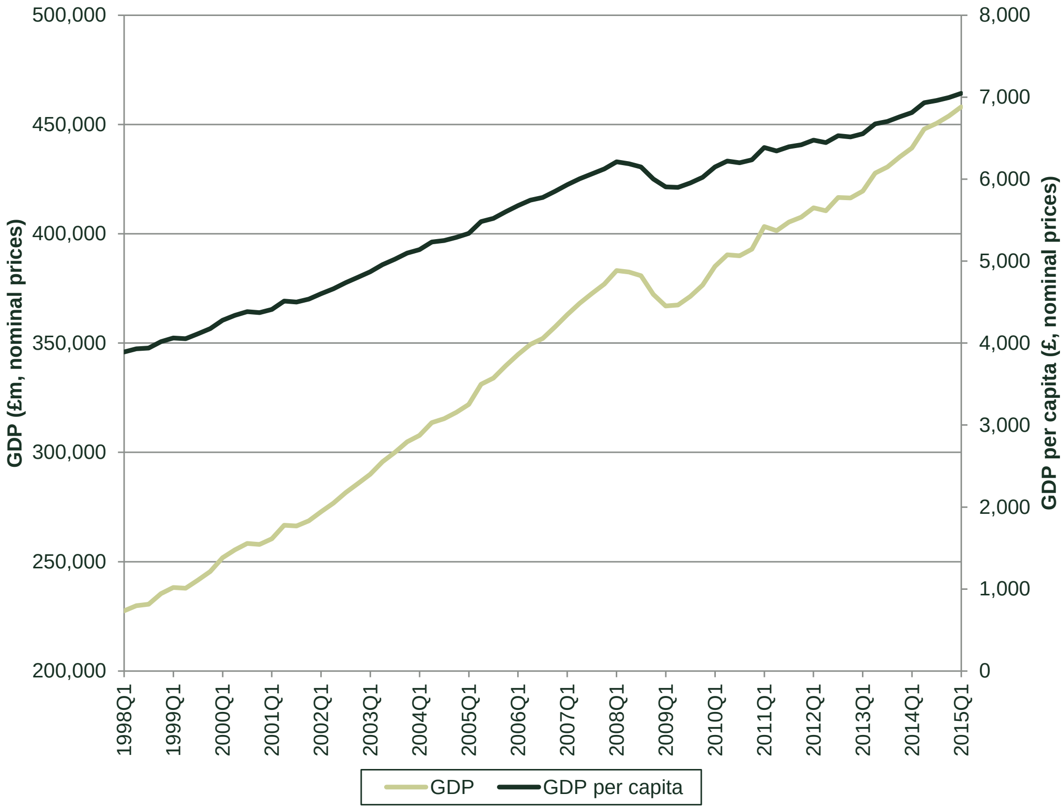
## TECHNICAL APPENDIX

### [1] PPM: percentage of trains arriving on time



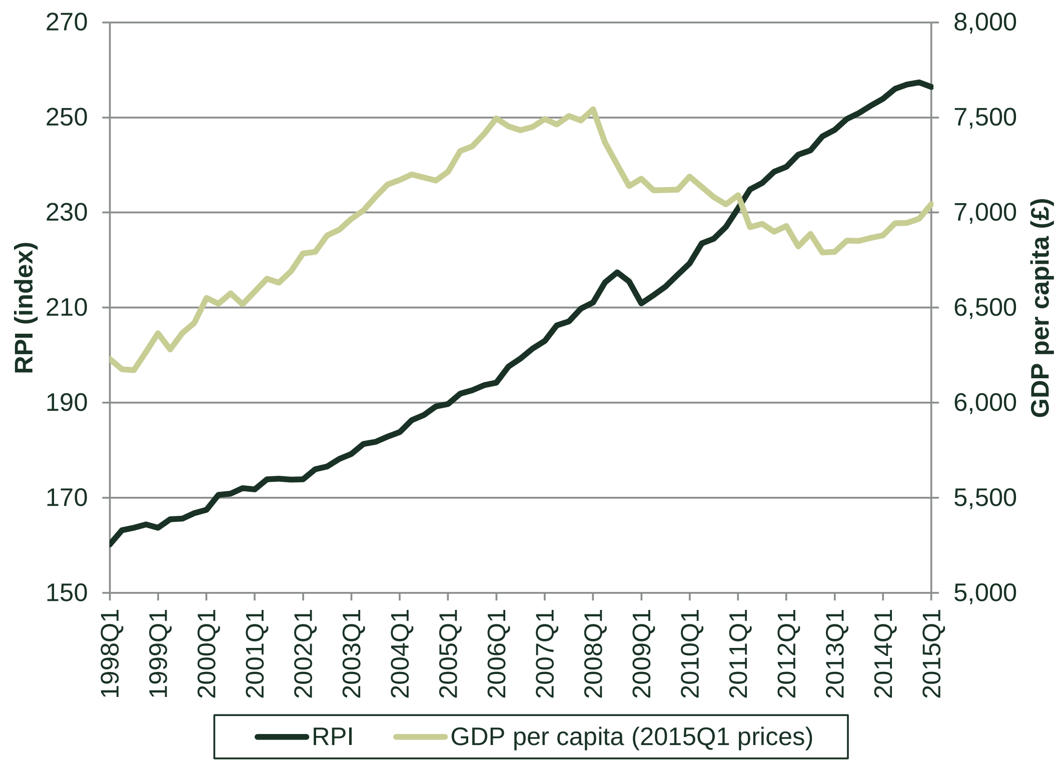

Source: Oxera/Office of Rail and Road.

## [2] GDP and GDP per capita



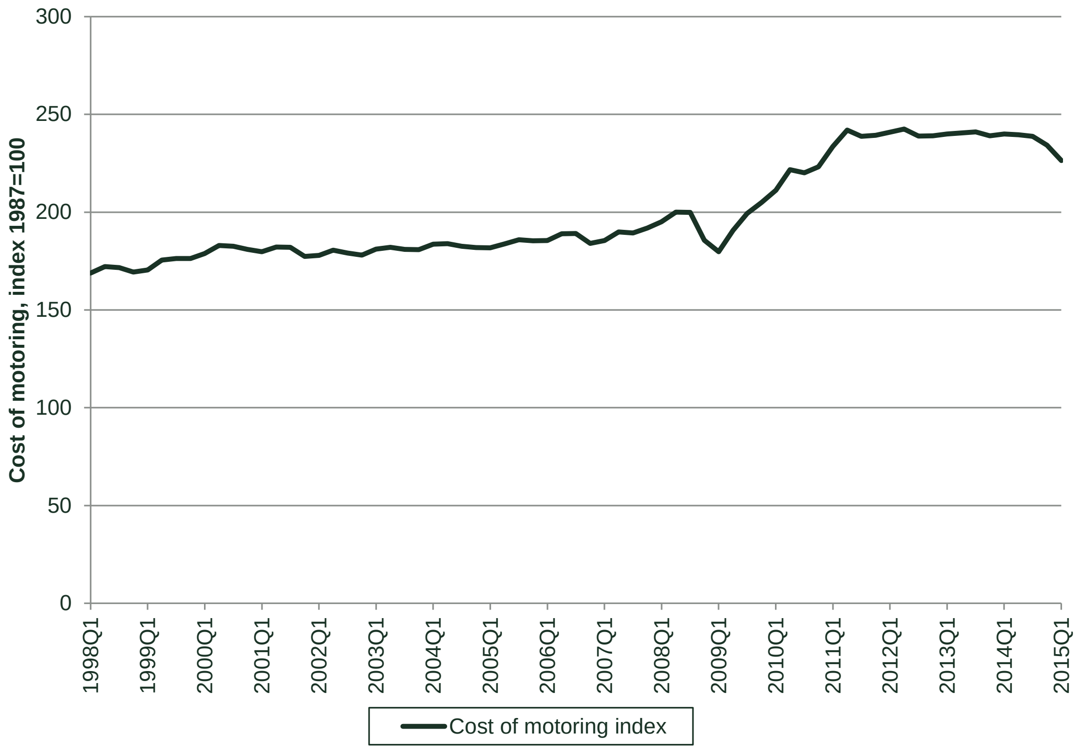

Source: Oxera/Office for National Statistics/Eurostat.

## [3] Real GDP per capita and RPI




Source: Oxera/Office for National Statistics/Eurostat.

## [4] Cost of motoring index




Source: Oxera/Office for National Statistics.

## [5] Results from unit root testing for stationarity of series

| | Augmented Dickey–Fuller Test | Augmented Phillips–Perron test |
|---|---|---|
| **ln(Long distance passenger journeys)** | NS | NS |
| **First Difference** | S | S |
| **ln(Nominal yield)** | NS | NS |
| **First Difference** | S | S |
| **ln(Real yield)** | NS | NS* |
| **First Difference** | S | S |
| **ln(Nominal GDP per capita)** | NS | NS |
| **First Difference** | S | S |
| **ln(Real GDP per capita)** | NS | NS |
| **First Difference** | S | S |
| **ln(Cost of motoring)** | NS | NS |
| **First Difference** | S | S |
| **ln(Performance)** | NS | NS* |
| **First Difference** | S | S |

Notes: (1) S, stationary; NS, non-stationary.
(2) Default significance level is 5%.
(3) * indicates significant at 5% level but not 1% level.

Source: Oxera.

## [6] Zivot and Andrews test (intercept and slope) for structural break

| | Minimum t-statistic (period) | Minimum t-statistic | Evidence of structural break? (5% significance level) |
|---|---|---|---|
| **ln(Long distance passenger journeys)** | 2006Q2 | -6.12 | Yes |
| **ln(Nominal yield)** | 2006Q4 | -4.30 | No |
| **ln(Real yield)** | 2010Q3 | -4.78 | No |
| **ln(Nominal GDP per capita)** | 2008Q4 | -5.73 | Yes |
| **ln(Real GDP per capita)** | 2005Q1 | -3.11 | No |
| **ln(Cost of motoring)** | 2009Q4 | -3.00 | No |
| **ln(Performance)** | 2003Q4 | -5.54 | Yes |

Source: Oxera.

## [7] Johansen test for cointegration in the nominal ECM

| | | | | | |
|---|---|---|---|---|---|
| **Johansen tests for cointegration** | | | | | |
| **Trend: constant** | | | | | **Number of obs = 67** |
| **Sample 1998Q3–2015Q1** | | | | | **Lags = 2** |
| | | | | | |
| **Maximum rank** | **Parms** | **Log-likelihood** | **Eigenvalue** | **Trace statistic** | **5% critical value** |
| **0** | 30 | 748.9572 | . | 99.433 | 68.52 |
| **1** | 39 | 778.81662 | 0.58989 | **39.7141*** | 47.21 |
| **2** | 46 | 788.53311 | 0.25177 | 20.2811 | 29.68 |
| **3** | 51 | 795.54003 | 0.18874 | 6.2673 | 15.41 |
| **4** | 54 | 797.70736 | 0.06265 | 1.9326 | 3.76 |
| **5** | 55 | 798.67368 | 0.02843 | | |

Notes: (1) * marks the number of cointegrating equations – the maximum rank. We reject a null hypothesis of zero cointegrating equations as 99.433>68.52. However, we are unable to reject a null hypothesis of a single cointegrating equation since 39.7141<47.21.

Source: Oxera.

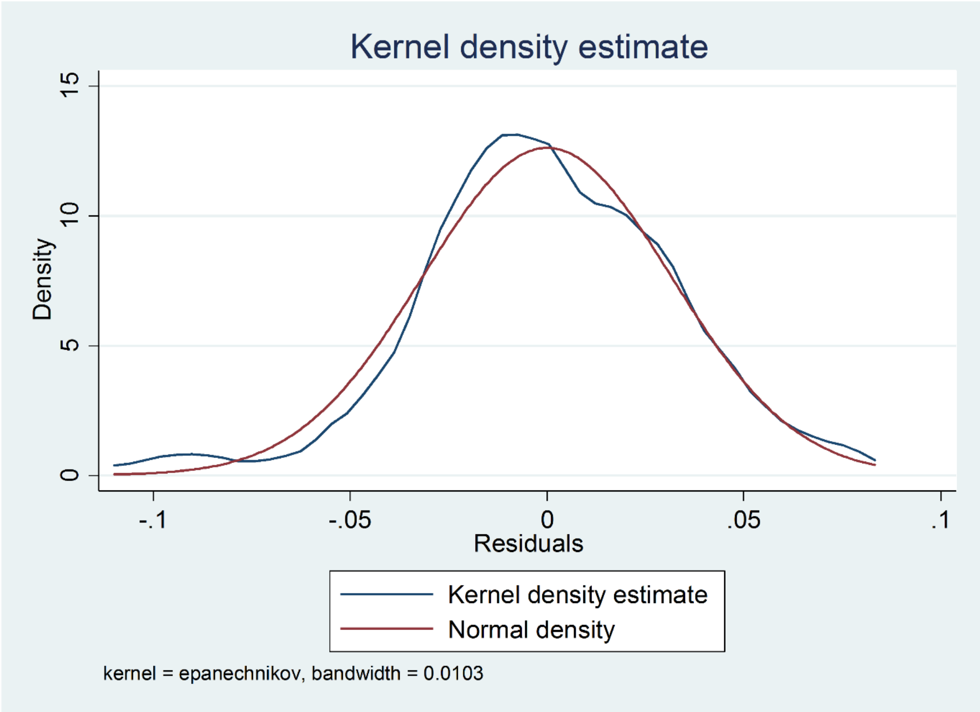
## [8] Johansen test for cointegration in the real ECM

| | | | | | |
|---|---|---|---|---|---|
| **Johansen tests for cointegration** | | | | | |
| **Trend: constant** | | | | | |
| **Sample 1998Q3–2015Q1** | | | | | |
| | | | | | |
| **Maximum rank** | **Parms** | **Log-likelihood** | **Eigenvalue** | **Trace statistic** | **5% critical value** |
| **0** | 30 | 751.94948 | . | 96.2816 | 68.52 |
| **1** | 39 | 776.50171 | 0.51949 | **47.1772*** | 47.21 |
| **2** | 46 | 787.25072 | 0.27448 | 25.6792 | 29.68 |
| **3** | 51 | 794.73385 | 0.20019 | 10.7129 | 15.41 |
| **4** | 54 | 799.42849 | 0.13076 | 1.3236 | 3.76 |
| **5** | 55 | 800.0903 | 0.01956 | | |

Notes: (1) * marks the number of cointegrating equations – the maximum rank. We reject a null hypothesis of zero cointegrating equations as 96.2816>68.52. However, we are unable to reject a null hypothesis of a single cointegrating equation since 47.1772<47.21.

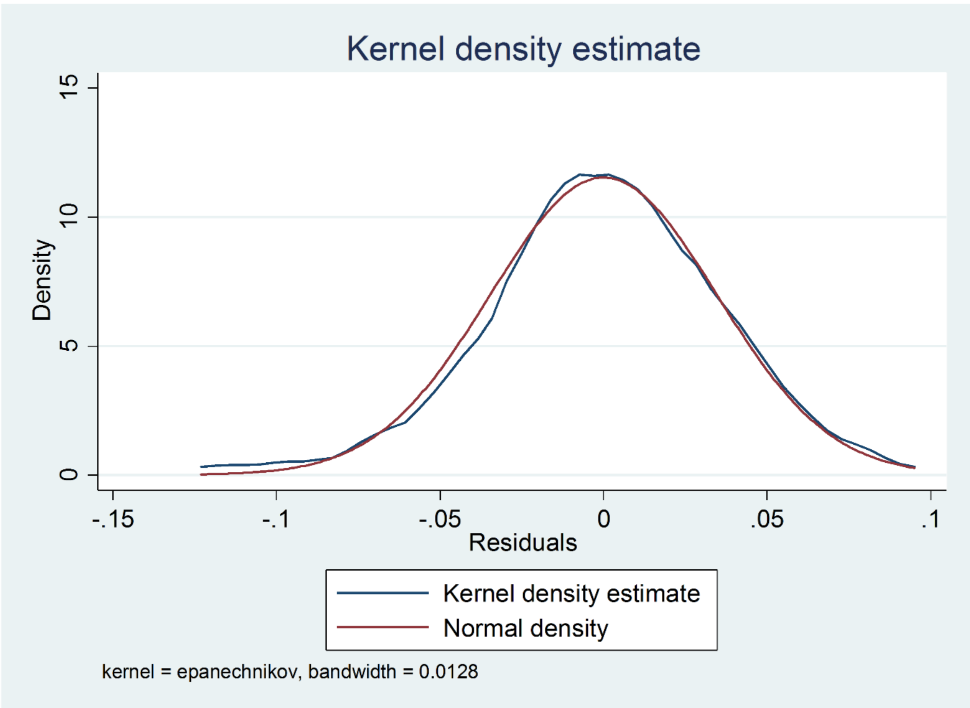
Source: Oxera.

## [9] Testing for normality of residuals in the nominal model




Source: Oxera.

## [10] Testing for normality of residuals in the real model




Source: Oxera.

### [11] Sensitivity forecast (with complete dummy set)