Communities and Local Government

Analysis of fire and rescue service performance and outcomes with reference to population socio-demographics

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The findings in this report are those of the authors and do not necessarily represent those of the Department for Communities and Local Government

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Contents

Executive Summary

Aims of this study

It is known from previous work[1] that dwelling fires and injuries are not uniformly spread among the population, but are more likely to occur in areas with a high proportion of people from 'at-risk' groups. A better understanding of the relationships between various measures of disadvantage within the population and the risk from dwelling fire in these areas would enable Fire and Rescue Services (FRSs) to target Community Fire Safety (CFS) work more effectively, and therefore reduce fire casualties and possibly other unwanted outcomes such as deliberate fires and false alarms. Therefore, the first aim of this work is to identify socio-demographic indicators of dwelling fires/ dwelling fire injuries and deaths that could be of value in targeting CFS.

In addition, FRSs employ various measures of fire frequency and fire casualties to monitor their performance, benchmarking station areas or districts within the FRS, and for monitoring performance against their Integrated Risk Management Plan (IRMP). A fuller understanding of the effect of demographics on fire casualties and related statistics will also aid FRS internal and external benchmarking. Therefore, the second aim of this work is to exemplify the use of the socio-demographic measures within benchmarking.

This final report

This report provides a summary of work completed using the Indices of Multiple Deprivation (IMD), the census, population density and proportion of dwelling fires with smoke alarms.

MOSAIC[2] data categorises households and postcodes into one of a series of 'socio-demographic' types. We have ranked (subjectively) the MOSAIC categories from low to high risk using the results of the analysis of the IMD and census. No further analysis has been completed using the MOSAIC data due to the lack of population data at postcode level. In addition, as MOSAIC is categorical it will not support the production of a regression formula for use in predicting risk.

1 Development of the Fire Service Emergency Cover Planning Methodology: Final Report (C645 R2 1A) by Wright *et al*. November 2003

2 Mosaic UK is a people classification system that combines over 400 separate data sources and divides the UK adult population into 61 different types and eleven groups, covering the full spectrum of British and Northern Ireland society.

Data used in this study

The data sets used in previous studies were limited. The Fire Service Emergency Cover (FSEC) model development work relied on data from six FRSs whilst a 2004 evaluation[3] was limited to one year of geocoded fire data. The current study had the opportunity to use a three year data set for 2002, 2003 and 2004. Thus, this current study can explore whether assessment of a newer, larger and hence more powerful data set identifies an alternative set of variables.

In the current study we have assessed:

- The Indices of Multiple Deprivation (at Lower Super Output Area and Local/Unitary Authority Area)
- The census (an exploratory analysis of the census as a whole)
- A selection of census variables cited in previous work:
  - Single parent families
  - Single persons households
  - Lone pensioners
  - Rented accommodation (privately rented vs. socially rented)
  - Sick/disabled
  - Population density
- MOSAIC.

In all cases we have assessed dwelling fires and dwelling fire non fatal injuries for the period 2002, 2003 and 2004[4]. Dwelling fire data was geocoded and aligned with the IMD and census data. The relatively small number of dwelling fire fatalities rendered the development of associations and regressions impractical using 'small area' data and were therefore excluded from the majority of analysis. Accordingly this work focuses on dwelling fires and non fatal injuries. The dwelling deaths results are not included in the analysis in the main part of this report; however a few results are presented in the appendices.

[3] Evidence base for evaluation of effectiveness of community fire safety. Wright, M and Genna R. Report to ODPM 2004.

[4] This data was for dwelling fires for all FRSs in England

Main findings for IMD and Census for rate of dwelling fires per million people

The main analysis used an 'all England' dataset, namely the 353 point dataset for unitary and local authorities, and (for the IMD) the >32,000 lower super output area (LSOA) dataset. As shown in Table 1:

- A combined regression model using the Census and IMD together explained the same amount of variance as a regression model based on the census alone – both explaining 69% of the variance in the rate of dwelling fires
- The regression models for (1) the IMD and census combined and (2) the census alone explained 54% of the variance for rate of dwelling fire injuries;
- A selection of the previously identified variables also explains a high proportion of the variance in the rate of dwelling fires namely 63% and 50% of the variance in the rate of dwelling fire injuries
- Although application of the IMD alone (compiled for each of the 353 unitary/local authorities) explains a high (60%) proportion of variance in dwelling fires and a moderate amount (48%) of the variance in the rate of dwelling fire casualties, the census variables explain a higher proportion of the variance than the IMD
- The analysis of the IMD using data compiled for each of the ~32,000 LSOA explains only 46% of dwelling fires variance and only 20% of dwelling fire casualties– demonstrating how the analysis is sensitive to the data set being used.

It is conventional to describe a model that explains 60% to 80% of variance to be 'strong', suggesting that the census model and the regression model that combines the census and IMD model for dwelling fires is strong. The regression models for fire injuries would be classed as having a 'moderate' power of 54% (between 40% and 59%).

Table 1: Percentage of variance in dwelling fires per million population (pmp) explained by each set of socio-demographic indicators

Model	**Socio-demographic model** (factors ranked in order of influence in the model)	% of variance accounted for in	
		rate of dwelling fires	dwelling fire injuries
Census combined with IMD data	Lone parent with dependent child(ren); Caribbean/African and other black; Never worked; Single adult household; IMD score	69%	54%
Census exploratory analysis	Lone parent with dependent child(ren); Caribbean/African and other black; Never worked; Single adult household; Age 70+	69%	54%
Census – previously identified variables	Selection of previously identified census variables (single adult households, sick disabled, single person families)	63%	50%
IMD – analysis of 353 unitary and local authorities	IMD overall score	60%	48%
IMD – analysis of >32,000 LSOA	Employment score; Crime and disorder score; Education skills and training score; Living environment score.	46%	20%

The factors in the combined census/IMD model are ranked in order of most to least influence in the model below. All factors are associated with more fires except Caribbean/African and other black that is associated with fewer fires:

- Lone parent with dependent child(ren)
- Caribbean/African and other black (associated with fewer fires)
- Never worked
- Single adult household
- IMD score.

Thus, being a single parent, never worked, single adult and deprived are the top factors associated with higher rates of fire. Whilst bi-variate correlations between proportion of people who are 'Caribbean/African and other black' and the rate of fire gives a positive correlation (i.e. more 'Caribbean/African and other black' is associated with more fire) once you control for the other factors in the multiple regression the direction of the relationship is reversed (i.e. more 'Caribbean/African and other black' is associated with fewer fires). This indicates that it is the higher rates of deprivation/single parents amongst 'Caribbean/African and other black' that is associated with increased rates of fire amongst this section of the population rather than ethnicity.

A series of regressions were run for each of the IMD and census, using progressively smaller sets of variables. The census and IMD models shown in Table 1 are the most powerful of those tested.

Considering the previously identified census variables, we found that, in the case of assessment of the rate of dwelling fires:

- Single parent families explained the highest proportion at 57%;
- Sick disabled, socially rented and single person households explained 42%, 31% and 37% respectively – all moderate predictors;
- Lone pensioners and privately rented explained very little of the variance in rate of dwelling fire – 2% and 5% respectively;
- Population density explains only 17% of variance in dwelling fires.

Population density dropped out of the regression model indicating it is not a strong factor once other factors are controlled for.

Comparison of models between types of FRSs

The regression models were also re-run for:

- Metropolitan versus non-metropolitan FRSs
- The five FRS family groups
- Greater Manchester FRS.

The aim was to see if the models, and hence the socio-demographic factors, differ according to the type of FRS.

The results revealed that regressing sub-sets of the census data (for example, FRS family groups), explained more variance in the data than the 'all England' regression model did. However, the statistical reliability of regression decreases when you use smaller numbers of data points. This is because as a rule of thumb when carrying out regression models there should be at least 15 data points for each variable included in the regression model. If this is not met then the results of that regression model should not be generalised. For example, in the case of Greater Manchester there are fewer than 10 local authorities and hence fewer than 10 data points. This renders the model statistically unreliable. The option of using LSOA data (which would give more data points within a FRS) is limited by the high volatility of fire data at LSOA level.

Also, there are some variables that are common across the majority of regression models, these include;

- Being single (either a single person or single parent)
- Never worked
- Black/African and other black.

These variables are also in the 'all England' census model

Age and ethnicity are factors that do appear in the regression models however they do not appear consistently throughout. Some models include one type of ethnicity, while others include another. Therefore it is difficult to draw out any clear conclusions from this. Some age groups also appeared in some of the regression models and were more evident in the Census regression models, again, it is hard to see a particular pattern in this and it is not consistent throughout the regression models.

Predicted versus reported rates of fire and casualty

The regression formulae for the combined census and IMD, the IMD and the exploratory census analysis were applied to each FRS to produce a series of predicted rates of fire and casualty. The predictions (using 2001 census and 2004 IMD) were compared with the reported rates of fire and casualty for 2002-2004. The predictions are very consistent with the reported rates of dwelling fire and injury.

Predicted rates versus national average rates

The predicted rates (using the regression models) of dwelling fire and injury were also compared with the average reported rates (2002-2004) for England as a whole. The predicted rates far exceed the national average in some cases, double in some cases. In other cases the predicted rate of fire/casualty is far below the national average.

Discussion

Socio-demographics and dwelling fire indicators

The assessments (both the current ones and previous ones) consistently indicate that deprivation (such as unemployment) and being single is associated with dwelling fire risk. The census provides the strongest model explaining up to 69% of the variance in the data. The combined IMD and Census regression model and the individual IMD and Census regression models do produce similar predictions for FRSs.

Care must be taken in interpreting the finding that analyses of different sub-sets of England identify somewhat different sets of socio-demographic factors. These differences may simply reflect spurious differences arising from the use of smaller data sets.

Also, whilst the exploratory analysis of the census produces the strongest model, a selection of the previously identified variables also explains a high proportion of variance.

The strongest model is provided for dwelling fires, as opposed to fire deaths or injuries. This is probably due to relatively higher rate of dwelling fires than injuries or deaths, leading to fewer areas with zero incidents. However, the census model for fire injuries has a moderate power (54%). Thus, it would be reasonable to use either the dwelling fire or the dwelling fire injury model for targeting CFS.

The role of age in dwelling fire risk

This assessment has developed the understanding of the role of age in fire risk. It indicates that being single, sick disabled and deprived are factors. It is possible that being elderly is not in itself a factor. Rather it may be the combination of being single, sick/disabled and deprived is more common amongst elderly people. Multiple regression is intended to detect co-linearity between factors and isolate the main factors. Thus, it is possible that it is the commonality of being single, disabled and poor amongst elderly persons that has previously led to the identification of age being a factor.

Age of census and IMD data

Both the census and the IMD suffer from the disadvantage of being rarely updated, once every 10 years for the census. The IMD uses a mixture of data sources such as the Department for Work and Pensions (DWP) data on income support and Inland Revenue working family's tax credit. The IMD 2000 was updated in 2004 using 2001 and 2002 data, which is the most recent version identified. Accordingly, neither the census nor the IMD offers an advantage in respect of currency.

Updating FSEC toolkit

This study has produced updated and more powerful models that could replace those currently in the FSEC toolkit. FSEC contains a regression formula to predict the rate of casualty. The exploratory census regression for dwelling fire injuries could replace the one within FSEC without any additional data being added to FSEC. If the IMD is loaded into FSEC, having being 'read down' to output areas, the combined census-IMD regression formula for dwelling fire injuries could be applied although this does not offer any modelling advantage.

FSEC also used four socio-demographic factors to group output areas. The Potential Risk Factors used for grouping risk areas could also be updated. If FSEC is limited to the census, we would advise that grouping is achieved using only 4 census factors to avoid excessive computation, namely; single parents, never worked, 'Caribbean/African and other black' and single adult household.

Benchmarking and targets

The finding that dwelling fire risk varies greatly according to socio-demographic factors is thought to have potential implications for target setting and benchmarking. Firstly, it indicates that there are large (four fold) differences in the rate of dwelling fire/casualty arising from differences in socio-demographic factors such as deprivation, disability, being single and unemployment. It could be argued that targets for reducing the rates of dwelling fire and casualty should recognise this social inequality in risk.

Secondly, a simple comparison between FRSs of rates of fire and casualty would not take account of the impact of their socio-demographic profiles. A FRS whose predicted rate of fire casualty is, for example, twice the national average may be performing well if the reported rate is 1.5 of the national average.

These findings support the notion of risk weighted (socio-demographic risk) targets and performance measures.

Chapter 1

Introduction

1.1 Background

Dwelling fire risk and socio-demographics

A number of studies (e.g. Wright et al 2003, 2004 and 2005) have found that the rate of dwelling fires and dwelling fire injuries is associated with a number of socio-demographic variables. This has led to a number of key practices within the FRS, including:

- Using socio-demographic indicators to help predict dwelling fire risk
- Targeting national and local community fire safety at the 'at risk' sections of the community.

Examination of national fire statistics shows that the rate of fatal fires per million population is far higher for older persons, indicating that dwelling fire risk is associated with age.

As part of the development of the Fire Service Emergency Cover toolkit, Greenstreet Berman Ltd (GSB) (2001) used data from six FRSs to develop dwelling fire risk assessment metrics. The work found that single parent families were the single most powerful indicator of the rate of dwelling fires, accounting for 63.7% of the variance. This research also concluded that percentage of rented homes, percentage of homes with lone pensioners, people with long term limiting illness and the rate of fire were all good indicators of rate of fire casualties accounting for 49.3% of the variance. These factors are used in FSEC as of 2006.

In 2004, GSB explored risk measures for potential use in the FRS funding formula. The study used national geocoded fire data for a single year (2002) and found that the following factors were good indicators of the rate of dwelling fires:

- Household type (children and pensioners)
- Ethnicity
- Occupation
- Work status.

The London Fire and Civil Defence Authority, as part of their contribution to the review of the FRS funding formula, explored socio-demographic risk factors and found that population density was a factor.

GSB work for Communities and Local Government in 2006 on human behaviour in fatal fires (2006) found that in 75% of all the fatal fires investigated, the victim was a single person, or part of a single person household. The research also revealed that 77% of the victims of the fatal fires were impaired in some way, either through substance abuse, or physical/ mental or age related impairment.

1.2 Aims of this work

This study has two main aims.

The first aim is to identify socio-demographic indicators of dwelling fires/ dwelling fire injuries and deaths. The dwelling fire data sets used in previous studies were limited. The FSEC development work relied on data from 6 FRS whilst the 2004 work was limited to one year of fire data. The current study had the opportunity to use a three year data set for 2002, 2003 and 2004. Thus, this study can explore whether assessment of a larger and hence more powerful data set identifies an alternative set of variables.

In addition, there are a number of composite socio-demographic measures, namely the Indices of Multiple Deprivation and MOSAIC. Mosaic UK is a people classification system that combines over 400 separate data sources and divides the UK adult population into 61 different types and eleven groups, covering the full spectrum of British and Northern Ireland society.

Previous work has focused on census data. Therefore, this study also aims to explore whether alternative socio-demographic measures provide more powerful predictors of dwelling fire risk.

In addition, this study also aimed to re-test, using the larger data set, those variables that have been identified in previous studies including:

- Single parent families
- Single person households
- Lone pensioners
- Rented accommodation
- Sick/disabled
- Age
- Population density.

Feedback from some FRS has queried whether 'rented accommodation' is a valid indicator of dwelling fire risk, as accommodation can be rented by affluent households. Therefore, we also tested 'socially rented' accommodation separately from 'privately rented' accommodation.

The second aim is to predict the rate of dwelling fire in each FRS using the socio-demographic factors and compare the predicted with the reported rate of fire. This may help FRSs judge whether the reported rate of fire in their FRS is higher or lower than may be expected given the local population profile.

The ultimate aim of this work is to support decisions on how best to reduce the number of dwelling fires and casualties. The government has set a number of targets for the FRS, including:

- A target for a 20% reduction in number of fatal fires by 2010
- The rate of fire death in any one FRS should not exceed the national average by more than 1.25.

By identifying the influence of socio-demographic factors, FRSs may be able to better target their CFS and hence further improve the reduction in fire deaths.

1.3 Approach

1.3.1 Variables and data sets

A key part of this study involved completing a multiple regression between socio-demographic (independent) variables and dwelling fire (dependent variables), to explore whether an increase in socio-demographic variables is associated with an increase in fire variables.

Fire dependent variables

Geocoded fire data for England and Wales was used from 2002, 2003 and 2004. The number of dwelling fires, casualties and deaths per postcode were counted. The postcodes were aligned with lower super output areas, to give the number of fires etc per Lower Super Output Areas (LSOAs)[5] and for each Local/unitary authority. The total number of fires for the period 2002, 2003 and 2004 was first divided by 3 to give an average per year. Thus, there was a dataset for LSOAs and a dataset for unitary/local authorities.

The number of residents is provided for each LSOA and for each local/unitary authority. This was used to produce a calculation of the rate of dwelling fire per million population for each LSOA and for each local/unitary authority, as well as a rate of dwelling fire injuries (non-fatal fire injuries of members of the public) and dwelling fire deaths per LSOA and for each local/unitary authority. Thus, there are three fire dependent variables (fire risk measures):

[5] Each Lower Super Output Area comprises a number of Output Areas. Output Areas are the smallest area used in the census. Each local/unitary authority has a number of LSOAs.

- Rate of dwelling fire per million population
- Rate of dwelling fire injuries per million population
- Rate of dwelling fire deaths per million population.

As some of the FDR1 reports submitted for dwelling fires lacked postcodes and grid references, a few per cent of incidents could therefore not be geocoded and were excluded from the assessment.

A series of correlations (as explained in section 1.3.2) were carried out between the three fire data variables at local authority area level. Dwelling fires and injuries do correlate very strongly at the local authority area level. Dwelling fires and injuries have a low correlation with deaths. This reinforces the view that the number of fire deaths within FRSs is very volatile and hence difficult to assess. The p values of less than 0.02 indicate that all of the correlations are statistically significant (i.e. they are not spurious), with a 2% probability that the correlation is due to chance, i.e. a 98% probability that the correlations are NOT due to chance (Table 2).

Table 2: Correlations between measures of dwelling fire using local authority level data

		Dwelling fires	Injuries	Deaths
Dwelling fires	Correlation	–	0.84	0.33
	P value	–	<0.02	<0.02
Injuries	Correlation	–	–	0.28
	P value	–	–	<0.02

Census 2001 data

The 2001 census data was available for each Local Authority down through the geographies (Local and Unitary Authorities, and Lower Supper Output Areas) to Output area. Analysis was carried using data at Local/Unitary Authority level. Two assessments have been completed using census data.

First an 'exploratory' analysis was completed. The exploratory analysis aimed to identify the smallest set of factors that account for variations in dwelling fire risk.

Secondly, the census data was used to re-test those variables identified in previous work. In each case the variables were first correlated with rate of fire, then each one was run through a regression by itself and then they were all entered into a regression model (deleting those that explained least proportion of the variance).

In all cases dwelling fire rates and injury rates were assessed against the census at the level of local/unitary authority codes, 353 areas in total.

Population density

Population density was available at the level of local authorities.

Proportion of dwelling fires with smoke alarms

The 2002 to 2004 dwelling fire incident data set was used to calculate the proportion of dwelling fires in each LSOA that had a smoke alarm.

Indices of Multiple Deprivation (Lower Super Output Area)

The 2004 Indices of Multiple Deprivation (IMD) is provided at the LSOA level measure of deprivation. The 2004 index of multiple deprivation is based on 2001 data. The IMD is made up of seven sub-domains. The seven different sub domains that make up the IMD are as follows:

- Income Score – This captures the proportion of the population experiencing income deprivation in an area
- Employment Score – This captures the employment deprivation conceptualised as voluntary exclusion of the working age population from work
- Health deprivation Score – This domain identifies areas with high rates of people who die prematurely or whose quality of life is impaired by poor health or who are disabled across the whole population
- Education skills and training Score – This indicator falls into two sub domains, the first concerns education deprivation for children/young people in the area and the other relating to lack of skills and qualifications among the working age population
- Barriers to housing Score – This domain measures the barriers to housing (for example overcrowding) and key local services
- Crime and disorder Score – This indicator measure the incident of reported crime for four major crime themes (Burglary, Theft, Criminal damage and Violence)
- Living environment Score – This indicator focuses on living environment. Two sub-domains make up this domain. Firstly 'indoors' living environment which involved the quality of housing. The second sub-domain is 'outdoors' living environment which contains two measures about air quality and road traffic collisions.

The IMD is derived from a wide range of data. For example:

The income domain includes:

- Adults and children in Income Support households (2001, Source: DWP)
- Adults and children in Disabled Person's Tax Credit households whose equivalised income (excluding housing benefits) is below 60% of median before housing costs (2001, Source: Inland Revenue and DWP).

The employment domain includes:

- Unemployment claimant count (JUVOS) of women aged 18-59 and men aged 18-64 averaged over 4 quarters (2001, Source: ONS)
- Severe Disablement Allowance claimants women aged 18-59 and men aged 18-64 (2001, Source: DWP).

The health deprivation domain includes:

- Comparative Illness and Disability Ratio (CIDR) (2001, Source: IS, AA, DLA, SDA, IB from DWP)
- Measure of adults under 60 suffering from mood or anxiety disorders, based on prescribing (2001, Source: Prescribing Pricing Authority), Hospital Episode Statistics (1998/1999 to 2001/2002, Source: Department of Health), suicides (1997 to 2001, Source: ONS) and health benefits data (1999, Source: IB and SDA from DWP).

The IMD data was aligned to the fire data at lower super output area level. This data comprised of the overall Indices of Multiple Deprivation (IMD) score together with each of the sub indices that go into making up the overall Deprivation score.

The IMD was assessed against fire variables at the level of lower super output areas and local/unitary authority level.

Indices of Multiple Deprivation (Local Authority Level)

The 2004 Indices of Multiple Deprivation are also available at a summary level at Local Authority and Unitary Authority Level. However, this summary version does not have the full set of sub groups as presented in the section previously. Instead the IMD score is available together with:

- Income Score – This captures the proportion of the population experiencing income deprivation in an area
- Employment Score – This captures the employment deprivation conceptualised as voluntary exclusion of the working age population from work
- Extent – This provides the proportion of a district's population living in the most deprived SOA in the Country.

Mosaic

Mosaic provides demographic data and is a consumer classification system which is used by many supermarkets to aid them in making decisions about what food to sell in their stores plus whether or not to build additional stores. In addition to the 2001 Census, data sources for Mosaic UK include the electoral roll, Experian's lifestyle information, house price data and ONS local area statistics. These classifications profile UK consumers in terms of their social-demographics, lifestyle, culture and behaviour. Mosaic divides the population into 11 groups and 61 sub-groups and is updated each year. MOSAIC is provided at household and postcode level.

As part of this study Mosaic has been qualitatively categorised into fire risk categories depending on the Mosaic group.

1.3.2 Overview of statistical concepts

The two statistical procedures used to analyse the data were correlation and multiple regression. A description of both these techniques is given below.

Correlation

Pearson's correlation co-efficient is best thought of as a description of the strength of association between two variables (bi-variate correlation). The test is not designed to be predictive and as such, correlation is not causation.

Pearson's correlation co-efficient (r) can only vary between zero and one, and can have either a positive or negative sign. The r value indicates the strength of the relationship and the sign indicates the direction of the relationship between the two variables. The r value can range from –1 to +1, with +1 indicating a perfect positive relationship, 0 indicating no relationship, and –1 indicating a perfect negative relationship (as one variable grows larger, the other variable grows smaller).

For correlation, two basic objectives can be identified:

- A description of the strength of the relationship between two variables
- A test of significance to see if the relationship between these two variables is greater than expected by chance.

Multiple Regression

Multiple regression analysis is a multivariate statistical technique used to examine the relationship between a single dependent variable and a set of independent variables. The objective of multiple regression analysis is to use the independent variables whose values are known to predict the single dependent value selected by the researcher. Overall, multiple regression provides an objective means of assessing the predictive power of a set of independent variables.

In this data set, the dependent variables (outcome variables) are the three fire variables.

The independent variables (predictive variables) are the census, IMD, population density and proportion of dwelling fires with smoke alarms.

For regression, three basic objectives can be identified:

- A description of the strength of the relationship between variables
- A test of significance to establish if the relationship between these variables is greater than expected by chance
- The ability to formulate a simple rule that will allow the prediction of a value of the dependent variable from the values of the independent variables.

Multiple regression provides a set of scores:

- Unstandardised B values – these give the amount of change in the independent variable from a single unit change in the dependent having controlled for the effect of all other variables
- Std error – this is a measure of the error in the prediction
- t values – these give a rough indication of the impact of each variable. A large value shows the variable has a large effect
- Standardised beta coefficients – a measure of the contribution of each variable to the model. A large value shows the variable has a large effect. As these values are standardised you can compare the values across all of the variables
- Significance – this is a measure of the probability that the variable has an impact, smaller significance values indicate that there is a greater probability of an impact.

The unstandardised B values can be used to produce regression formula to predict the dependent variable.

You can also produce an estimate of the proportion of variance (R^2) explained by each regression model, such as 60%. This means that the set of independent variables in your multiple regression model explains 60% of the variance in the dependent variable data. This is a measure of the power of the model. As a simple guide, the higher the per cent of variance explained by a set of indicators the better, with the 'power' of the percentages described as follows:

Table 3: Power of percentage for variance explained in regression models

Very low	Low	Moderate	High	Very high
<20%	20 to 39%	40 to 59%	60 to 79%	>80%

Significance values

Throughout the report the term 'statistical significance' is referred to. The significance level has been set at 0.05 for all the statistical analysis. This probability level (p) of 0.05 tells the likelihood of a given result being due to random sampling error. Thus a probability level of 0.05 indicates that there is a 5% likelihood of a given test result occurring by chance. However, when the p-value of a statistic is less than the significance level of 0.05 the value of the statistic is said to be significant and we can be 95% confident that the results are not due to random sampling error.

1.3.3 Analysis steps

Census

The census data is made up of over 300 variables, many of which have very low associations with dwelling fire risk. At the same time it is poor practice to attempt to test the relationship of such a large number of variables using regression analysis. Therefore, a number of preparatory steps were completed:

1. As a first step, for the purpose of this investigation, factors with no theoretical association with fire were excluded.
2. As a second step correlations were calculated between the remaining census variables and the three fire variables. Those variables with lower correlations (less than 0.6) were also excluded from further examination.
3. As a third step a correlation matrix was produced for the remaining census variables to check for co-linearity. Colinearity is where variables are so highly correlated that it is impossible to come up with a reliable estimate of their individual regression co-efficients. Those variables with correlations greater than 0.8 were identified. Where they were judged to be qualitatively similar one (the one with lower correlation with rate of fire) was deleted.

Once the set of census variables was reduced they were entered into the multiple regression analysis. There were several steps involved in regression, these are as follows:

4. Ran step wise regression – stepwise regression model was run to exclude weaker variables and retain the significant ones.
5. Checked for suppression by comparing co-efficients – the co-efficients were examined and the direction of the unstandardised B value co-efficients were compared to that of the bi-variate correlation. For example, a correlation may reveal that there is a positive relationship between being sick and disabled and the rate of dwelling fires per million people. However, the co-efficient in the regression model for sick/disabled may be negative. There fore this would suggest that 'suppression' maybe taking place.
6. Validated suppression by partial correlation. This is where a correlation of one independent variable with the fire variable is calculated whilst controlling for one other independent variable.

There were a number of examples of suppression within the multiple regression, for which a series of partial correlations were completed. In each case, the variable was correlated with the rate of fire whilst controlling for one other independent variable. This was completed for each of the other independent variables one at a time. If the partial correlation shows that the sign of correlation switches between the bi-variate correlation and the partial correlation, this indicates classical suppression. For example, if being Caribbean African and other black is positively correlated with fire in a bi-variate correlation but has a negative correlation after controlling for deprivation, this indicates that the negative association of being black is suppressed by the deprivation factor.

If the direction of the partial and bi-variate correlation (between the independent and dependent variables) remains the same, but changes in the multiple regression, this suggests spurious suppression.

IMD (LSOA and LA)

The method that was used to analyse the IMD data included the following steps:

- Test for Co-linearity – the factors were entered into a correlation matrix to test for co-linearity. Those variables with correlations greater than 0.8 were identified. Where they were judged to be qualitatively similar one (the one with lower correlation with rate of fire) was deleted
- Step wise regression – stepwise regression model was run to exclude weaker variables and retain the significant ones
- Check for suppression by comparing co-efficients – the co-efficients were looked at and by comparing them direction of the co-efficient to that expected from a simple correlation
- Validate suppression by partial correlation.

Chapter 2

Socio-demographic factors and dwelling fire risk

2.1 Introduction

We first explored the association between dwelling fires/injuries with (1) the census, (2) the IMD and (3) IMD combined with the census for England as a whole. In each case we completed assessments against dwelling fires and then dwelling fire injuries for:

- England as a whole

We then repeated analysis for dwelling fires for:

- Each FRS family group
- Metropolitan FRS separate from non-metropolitan FRS
- Greater Manchester FRS.

We completed two analyses of the census, namely:

- **Exploratory analysis:** An exploratory analysis of the association between census variables and the incidence of dwelling fires and injuries.
- **Previously identified factors:** An analysis of the census variables identified in previous work, specifically a regression of these variables against the rate per million population of dwelling fires and dwelling fire injuries. The regression was iterated, excluding variables with limited power.

We completed two main analyses of the IMD, namely:

- **Local and unitary authority dataset:** A regression of the IMD overall score against each of the rate per million population of dwelling fires and dwelling fire injuries using the 353 data points for unitary and local authorities
- **Lower Super Output Area dataset:** A regression of the IMD and its 7 sub-indicators using the >32,000 LSOA dataset, against the rate per million population of dwelling fires, dwelling fire injuries and dwelling fatalities.

It is clear that the use of the >32,000 LSOA dataset produces less powerful models. We believe that this is due to the occurrence of zero rates of fire pmp when data is aggregated to the LSOA level. The analysis of the IMD aggregated at the 353 unitary and local authority level produces a more powerful model. This has a number of implications:

- It is important to use data aggregated at the same geographic level when comparing two or more socio-demographic indicators
- The power of any one predictive model will be sensitive to the size of the geographic area used to aggregate data
- Any analysis that uses LSOA or smaller geographic units may (without some form of additional aggregation) produce misleadingly weak results.

Census and IMD

Further analysis was conducted to explore the predictive power of combining the IMD data (at local authority level) with census data. Exploratory analysis was conducted using this combined data set to develop the model that explains the most variance in the dwelling fires and dwelling fire injuries data.

2.2 Summary of key findings

2.2.1 Dwelling fires

This section of the report presents the key findings for the rate of dwelling fires per million people. The full set of results is presented in appendix b assessment of dwelling fires. Table 4 presents the results for dwelling fires. For the sake of simplicity we have only presented the proportion of variance explained by each regression model in the table. As shown in Table 4:

- The combined regression model of Census and IMD and the Census model alone produced the most powerful regression models, each explaining 69% of the variance in the data
- Therefore the inclusion of the IMD did not add any power to the Census regression model
- A selection of the 'previously identified' variables also explains a high proportion of the variance namely 63%
- The census variables explain a higher proportion of the variance in the rate of dwelling fire than the IMD, although the IMD analysis (at unitary/local authority level) still explains a relatively high proportion of variance (60%)
- The analysis of the IMD at LSOA explains only 46% of variance – demonstrating how the analysis is sensitive to how granular the data set being used is.

Table 4: Percentage of variance in dwelling fires pmp explained by each set of socio-demographic indicators

	Socio-demographic model **(ranked in order of influence in the model)**	***% of variance*** **in rate of dwelling fire accounted for**
Census combined with IMD data	Lone parent with dependent child(ren); Caribbean/African and other black; Never worked; Single adult household; IMD score.	69%
Census exploratory analysis	lone parent with dependent child; Caribbean/African and other black; Never worked; Single Adult household; Age 70+.	69%
Census – previously identified variables	Single person families; Sick disabled; Single adult households.	63%
IMD – analysis of 353 unitary and local authorities	IMD overall score.	60%
IMD – analysis of >32,000 LSOA	Employment score; Crime and disorder score; Education skills and training score; Living environment score.	46%

The census and IMD models shown above are the most powerful of those tested and are also ranked in order of their power. The most powerful model is the top of the table with the least powerful at the bottom.

Previously identified census factors

Considering the previously identified census variables, taken individually they explain lower proportions of variance than when they are assessed in combination. We found that, in the case of assessment of the rate of dwelling fires:

- Single person families explained the highest proportion at 57%
- Sick disabled, socially rented and single person households explained 42%, 31% and 37% respectively – all moderate predictors

- Lone pensioners and privately rented explained very little of the variance in rate of dwelling fire – 2% and 5% respectively. Both of these variables had previously been identified by earlier research to be a factor. However, during this analysis they were not significant indicators of risk
- Population density explains only 17% of variance in dwelling fires.

Caribbean/African and other black

The factor 'Caribbean/African and other black' had:

- A negative co-efficient in the multi-variate regression models (which indicates that there are fewer fires in areas with more 'Caribbean/African and other black') but
- A positive bi-variate correlation with the rate of fire (which indicates that there are more fires in areas with more 'Caribbean/African and other black').

Thus, the results of the bi-variate correlation are the opposite of the results of the multivariate regression. This is due to 'suppression' occurring with in the model. Suppression is where one independent variable within a regression model is affected by the other independent variables in such a way that it reverses the direction of the association between the independent and dependent variable.

In the case of 'Caribbean/African and other black' other independent variables (such as never worked and single parent families) were influencing the direction of the co- efficient. This is illustrated in Figure 1 where:

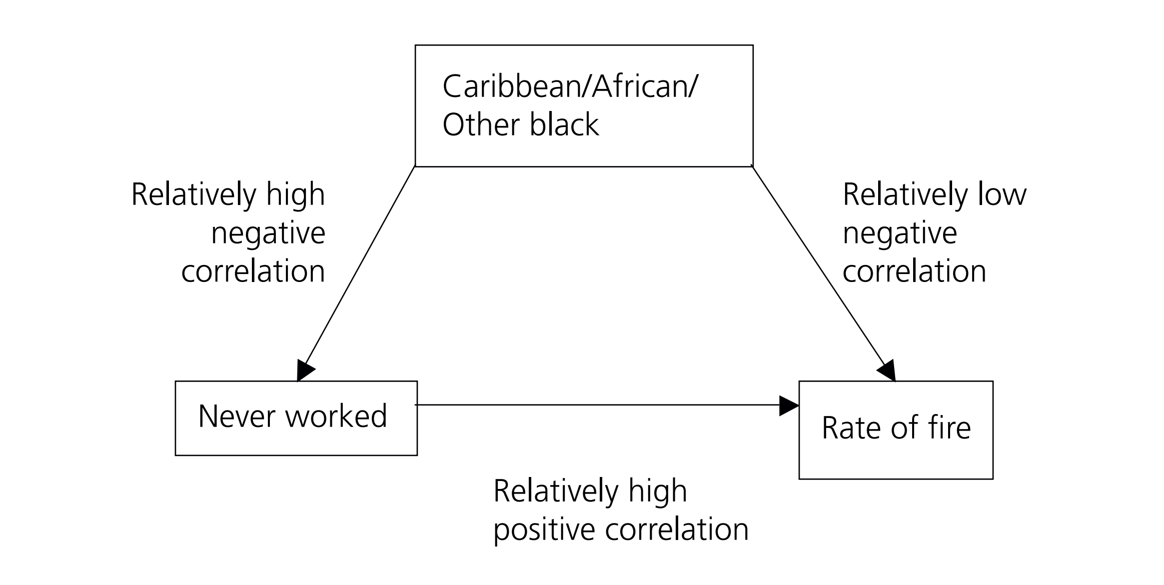
- There is a relatively strong positive association between being Caribbean/African/ other black and (in this example) 'never worked', i.e. areas with more Caribbean/ African/other black also have more people who 'never worked'
- Having 'never worked' has a relatively strong positive association with the rate of fire.

If you only complete a correlation between being 'Caribbean/African/other black' and the rate of fire it shows a positive correlation. However, if you control for the effect of 'never worked' in the multiple regression, the regression finds a negative association between being Caribbean/African/other black and the rate of fire. Thus, the correlation result for 'Caribbean/African/other black' with the rate of fire is actually showing the correlation between 'never worked' and the rate of fire.

Further analysis using partial correlations[6] revealed that there is negative association between 'Caribbean/African and other black' and rate of dwelling fires per million people once other variables are controlled for. It is these variables (deprivation, single parents and never worked) that are statistically associated with there being more fires, not being 'Caribbean/African and other black'.

[6] Partial correlations test the correlation between one independent variable and the dependent variables after controlling for the affect of one other independent variable.

Figure 1: Illustration of 'suppression' within multivariate regression



Other ethnic groups (e.g. Asian) had a very low correlation with rate of dwelling fires/injuries. Therefore, ethnic groups did not appear in the stepwise regression models as this process eliminated the weaker variables and only kept in the significant ones.

Sick disabled/not good health

Correlations and individual regression models revealed that there was a significant correlation between sick/disabled and rate of dwelling fires per million people. A correlation matrix was used to investigate co-linearity. This revealed that the factors 'sick/disabled' and 'not good health' were very highly correlated (>0.8). Therefore, best practice states that only one of these models should be included in the regression models. It was decided that 'not good health' be used in the regression models.

Initial regression analysis of the census (prior to removing sick/disabled due to co-linearity) revealed that the co-efficient for sick/disabled in the model was negative despite there being a strong positive bi-variate correlation between sick/disabled and rate of dwelling fires. However, further analysis using partial correlations revealed that the other factors were not suppressing sick/disabled. Therefore one can infer that this was a spurious result and that poor health is associated with more fires. This factor was excluded by the step wise multiple regression, once you control for other factors it was not significant.

2.2.2 Dwelling fire injuries

This section of the report presents the key findings for rate of dwelling fire injuries per million people. The full results section is presented in Appendix C: Assessment of dwelling fire injuries.

Table 5 summarises the results for the prediction of dwelling non fatal casualties. The percentages are lower in all cases than those produced for dwelling fires. This is thought to be due to the increased 'noise' in the injury data created by the relatively lower rate of fire injuries. It shows:

- Overall the most powerful models were the combined data set of Census and IMD data and the census data set alone, these models each explained 54% of the variance in the data
- The regression model for the IMD (LA) explains only 48% of the variance in the data
- The IMD assessment using LSOA data explains a very low per cent of only 20% – further highlighting the difficulties of using small area data.

The inclusion of the IMD did not add any power to the census regression model.

Table 5: Percentage of variance in dwelling fire injuries pmp explained by each set of socio-demographic indicators

	Socio-demographic model	**% of variance in rate of dwelling fire injuries accounted for**
Combined Census and IMD regression model	Lone parent with dependent child(ren); IMD score; Caribbean African other black.	54%
Census exploratory analysis	Lone parent with dependent child(ren); Caribbean/African and other black; Never worked.	54%
Census – previously identified variables	Single parent families; Sick disabled.	50%
IMD – analysis of 353 unitary and local authorities	IMD overall score.	48%
IMD – analysis of >32,000 LSOA	Employment score; Crime and disorder scores; Living environment score.	20%

When we assessed the rate of dwelling fire injuries using previously identified factors, single person households and sick disabled explained the greatest proportion of variance (50%). This is similar to previous assessments of dwelling injury rates currently used in FSEC. However, the new regression retains just two of the four variables currently used in FSEC, i.e. the FSEC variables 'Lone pensioners' and 'rented accommodation' are not retained. Lone pensioners had a R^2 of just 0.02. Rented accommodation was split into socially and privately rented with R^2 of 0.22 and 0.01 respectively. Thus, whilst privately rented is clearly of little significance, socially rented is associated (at a low level) with the incidence of fire injuries. Thus, assessment using the current, larger, dataset confirms the use of some but not all of the variables identified in previous work.

2.2.3 Smoke alarms

As a supplementary analysis we re-ran the IMD regression including 'proportion of dwelling fires with smoke alarms'. This did increase the power of the models, indicating that use of smoke alarms has a statistical association with the rate of dwelling fire and injury. Taking the IMD model developed using LSOA data (the level at which the alarm data was compiled) the dwelling fire model explained 46% with smoke alarms included and 44% without smoke alarms. The IMD model using LSOA data for fire injuries explained 20% without smoke alarms and 22% with smoke alarms.

The 'proportion of fires with smoke alarms' has a positive co-efficient, indicating that as the proportion of fires with alarms increases so does the rate of fire (and the rate of fire injury). It should be noted that regression indicates association not causality or the direction of the association. It is possible that areas with higher rates of fire leads to the FRS promoting smoke alarm installation, hence high rates of fire lead to more alarms. It is also possible that areas with a higher rate of fire alarms have also had a higher rate of home visits from the Fire and Rescue Service, which could lead to an increase in the rate of reporting of fires.

2.2.4 Comparison of indicators between types of FRSs

The regression models were re-run for:

- Metropolitan versus non-metropolitan FRS
- The five FRS family groups
- Greater Manchester FRS.

The aim was to see if the models, and hence the socio-demographic factors, differ according to the type of FRS.

Table 6 presents the variables included in each model together with the percentage of variance explained for rate of dwelling fires per million people. The results display the range of the models together with the variance explained for each. For the IMD data (at both SOA and LA level) the percentage of variance explained by each separate regression model is not greater than (or not by much) the other regression model. However, this is not the case for the census regression models. Firstly we found that some of the FRS separate regression models explained more variance than the rates of fires in all cases, the variance explained varied from 54% – 74%

Notwithstanding the differences in census models between types of FRS, we recommend that in each case the all England regression model that includes all 353 data points be used (as is presented in section 2.3 of this report). This is because as a rule of thumb when carrying out regression models there should be at least 15 data points for each variable included in the regression model[7]. If this is not met then the results of that regression model should not be generalised. Table 6 presents the findings for each of the regression models including those for each FRS family group. Due to the fact that each FRS group is a sub-group of the main all England data set, there are significantly less data points. Therefore it would be harder to generalise the findings from these regression models as they are less stable and potentially weaker than the main regression model that includes all data points.

This is especially relevant for the case of Manchester FRS. The regression models do appear to be very powerful, explaining up to 91% of the variance in the data. However, as with the FRS family groups this is a very small sub set of the main data set (10 data points) and it is not advised to be used instead of the main regression model for all England data points.

The option of using LSOA data (which would give more data points within a FRS) is limited by the high volatility of fire data at LSOA level.

In addition, the same types of variables are cited, such as deprivation related factors and type of household. Table 6 highlights each of the different factors that appear in the regression models. The key variables that are common across the majority of regression models, these include;

- Being single (either a single person or single parent)
- Unemployed
- Not good health.

These variables are repeated in the all England census model.

Age and ethnicity are factors that do appear in the regression models however they do not appear consistently throughout. Some models include one type of ethnicity, while others include another. Therefore it is difficult to draw out any main conclusions from this. Some age groups also appeared in some of the regression models and were more evident in the Census regression models, again, it is hard to see a particular pattern in this and it is not consistent throughout the regression models.

It is also important to note that the combined IMD and census regression model for dwelling fires indicates that Caribbean African and other black has a negative value (i.e. fewer fires in areas with more Caribbean African and other black persons) whilst Asian has a positive value (i.e. more fires in areas with more Asian persons).

[7] Dancey C., & Reidy J. (1999) Statistics without Maths for Psychology – Using SPSS for Windows. Prentice Hall. London

Table 6: Main findings for dwelling fires for Census and IMD (LSOA and LA)

Data set	Combined Census and IMD	% of variance explained (combined Census and IMD)	Census variables for exploratory analysis	% variance explained (Census)	IMD (LA) variables	% variance explained (IMD LA)	IMD (LSOA) variables	% variance explained (IMD LSOA)
Overall data	Lone parent with dependent child(ren); Caribbean/ African and other black; Never worked; Single adult household; IMD score.	69%	lone parent with dependent child Caribbean/ African and other black; Never worked; Single Adult household. Age 70+;	69%	IMD score.	60%	Employment score; Crime and disorder score; Education skills and training score. Living environment score;	46%
FRS Family group 1	Population density; Asian; Chinese and other ethnic; Not good health; Lone parent with dependent child(ren)	79%	Population density; Asian; Lone parent with dependent child(ren)	71%	IMD score.	35%	Employment score; Crime and disorder score; Living environment score.	35%

Table 6: Main findings for dwelling fires for Census and IMD (LSOA and LA)

Data set	Combined Census and IMD	% of variance explained (combined Census and IMD)	Census variables for exploratory analysis	% variance explained (Census)	IMD (LA) variables	% variance explained (IMD LA)	IMD (LSOA) variables	% variance explained (IMD LSOA)
FRS Family group 2	Single adult household; Lone parent with dependent child(ren).	69%	Irish and other white; Caribbean/ African and other black; Never worked; Lone parent with dependent child(ren).	78%	IMD score.	51%	Employment score; Crime and disorder score; Living environment score.	37%
FRS family group 3	Single adult household; Lone parent with dependent child(ren).	80%	Not good health; Single adult household.	74%	IMD score.	66%	Employment score; Education skills training score; Crime and disorder score; Living environment score.	46%

Table 6: Main findings for dwelling fires for Census and IMD (LSOA and LA)

Data set	Combined Census and IMD	% of variance explained (combined Census and IMD)	Census variables for exploratory analysis	% variance explained (Census)	IMD (LA) variables	% variance explained (IMD LA)	IMD (LSOA) variables	% variance explained (IMD LSOA)
FRS Family group 4	Irish and other white; Asian; Not good health; Lone parent with dependent child(ren).	67%	Never worked; Lone parent with dependent child(ren).	65%	IMD score.	58%	Employment score; Education skills training score; Crime and disorder score; Living environment score.	44%
FRS Family group 5/ Mets	Age 70 + Single adult household; IMD score.	56%	Age 50 – 69; Caribbean/ African and other black; Not good health; Single adult household; Lone parent with dependent child(ren).	54%	IMD score.	49%	Employment score; Education skills training score; Crime and disorder score; Living environment score.	43%

Table 6: Main findings for dwelling fires for Census and IMD (LSOA and LA)

Data set	Combined Census and IMD	% of variance explained (combined Census and IMD)	Census variables for exploratory analysis	% variance explained (Census)	IMD (LA) variables	% variance explained (IMD LA)	IMD (LSOA) variables	% variance explained (IMD LSOA)
Non-Mets	Age 70+; Never worked; Single adult household; Lone parent with dependent child(ren).	66%	Irish and other white; Caribbean/ African and other black; Never worked; Single adult household; Lone parent with dependent child(ren).	67%	IMD score.	54%	Employment score; Education skills training score; Crime and disorder score; Living environment score.	41%
Greater Manchester	Single adult household	77%	Never worked	91%	IMD score.	75%		54%

2.2.5 MOSAIC

A qualitative analysis of the Mosaic data was carried out to investigate what, if any, are the Mosaic type groups most at risk from fire using previously identified factors as a guide to determining the risk level of each Mosaic group. For example, if the Mosaic group detailed single people, then this has been identified in previous research as being a group significantly at risk from dwelling fires, therefore this group would be categorised as 'high risk'. Whereas, if a Mosaic group detailed a group who were families living in detached housing in the Suburbs, these are factors which have not previously identified as risk factors of dwelling fires and therefore this Mosaic group would be categorised as 'low risk'. Table 7 shows a sample of the MOSAIC categories and our judged risk ranking of them together with an identifying risk factor.

Table 7: Illustration of ranking of MOSAIC categories

Type	Name	Description	Fire risk rating	Identifying risk factor
I48	Old People in Flats	Single pensioners in small, publicly rented flats, many of which were built for this age group.	High	Single person households, pensioners, rented accommodation
I49	Low Income Elderly	Elderly people living in low rise council housing, often on low incomes.	High	Low incomes, elderly
E32	Dinky Developments	Singles and childless couples in cul de sacs of small, often Brownfield-site, newly built town houses	Medium High	Single people
F35	Bedsit Beneficiaries	Childless couples and singles renting in city centres from private or public landlords	Medium High	Single people
A05	Provincial Privilege	Well-educated older professionals living in established suburbs	Low	–
A06	High Technologists	Corporate high-fliers living in spacious, often modern, detached houses	Low	–

2.3 Prediction formula

2.3.1 Introduction

The following section of this report presents the prediction (regression) formula for rate of dwelling fires and of dwelling fire injuries. The prediction formulas were derived from the regression analysis conducted on (1) the IMD (LSOA) and (LA), (2) Census data and (3) IMD and census combined. Detail of this regression analysis can be found in the Appendices of this report. These formulas can be used to predict rates of dwelling fire and injury using the pertinent census or IMD data.

2.3.2 Dwelling fires

Prediction formula combined for IMD and Census

The IMD data and Census data were combined and regressed against the rate of dwelling fires per million people. The results revealed that the model that explained the greatest variance included the following factors (ranked in order of most to least influence in the model):

- Lone parent with dependent child(ren);
- Caribbean/African or other black;
- Never worked;
- Single adult household;
- IMD score.

This regression model explained 69% of the variance in the data and was significant at the 1% significance level. The following provides the regression model predictive formula:

y = (–448.355) + (–4074.408 x (Caribbean/African and other black)) + (6405.573 x (Never worked)) + (3072.483 x (Single adult household)) + (27000.036 x (Lone parent with dependent child(ren))) + (6.769 x (IMD score))

Prediction formula for Census (Exploratory analysis)

Exploratory analysis of the census data revealed that the model that explained the most variance included the following variables (ranked in order of most to least influence in the model):

- Lone parent with dependent child(ren)
- Caribbean/African or other black
- Never worked
- Single adult household
- Age 70 +.

This model explained 69 percent of the variance in the data and was significant at the 1% level. Therefore it can be inferred that this is the most accurate model from the census data to predict rate of dwelling fires per million people. From this regression model it is possible to predict rate of dwelling fires based on these variables. The full regression model formula for the census data will be as follows:

y = (–695.574) + (1277.732 x (Age 70 +)) + (–4404.823 x (Caribbean/African and other black)) + (8506.565 x (Never worked)) + (3069.902 x (Single adult household)) + (32799.640 x (Lone parent with dependent child(ren)))

Prediction formula for Census (previously identified factors)

Previous research has identified several factors which are thought to be good predictors of dwelling fires. Our analysis involved running a separate regression model for each of these previously identified factors against rate of dwelling fires. From this we were able to identify three key factors which explained the greatest variance. These factors were ((ranked in order of most to least influence in the model) :

- Single person families.
- Sick/disabled
- Single person households.

A regression model was run using these three factors. The results revealed that the model explained 63% of the variance in the data and was significant at the 1% level. This suggests that this is a fairly powerful model in terms of prediction of dwelling fires. The following provides the regression model predictive formula:

y = (–349.754) + (4261.167 x (Single adult household)) + (7957.337 x (Sick/disabled)) + (26848.104 x (Single person families))

Prediction formula for IMD (LSOA)

Analysis of IMD found that the model that explained the most variance included the following variables (ranked in order of most to least influence in the model):

- Employment score
- Crime and disorder score
- Health deprivation and disability score
- Education skills and training skills score
- Living environment score.

This model explained 43% of the variance in the data and was significant at the 1% level of significance. Therefore it can be inferred that this is the most accurate model of IMD data to predict rate of dwelling fires per million people. From this regression model it is possible to predict rate of dwelling fires based on these variables. The regression formula is as follows:

y = b0 + b1 (x1) + b2 (x2) +… bp (xp),

Therefore, for the full regression model formula for the IMD data (full data set) will be as follows:

y = (–55.868) + (9443.948 x (employment score)) + (5.117 x (living environment score)) + (124.592)) + (–4.992 x (Education skills and training score))

Prediction formula for IMD (LA)

Analysis of the IMD at local authority level included only one variable, this was:

- IMD score.

This model explained 60% of the variance in the data and was significant at the 1% significance level. From this regression model it is possible to predict the rate of dwelling fires per million people based on these two variables. The regression formula is as follows:

y = (158.122) + (35.197 x (IMD score))

2.3.3 Dwelling fire injuries

Prediction formula combined for IMD and Census

Analysis of the combined census and IMD data set revealed that the model that explained the most variance included the following variables (ranked in order of most to least influence in the model):

- Lone parent with dependent child(ren)
- Caribbean/African and other black
- IMD score.

This model explains 54% of the variance in the data and is significant at the 1% level of significance. The following provides the predictive formula that can be used to predict the rate of dwelling fire injuries:

y = (–110.890) + (–760.003 x (Caribbean and other black)) + (8384.445 x (Lone parent with dependent child)) + (3.219 x (IMD score))

Prediction formula for Census (exploratory analysis)

Analysis of the census data revealed that the model that explained the most variance included the following variables (ranked in order of most to least influence in the model):

- Lone parents with dependent child(ren)
- Caribbean African and Other Black
- Never worked.

This model explained 54% of the variance in the data and is significant at the 1% level. Therefore it is suggested that to predict the rate of dwelling fire injuries the following regression model prediction formula is used:

y = (–146.597) + (–1106.940 x (Caribbean/black)) + (1236.730 x (Never worked)) + (10620.448 x (Lone parent with child(ren))

Prediction formula of previously identified factors for census data

Previous research has identified several factors which are thought to be good predictors of dwelling fire injuries. Our analysis involved running a separate regression model for each of these previously identified factors against rate of dwelling fire injuries. From this we were able to identify two key factors which explained the greatest variance. These factors were:

- Single person families
- Sick/disabled.

A regression model was run using these three factors. The results revealed that the model explained 50% of the variance in the data and was significant at the 1% level. The following provides the predictive formula that can be used to predict the rate of dwelling fire injuries:

y = (–94.139) + (10345.083 x (Single person families)) + (1656.965 x (Sick/disabled))

Prediction formula for IMD (LSOA)

The regression model for dwelling fires explained 20% of the variance in the data. The factors that were included in this regression model are as follows (ranked in order of most to least contribution to the model):

- Employment score
- Crime and disorder score
- Living environment score.

Therefore the prediction formula that could be used to predict the rate of dwelling fire injuries should be:

y = (–33.695) + (1950.773 x (employment)) + (35.147 (crime)) + (.959 x (living))

Prediction formula for IMD (LA)

Analysis of the IMD (LA) data included only the IMD score.

This regression model explains 48% of the variance in the data and is significant at the 1% significance level. The prediction formula based on the regression model should be as follows:

y = (–.675) + (8.636 x (IMD score))

Chapter 3

Predicted versus reported fires and injuries

3.1 Introduction

This stage of the work involved applying the formulas generated from the Census and IMD regressions to calculate a predicted rate of fires and injuries for each FRS. We used:

- The combined IMD and census models for dwelling fires and injuries
- The exploratory census models for dwelling fires and injuries
- The IMD models for dwelling fires and injuries.

In all cases we used the models developed using the 353 local and unitary authority data sets (the all England dataset).

Predicted rates of fires and injuries were compared with reported rates and also the national averages for 2002-2004.

The regression formulas were also used to calculate a national projected rate of fires and injuries for 2010 using the exploratory census model. For the IMD data, predictor variables were increased or decreased by 10% in order to see the effect this would have on the national rate of fires and injuries.

FRS codes

FRSs are identified in each graph/table by their FRS number. Table 8 below lists all the FRSs in England included in this analysis and their respective FRS numbers:

Table 8: FRS numbers

London	50	Northumberland	29	Dorset	12
West Yorkshire	47	Northants	28	Devon	11
West Midlands	46	North Yorkshire	27	Derbyshire	10
Tyne & Wear	45	Norfolk	26	Cumbria	9
South Yorkshire	44	Lincolnshire	25	Cornwall	8
Merseyside	43	Leicestershire	24	Cleveland	7
Manchester	42	Lancashire	23	Cheshire	6
Wiltshire	39	Kent	22	Cambridgeshire	5
West Sussex	38	Isle of Wight	21	Buckinghamshire	4
Warwickshire	37	Humberside	20	Berkshire	3
Surrey	36	Hertfordshire	19	Bedfordshire	2
Suffolk	35	Hereford and Worc	18	Avon	1
Staffordshire	34	Hampshire	17		
Somerset	33	Gloucestershire	16		
Shropshire	32	Essex	15		
Oxfordshire	31	East Sussex	14		
Nottinghamshire	30	Durham	13		

3.2 Predicted versus reported rates

3.2.1 Reported versus predicted rates of fires/injuries

The aim of this task was to compare the predicted and reported rates of fires and injuries and assess how FRS reported rates compared to what is predicted given the local population profile of the area covered by each FRS.

Where the reported rate of fires/injuries was below the predicted rate, this was an indication that there are fewer fires or injuries in this area than would be expected taking into account the demographics of the local population. This could be a positive reflection on the work of the FRS in this area or simply the difference between the prediction (which does not explain 100% of variance) and reported rates.

Where the reported rate of fires/injuries was above the predicted rate, this indicated that there were more fires and injuries in this area than would be predicted taking into account the demographics of the local population. This would highlight areas where more work is needed by FRSs to achieve a reported rate of fires and injuries which is closer to the predicted rate, or as before simply the difference between the prediction (which does not explain 100% of variance) and reported rates.

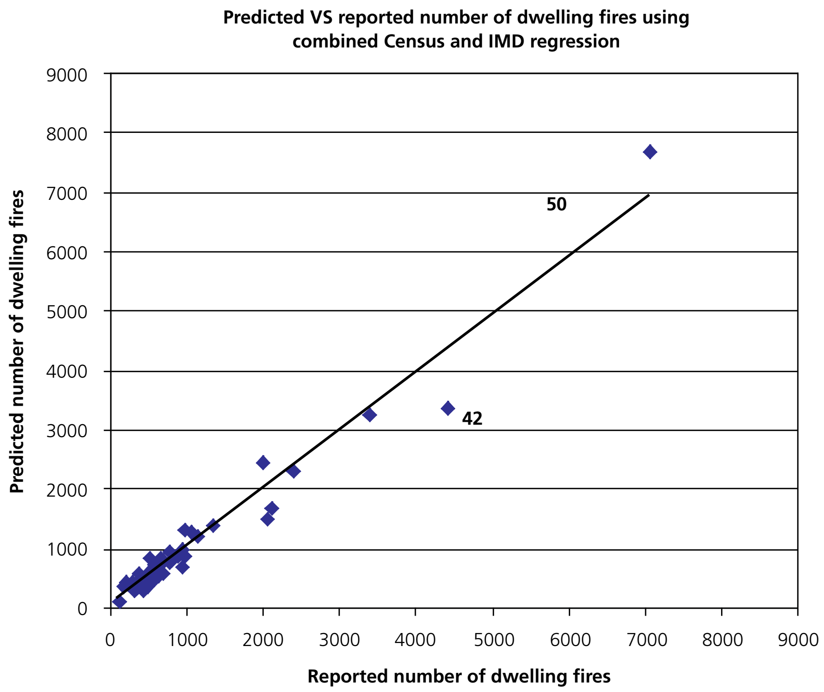
3.2.2 Combined Census and IMD model

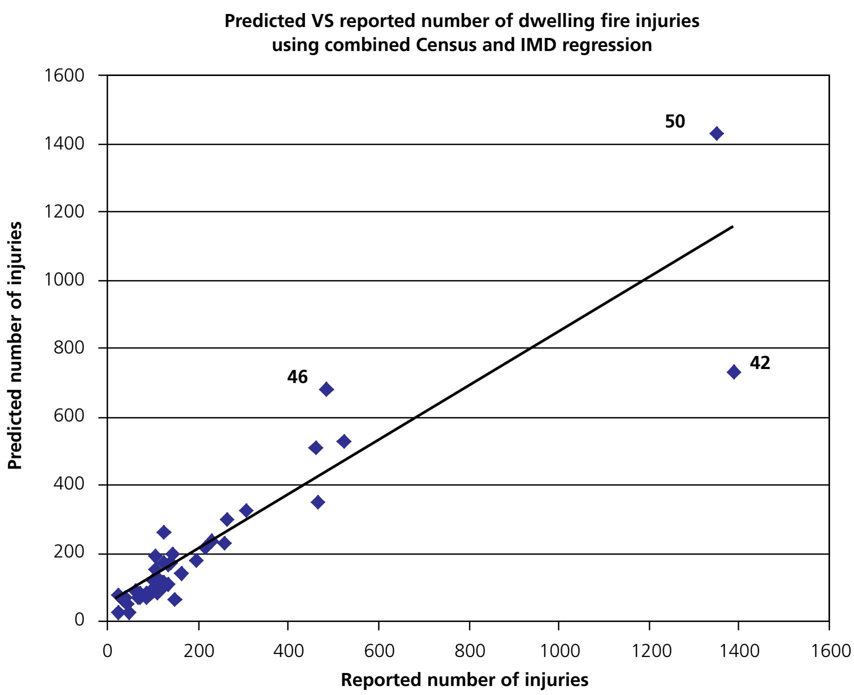
The predicted and reported number of fires and injuries using the combined Census and IMD data are shown in Figure 2.

The combined regression model predicts a similar number of fires and injuries as the actual reported rate, as does the individual Census and IMD data. In the case of dwelling fires, most points in the chart fall on or near the line of best fit, with few exceptions. Manchester (point 42) is shown to have a higher number of reported fires than would be predicted. London (point 50) is shown to have a lower number of reported fires than would be predicted.

In the case of dwelling fire injuries, again most FRSs have a similar reported number of injuries as would be predicted. However, Manchester (point 42) has a much higher number of reported injuries than would be predicted by the combined IMD and Census regression model. West Midlands (point 46) has a lower reported number of injuries than would be predicted by this model, as does London (point 50).

Figure 2: Predicted and reported number of fires and injuries using the combined Census and IMD data





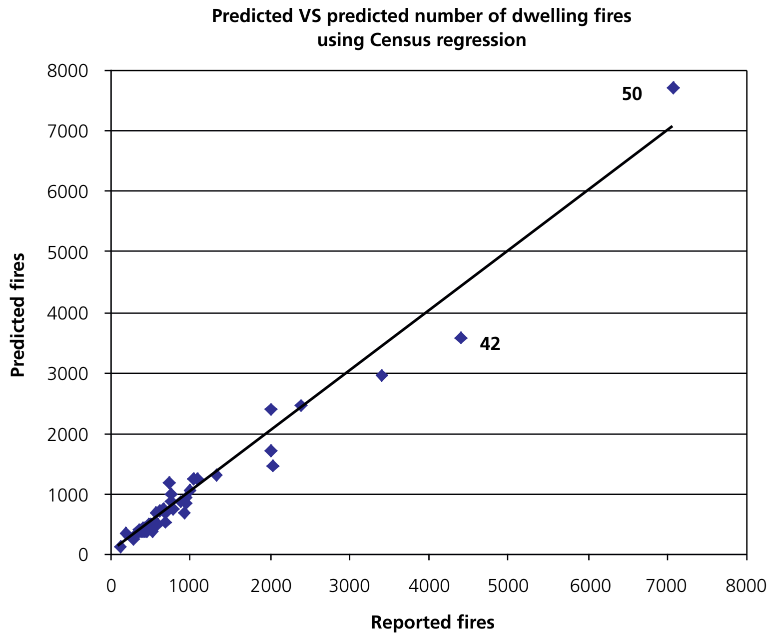
3.2.3 Exploratory census model

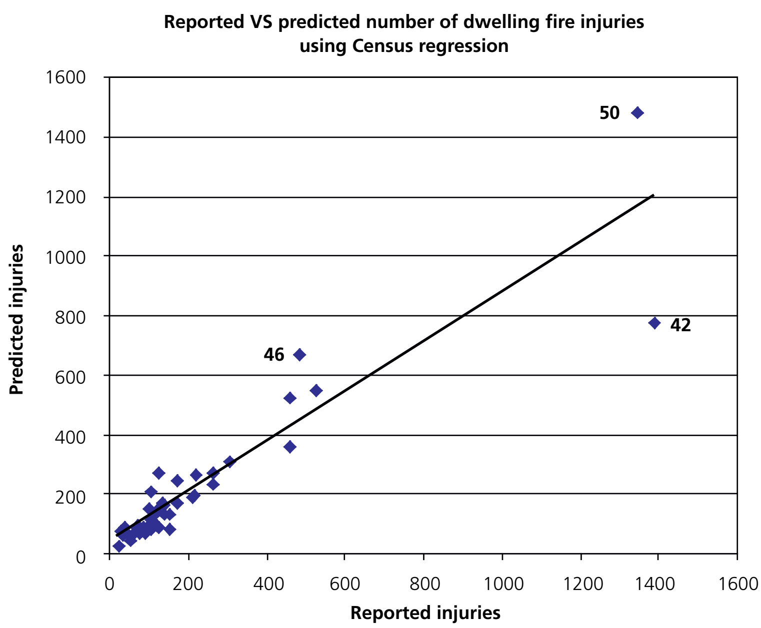
Predicted and reported numbers of fires and injuries using the Census data are shown in Figure 3.

Figure 3 illustrates that predicted number of dwelling fires using the Census regression are generally similar to the reported numbers for most FRSs (most points cluster around the line of best fit). However London FRS, illustrated by point 50, has a lower reported number of fires than the predicted number. For Manchester however, illustrated by point 42, the reported number of fires is actually higher than the predicted number.

In the case of injuries, the predicted number is, in most cases, similar to the reported number. However, London FRS (point 50) has a lower number of reported injuries than the predicted number, as does West Midlands (point 46). However, Manchester FRS (point 42) has a higher reported number of injuries than would be predicted.

Figure 3: Predicted and reported number of dwelling fires and injuries using Census exploratory model



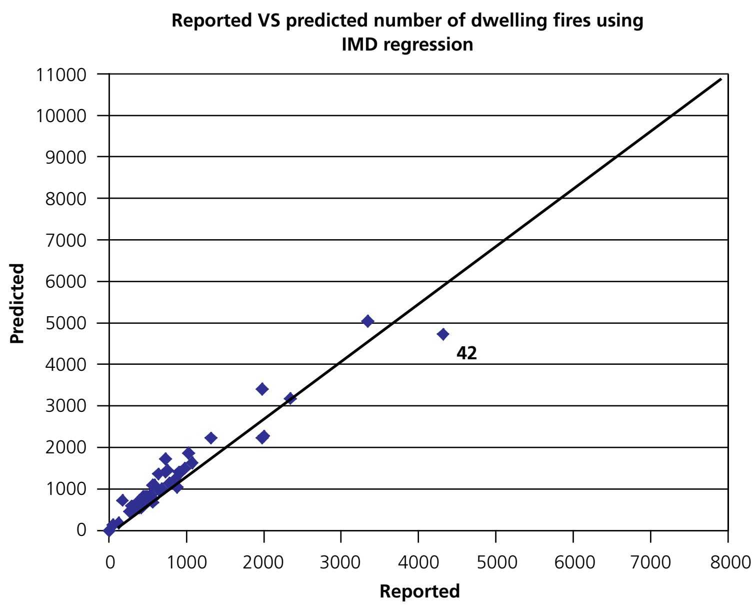


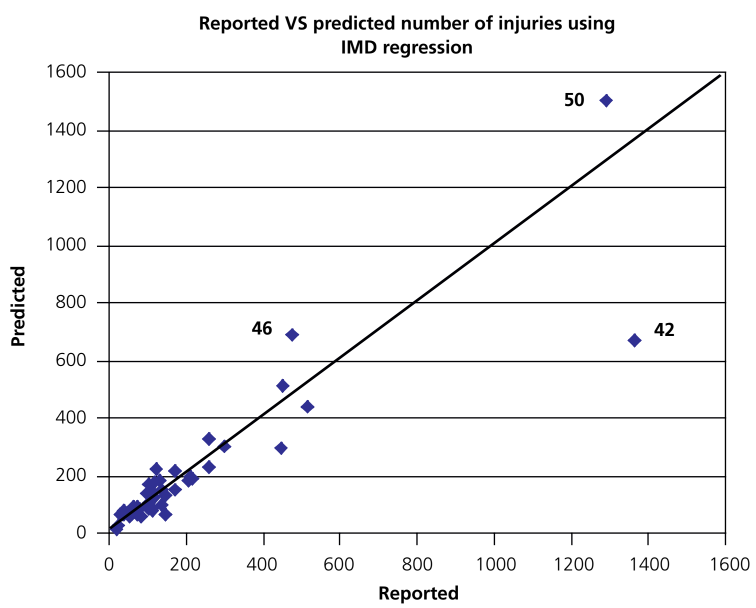
3.2.4 IMD model

The predicted and reported number of fires and injuries using the IMD data are shown in Figure 4. As illustrated in Figure 4 the IMD data shows that the majority of FRSs have a reported number of fires similar to what would be predicted. However, according to the IMD data Manchester FRS (point 42) has a lower number of reported fires than would be predicted. This is contrary to what is shown by the Census data in Figure 4.

There are more differences between the IMD predicted and reported number of fire injuries than for fires. There are some FRSs which have either higher or lower numbers of injuries than the predicted number. For examples, Manchester (point 42) has a higher number of reported injuries than would be predicted. However, West Midlands (point 46) has a lower reported number of injuries than would be predicted, as does London (point 50).

Figure 4: Predicted and reported number of dwelling fires and injuries using IMD data





3.3 Predicted and reported rates versus national averages

3.3.1 Predicted and reported rates versus national averages

The reported and predicted rate of fires and injuries for each FRS was also compared with the national average reported rates. The purpose of this task was firstly to see how the reported rates of fires and injuries for each FRS compared to the national average rate. This would identify which FRSs had reported rates which exceeded the national average by 1.25[8], those which were equal to the national average and those which were below it.

The second purpose was to identify which FRSs were predicted to have a particularly lower or higher rate of fires and injuries than the national average. This would indicate whether it is feasible to assess the performance of a particular FRS by comparing its reported rate of fires and injuries with the national average. For example, if the predicted rate of fire/injury for a FRS is double the national average, the guideline for not exceeding the national average by 1.25 may not be a 'stretch' target for this FRS.

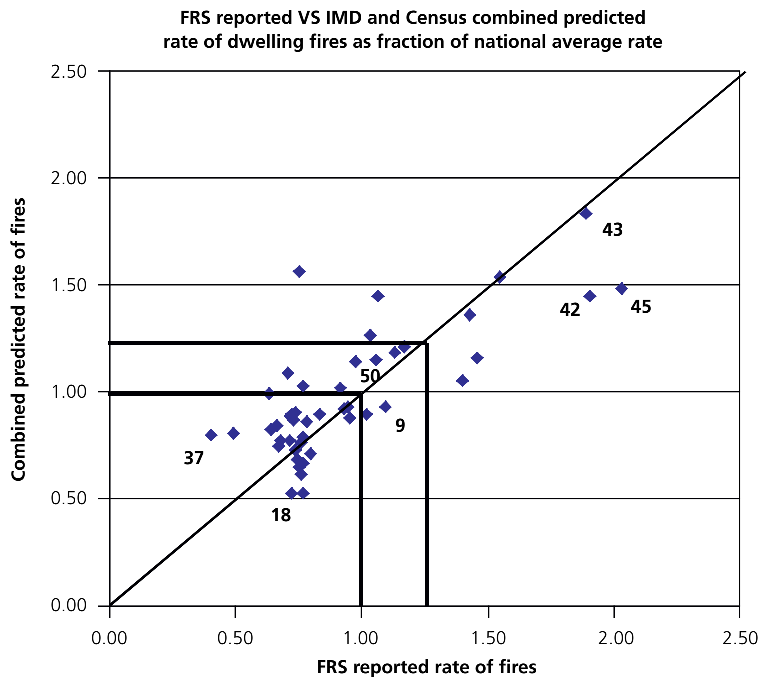
On the other hand, if the predicted rate is below the national average but the reported rate is above it, this should be considered when setting targets for reducing rates of fires and injuries for this FRS. The guideline for not exceeding the national average by 1.25 could be lowered for this particular FRS since it is already predicted to have a lower rate than the national average. Alternatively the FRS may be said to have hit a plateau.

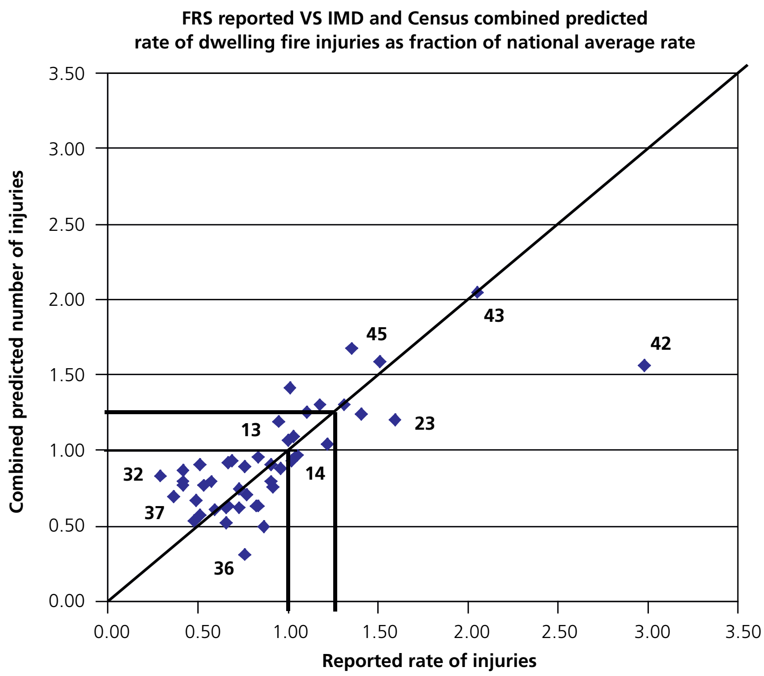
3.3.2 Combined Census and IMD model

Figure 5 the predicted and reported rate of dwelling fires and injuries as a fraction of the national average, using the combined IMD and Census regression model. The national average (=1) is shown by the smaller boxes in Figure 5. The larger boxes represent the target of '1.25 times the national average' rate. Points of data inside the national average box represent those FRSs which have a predicted and reported rate of fire/injuries which are below the national average.

[8] The PSA 3 target for the fire service includes a floor target that the rate of fire death in any one FRS should not exceed the national average by more than 1.25.

Figure 5: Combined Census and IMD predicted and reported rate of dwelling fires and injuries as a fraction of the national average





In the case of dwelling fires, the combined Census and IMD data shows that several FRSs have a predicted and reported number of fires below the national average rate. For example:

- Hereford and Worcester (point 18)
- Warwickshire (point 37)

In the case of dwelling fire injuries examples are:

- Shropshire (point 32)
- Surrey (point 36)
- Warwickshire (point 37)

Points of data within the '1.25 the national average' box represents those FRSs which have a reported and predicted rate of fires/injuries which are greater than the national average but within the target of 1.25. Figure 5 also shows that a number of FRSs have a predicted and reported rate of fires and injuries above the national average but within the 1.25 target. Examples for dwelling fires are:

- Cumbria (point 9)
- London (point 50)

Examples for dwelling fire injuries are:

- Durham (point 13)
- East Sussex (point 14)

Points of data outside these boxes represent those FRSs which have a predicted and reported rate of fires/injuries greater than 1.25 the national average. Figure 5 illustrates that Manchester (42), Lancashire (23), Merseyside (43) and Tyne and Wear (45) have a predicted and reported rate of fires or injuries above 1.25 of the national average. The IMD and Census data individually support these findings (see Figure 6 and Figure 7).

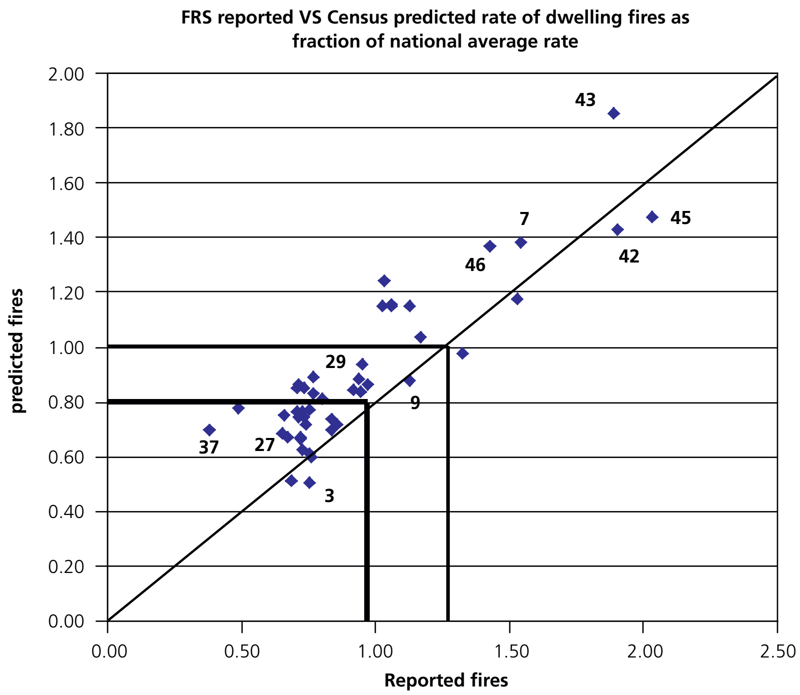
In the case of both fires and injuries, the same FRSs appear to have predicted and reported rates above the national average i.e. Manchester, Merseyside and Tyne and Wear. Setting a target of 1.25 may not be appropriate for these FRS since they are predicted to have a rate of fires and injuries which is greater than 1.25 of the national average, given the local population profile of the area. A target of 1.25 may therefore not 'bite.'

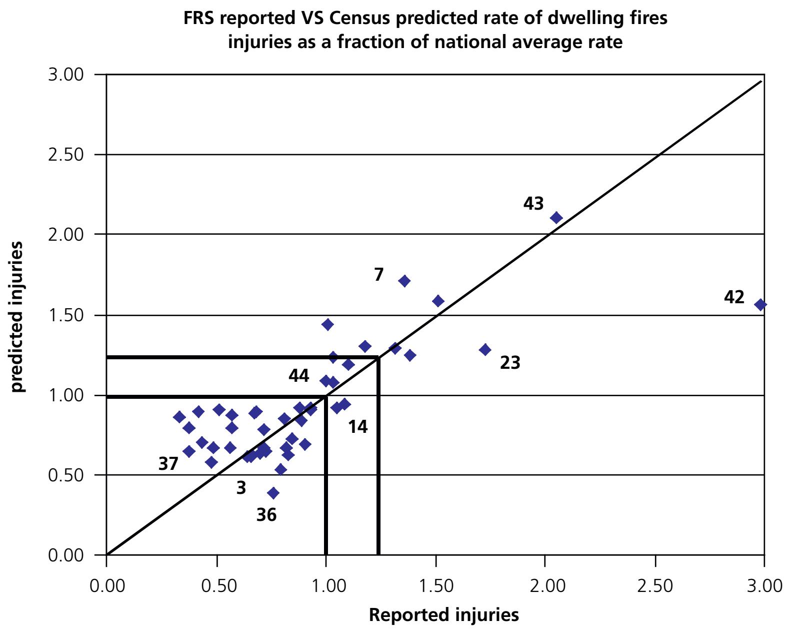
On the other hand, for those FRSs which have a predicted and reported rate of fires/ injuries well below the national average, the target of 1.25 may not be low enough to encourage further reductions in fires and injury rates.

3.3.3 Census data

Figure 6 illustrates the predicted and reported rate of dwelling fires and injuries as a fraction of the national average using the Census data:

Figure 6: Census predicted and reported rate of dwelling fires and injuries as a fraction of the national average rate





In the case of fires, examples of FRSs which have a predicted and reported rate equal to or below the national average are:

- Berkshire (point 3)
- North Yorkshire (point 27)

- Warwickshire (point 37)

In the case of injuries, examples are:

- Berkshire (point 3)
- Surrey (point 36)
- Warwickshire (point 37)

In the case of fires, examples of FRSs which have a reported and predicted rate of fires greater than the national average, but within the target of 1.25. are:

- Cumbria (point 9)
- Northumberland (point 29)

In the case of injuries, examples are:

- East Sussex (point 14)
- South Yorkshire (point 44)

Points of data outside these boxes represent those FRSs which have a predicted and reported rate of fires/injuries greater than 1.25 the national average. In the case of fires, examples are:

- Cleveland (point 7)
- Manchester (point 42)
- Merseyside (point 43)
- Tyne and Wear (point 45)
- West Midlands (point 46)

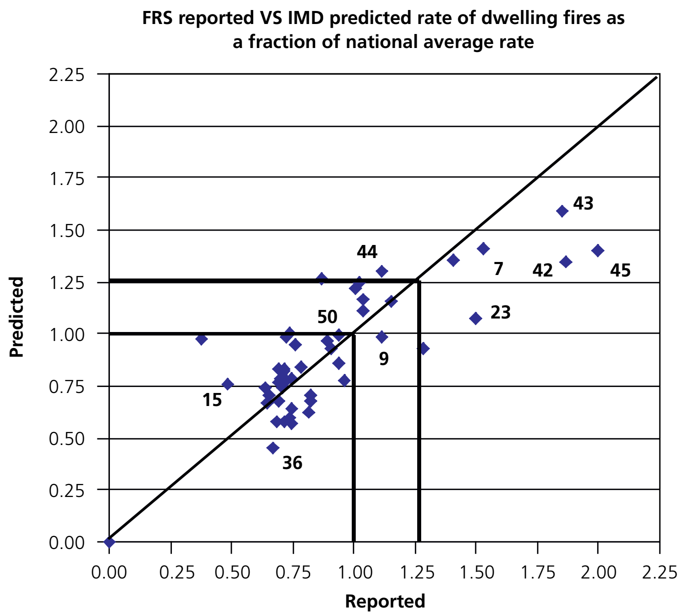
In the case of injuries, examples are:

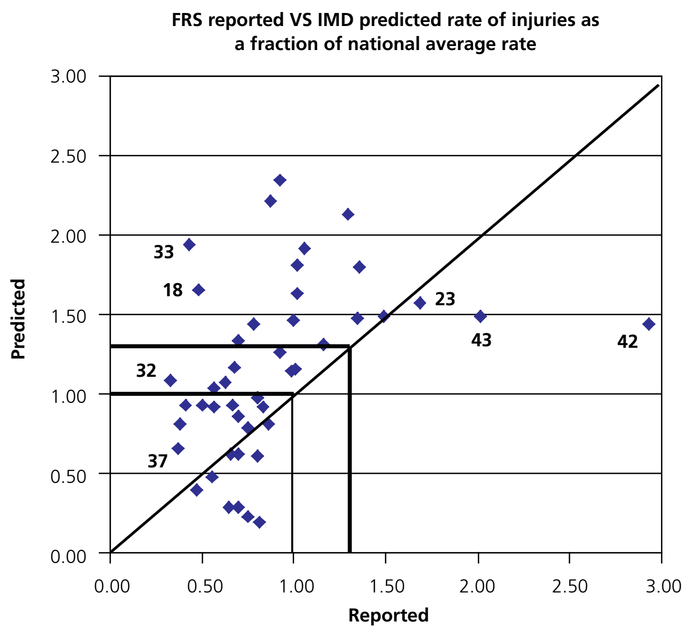
- Cleveland (point 7)
- Lancashire (point 23)
- Manchester (point 42)
- Merseyside (point 43

3.3.4 IMD data

Figure 7 represents the predicted and reported rate of dwelling fires and injuries as a fraction of the national average:

Figure 7: IMD predicted and reported rate of dwelling fires and injuries as a fraction of the national average





In the case of dwelling fires, the IMD data shows that there are many FRSs with predicted and reported rates of fire below the national average. For example:

- Essex (point 15)
- Surrey (point 36)

There are also a number of FRSs which have predicted and reported rates of dwelling fire injuries below the national average. For example:

- Warwickshire (point 37)

Examples of FRSs which have a reported and predicted rate of fires within 1.25 of the national average are:

- London (point 50)
- Cumbria (point 9)

In the case of dwelling fire injuries, an example of FRSs which have reported and predicted rates of injuries within 1.25 of the national average is:

- Shropshire (point 32)

According to the IMD data, there are 6 FRSs which have reported and predicted rates of dwelling fires above 1.25 of the national average. For example:

- Cleveland (point 7)
- Lancashire (point 23)
- Manchester (point 42)
- Merseyside (point 43)
- Tyne and Wear (point 45)

In the case of dwelling fire injuries, examples where the reported and predicted rate of injuries is well above the national average are:

- Merseyside (point 43)
- Manchester (point 42)

Figure 7 also shows that there are a number of FRS which have a reported rate of injuries within 1.25 of the national average but they are predicted to have a rate above 1.25 of the national average. For example:

- Hereford and Worcester (point 18)
- Somerset (point 33)

3.4 Comparison of Census, IMD and combined predicted rates of fires and injuries

Predicted rates of fires and injuries were calculated using three different regression formulas; one for the Census model, one for the IMD model and another for the combined Census and IMD model. This generated three different sets of predicted rates of fires and injuries for each FRS. The predicted rates using the Census, IMD and combined models were compared to see whether one was a better predictor of fire and injury rates than the others.

Some examples of similarities in the predicted rates of fires and injuries for Census, IMD and the combined model have been mentioned in 3.3. However, similarities and differences in predicted rates of fires and injuries for each FRS are shown below. Figure 8 shows the predicted rates of dwelling fires for each FRS for Census, IMD and the combined models.

As shown in Figure 8 the predicted rate of fires using the IMD, Census and combined models are similar in the majority of cases. On occasions, the combined model predicts a higher rate of fires than the IMD and the Census model i.e. in the case of Oxfordshire (point 31). In the case Merseyside (point 43), the IMD model has a lower predicted rate of fires than the combined model and the Census model.

In terms of dwelling fire injuries, Figure 9 illustrates the predicted rates of dwelling fire injuries per FRS for the Census, IMD and the combined models. As shown in Figure 9, the Census, the IMD and the combined models predict very similar rates of dwelling fire injuries for most FRSs. As with dwelling fires, the combined model and the Census model predict a higher rate of injuries for Merseyside than the IMD model.

On the whole, the three different sets of regression models produce similar predictions in terms of rates of fires and injuries per FRS.

Figure 8: Census, IMD and combined predicted rate of dwelling fires

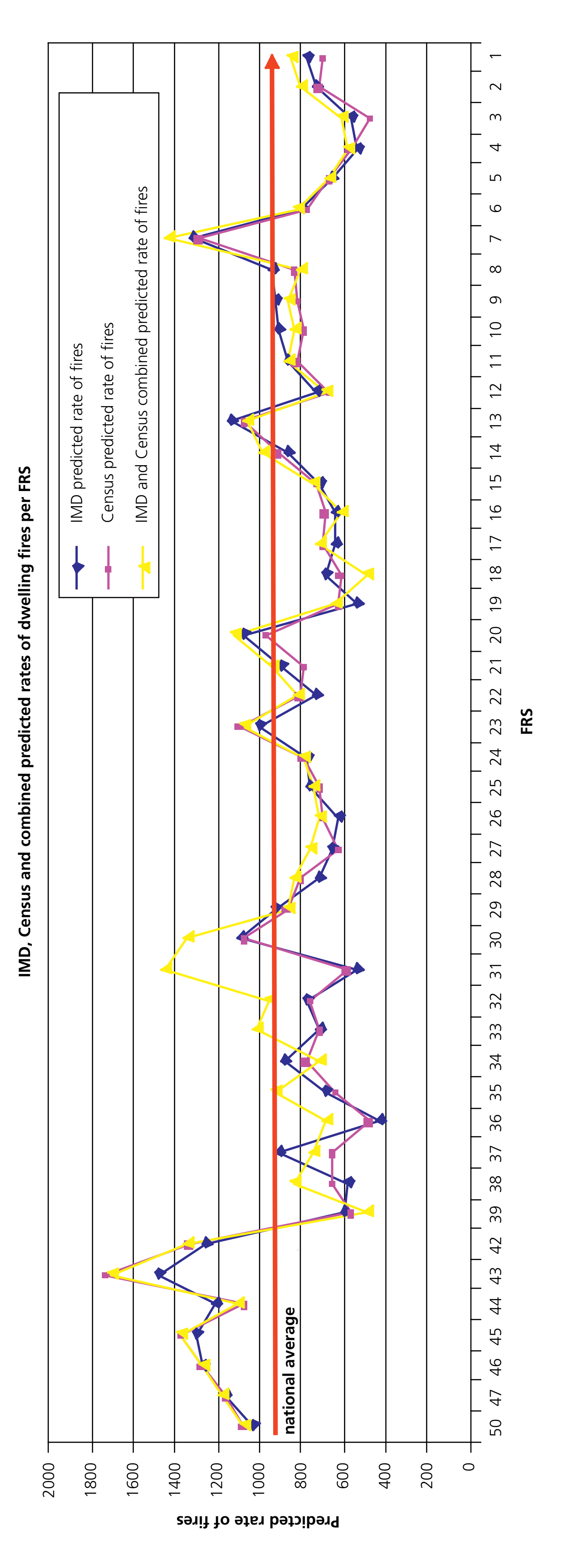
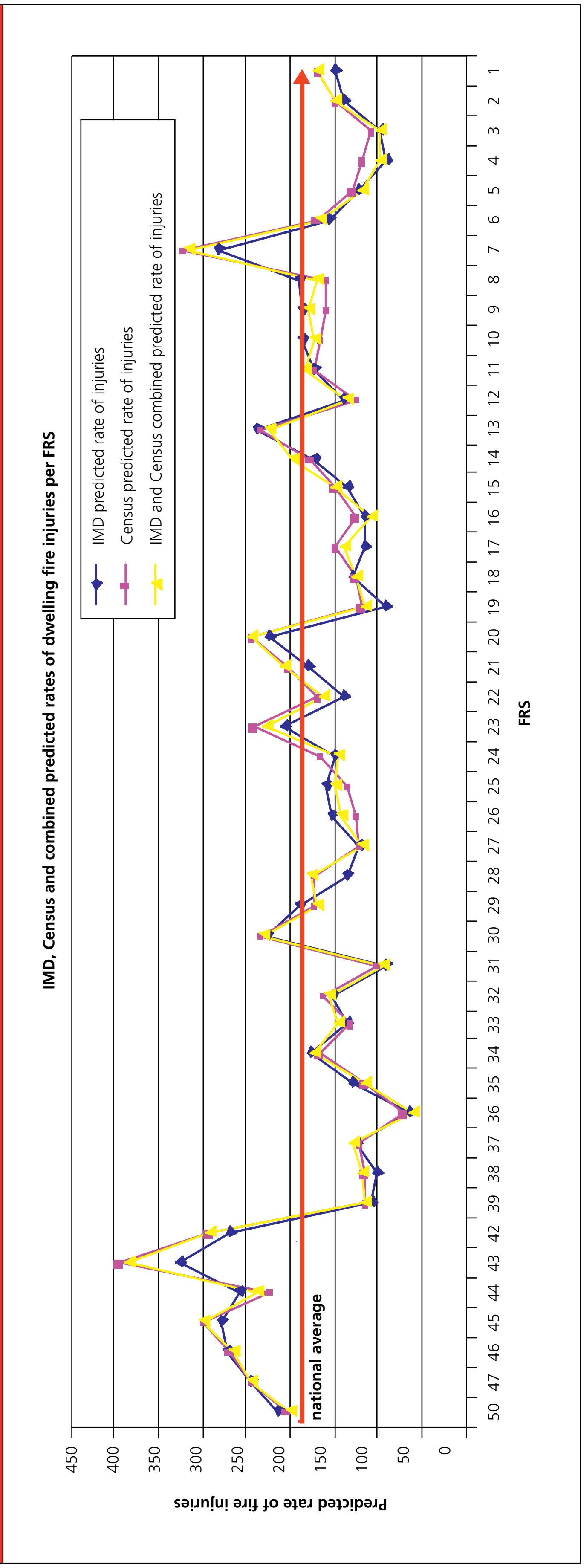


Figure 9: Census, IMD and combined predicted rate of dwelling fire injuries



3.5 FRS specific results

3.5.1 Dwelling fires

A full list of IMD, Census and combined model predicted rates of dwelling fires including the reported rate for each FRS is presented in Appendix F Specific FRS Results at the back of this report.

Although there are similarities in the predicted rates of dwelling fires for the IMD, the Census and the combined models, there are examples where the predicted rates differ from the actual reported rates. Figure 10 illustrates how the IMD predicted rates of fire differ from the reported rates for each FRS.

The left side of the graph illustrates examples where the reported rate of fires is lower than what is predicted by the IMD. For example, Warwickshire (FRS 37), Essex (FRS 15), Derbyshire (FRS 10) all have a lower reported rate of dwelling fires than is predicted.

The right hand side of the graph illustrates examples where the reported rate of fires is higher than the predicted rate. For example, Tyne and Wear (FRS 45), Manchester (FRS 42) and Lancashire (FRS 23).

There are a few FRSs which have a very similar reported rate of fire to what the IMD predicts (shown in the middle of the graph). For example, Devon (FRS 11), Norfolk (FRS 26) and Hampshire (FRS 17).

The Census model and the combined Census and IMD model show similar patterns between the predicted and reported rate of fires as the IMD model. Figure 11 illustrates how the Census predicted rates of dwelling fires differ from the reported rates. Figure 12 illustrates how the predicted rates of dwelling fires differ from the reported rates of fire for the combined Census and IMD model.

The IMD, the Census and the combined model predictions show that the same FRSs have a lower rate of reported fires than is predicted. For example, the same FRSs are seen on the left hand side of Figure 12, Figure 11 and Figure 10 (Warwickshire, Essex, and Derbyshire etc).Figure 10, Figure 11 and Figure 12 also suggest that Tyne and Wear, Lancashire and Manchester all have a higher reported rate of fires than is predicted.

There are some differences in the predicted rates for the 3 different models. For example, in the IMD model the predicted and reported rate of fires for Norfolk (FRS 26) is equal. However, in the Census and the combined model the reported rate of fires for Norfolk is actually lower than what is predicted.

The IMD model suggests that the reported rate of fires for Hertfordshire (FRS 19) is higher than the predicted rate. However, the Census model and the combined model suggest that the reported rate of fires for Hertfordshire is equal or almost equal to the predicted rate.

The following three graphs present the reported rate of fire and the predicted rates of fire for each metric (IMD, Census and IMD and Census combined). In each graph the FRSs have been sorted depending on the difference between the reported and the predicted rate of fire. Therefore the order of the FRSs varies for each of the following three graphs.

Figure 10: IMD predicted rate and FRS reported rate of dwelling fires per FRS

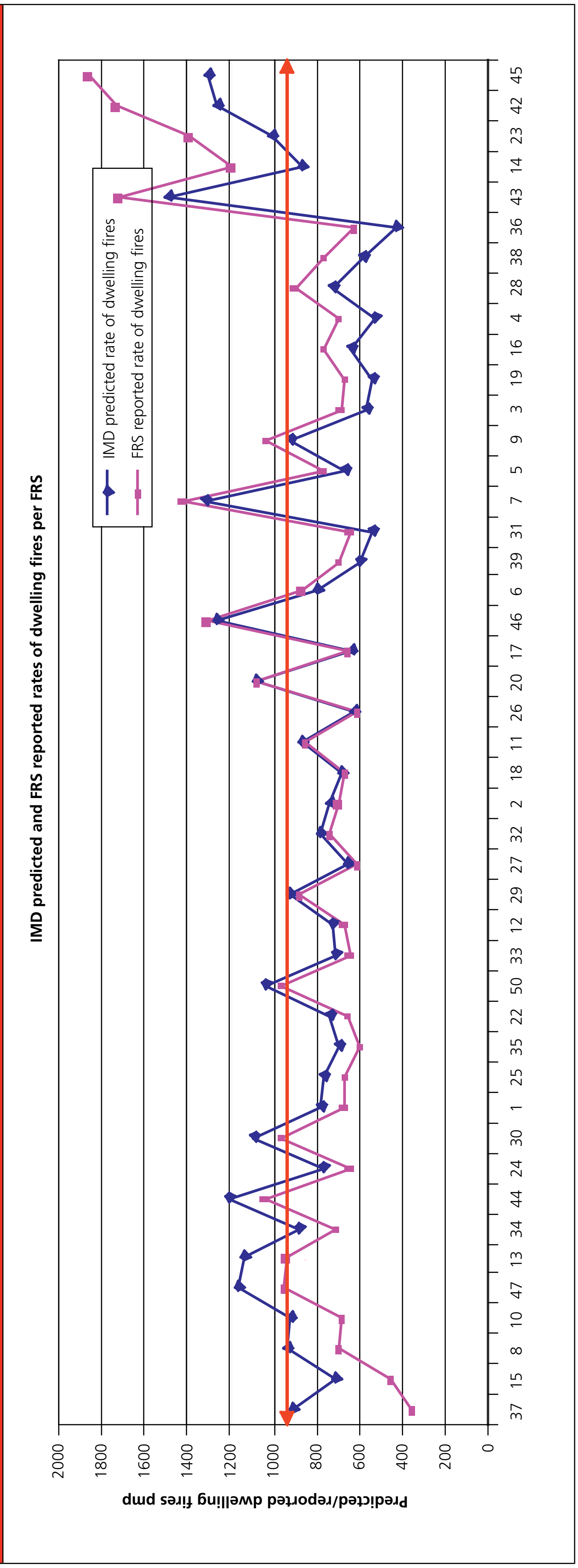


Figure 11: Census predicted rate and FRS reported rate of dwelling fires per FRS

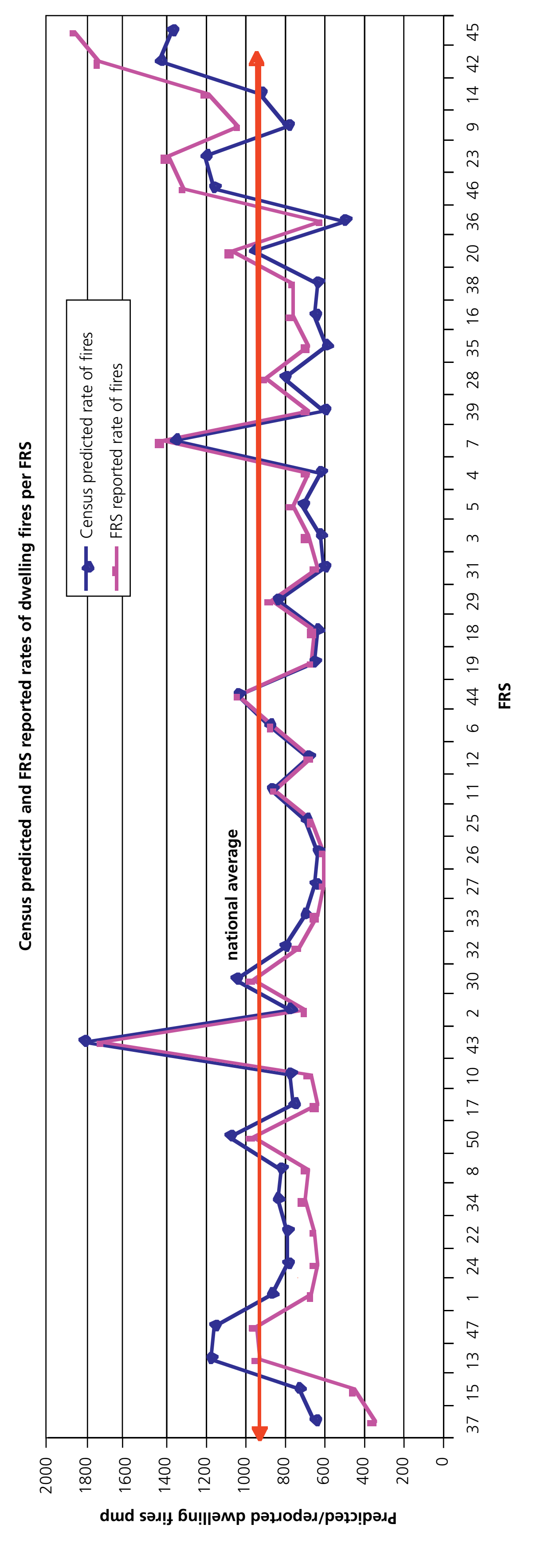
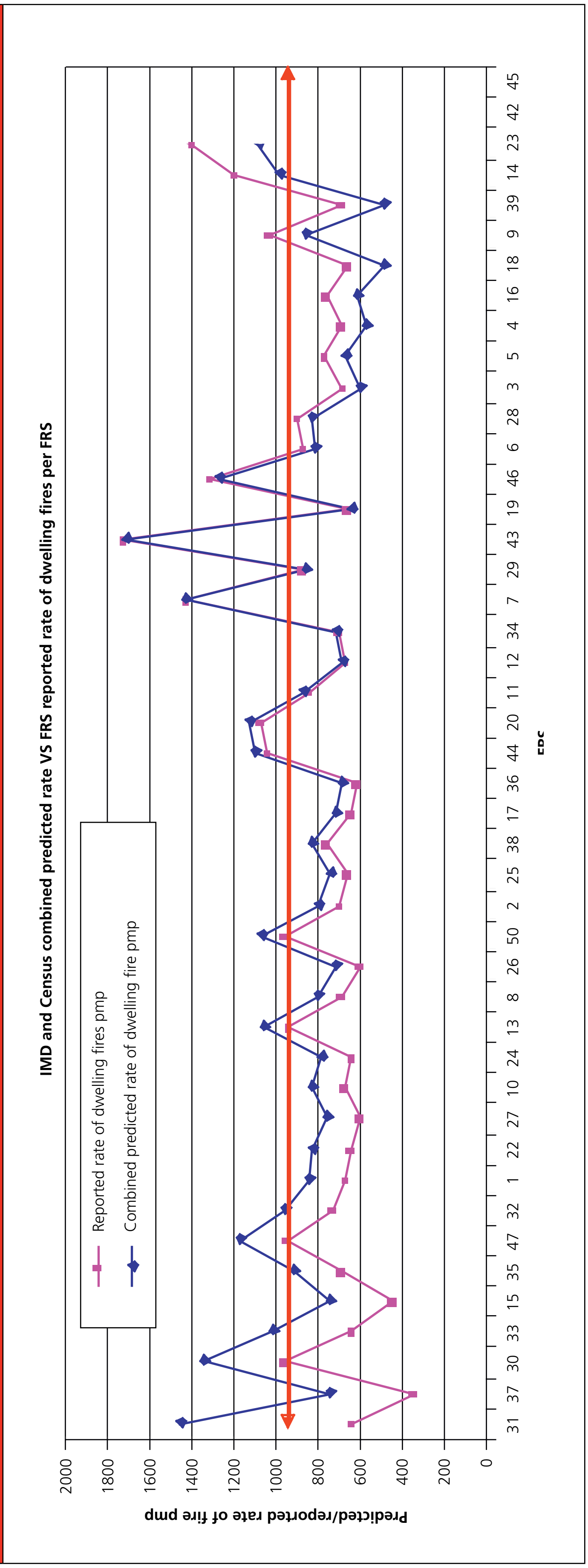


Figure 12: Combined Census and IMD predicted rate and FRS reported rate of dwelling fire per FRS



3.5.2 Dwelling fire injuries

A full list of the IMD, Census and combined data predicted rates of dwelling fire injuries including reported rates for all FRS is presented in Appendix F Specific FRS Results.

The relationship between the predicted and reported rate of dwelling fire injuries using each model is further illustrated in Figure 13, Figure 14 and Figure 15.

All three models suggest that the reported rate of injuries is lower than the predicted rate in about half of the FRSs included in this analysis. A small number of FRS have a reported rate of injuries which is equal to or almost equal to the predicted rate, and about half which have a reported rate which is higher than what would be predicted.

A few examples of FRSs which have a reported rate of injuries below the IMD predicted rate (shown on the left side of the graphs) are Shropshire (FRS 32), West Midlands (FRS 46) and Bedfordshire (FRS 2). This can be seen in Figure 13, Figure 14 and Figure 15.

A few examples of FRSs which have a reported rate of injuries above the IMD predicted rate (shown on the right side of the graphs) are Manchester (FRS 42), Lancashire (FRS 23) and Surrey (FRS 36). This is illustrated in all three graphs.

In terms of differences between the Census, the IMD and the combined model Figure 13 suggests that the reported rate of injuries for Merseyside (FRS 43) is actually higher than the predicted rate. However, in Figure 14 and Figure 15, Merseyside has a reported rate of injuries which is very similar to the predicted rate.

In general, however, most FRSs appear on similar points of each graph, suggesting that the Census, IMD and also the combined model are generally consistent in predicting whether the reported rate of fires/injuries for a particular FRS is above or below the predicted rate.

The following three graphs present the reported rate of dwelling fire injuries compared with the predicted rate of dwelling fire injuries. And as with the previous graphs, the FRSs have been sorted in order of the difference between the predicted rate of dwelling fire injuries and the reported rates of dwelling fire injuries.

Figure 13: IMD predicted rate and FRS reported rate of dwelling fire injuries per FRS

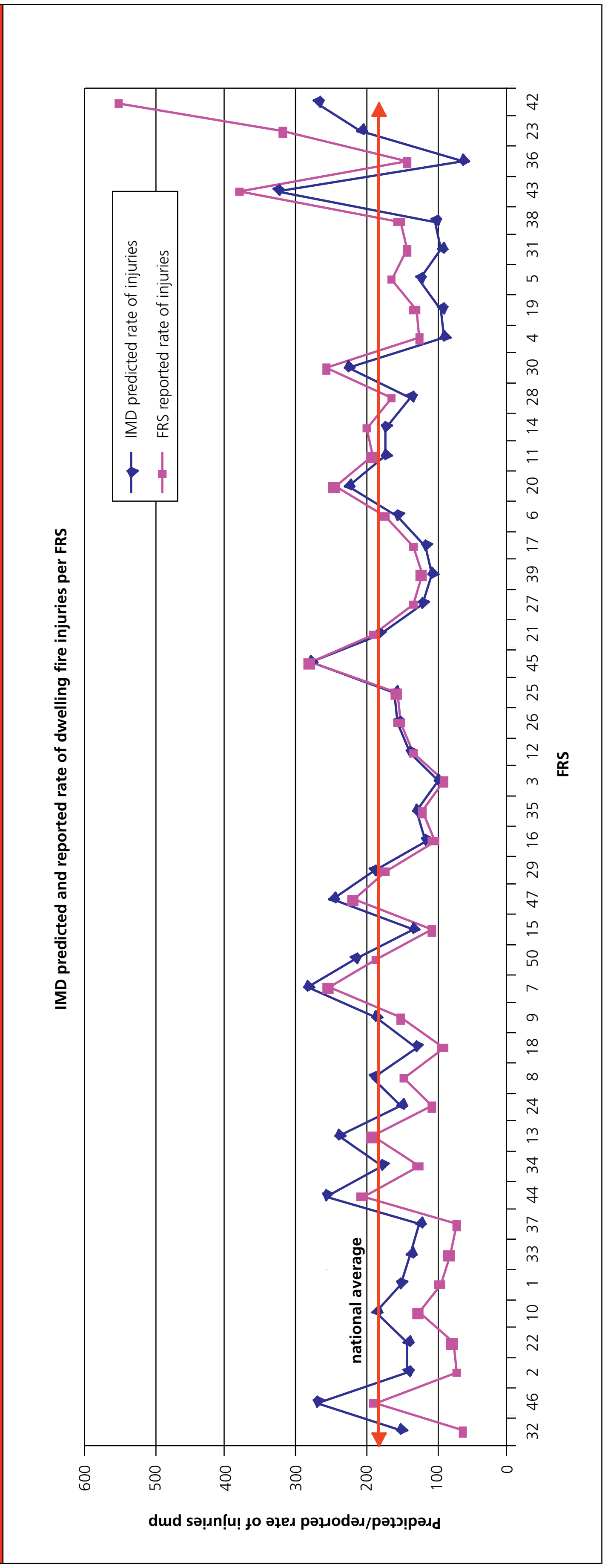


Figure 14: Census predicted rate and FRS reported rate of dwelling fire injuries per FRS

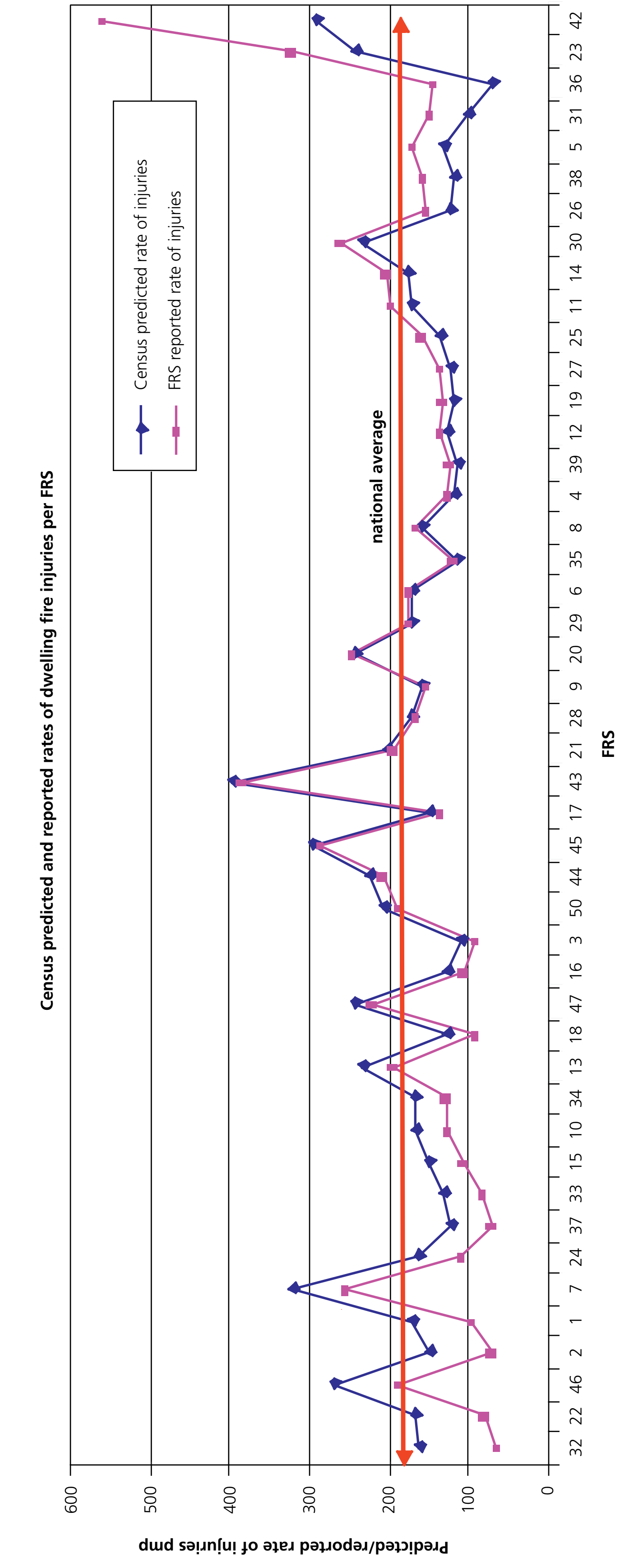
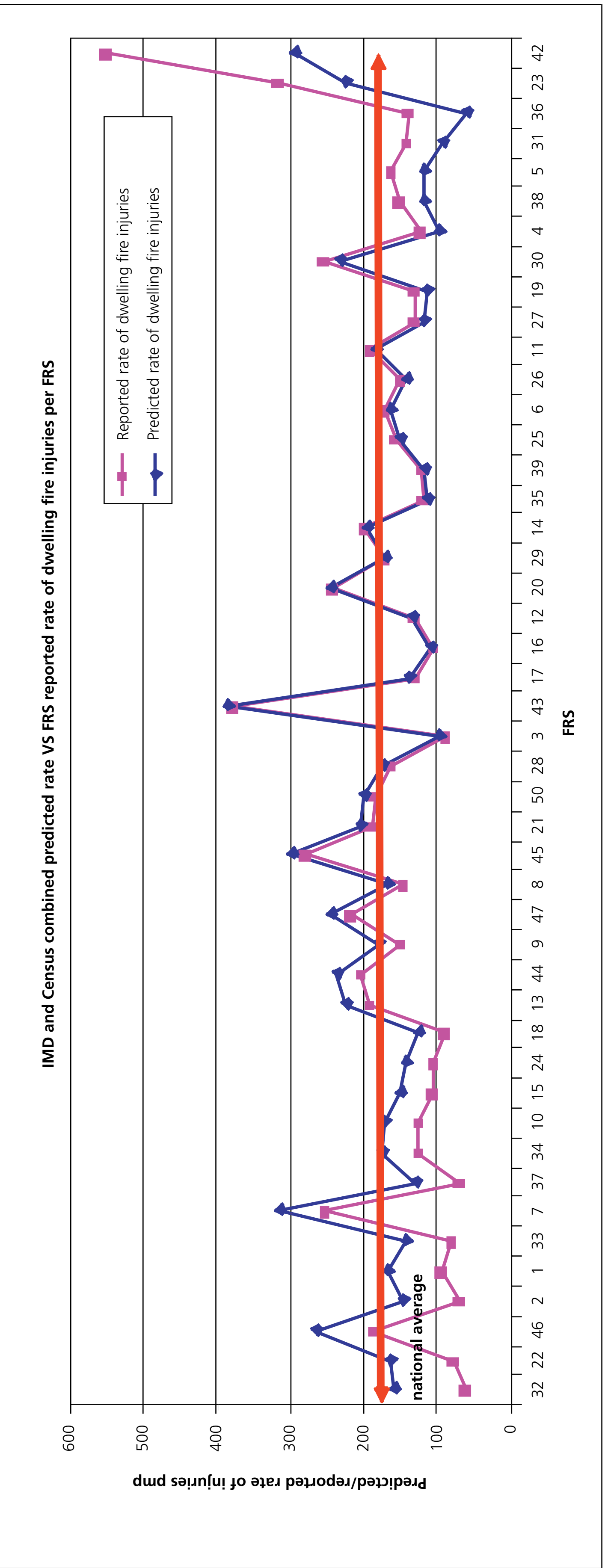


Figure 15: Combined Census and IMD predicted rate and FRS reported rate of dwelling fire injuries per FRS



3.6 Projected rates of dwelling fires and injuries for England

A national projected rate of fires and injuries was calculated for the Census and the IMD data using the two regression formulas. The formula was applied to projected figures of the Census and IMD predictor variables.

For the Census predictor variables, projected figures for 2010 were used. These were obtained from the Department of Communities and Local Government and also from the Government Actuary's Department. Projected figures for the population in England as whole and for the proportion of households with lone parents in 2010 were used. Since projected figures for the remaining predictor variables were unavailable, the current figures were re-calculated as a fraction of the projected 2010 population.

For the IMD data, projected figures for the UK population were unavailable. Projected rates were therefore calculated by increasing and decreasing the predictor variables by 10% to see the effect this would have on fire and injury rates.

The purpose of calculating a projected rate of fires and injuries was to see the impact of changing population profile on future rate of fire and injury and hence the impact on the target of reducing fires and injuries by 20% by 2010.

Using projected figures for the variables included in the regression formulas, projected rates of fire and injuries were calculated for England as a whole.

Table 9 displays the projected rates of fires and injuries using the IMD and Census regression formulas:

Table 9: Projected rate of fires and injuries using IMD and Census regression formulas

Dwelling fires per million population				Dwelling fire injuries per million population			
National average (02-04)	Census projected 2010	IMD projected +10%	IMD projected –10%	National average (02-04)	Census projected 2010	IMD projected +10%	IMD projected –10%
932	1285	989.9	838.5	188	244	204	166
As fraction of 02-04 average	1.38	1.06	0.90	As fraction of 02-04 average	1.30	1.09	0.88

The table shows that both fires and injuries are predicted to increase by the year 2010 according to the projected Census data. The rate of dwelling fires is predicted to be 1.38 times the current national average. The rate of dwelling fire injuries is predicted to be 1.3 times the national average.

The IMD projections suggest that if all the predictor variables are increased by 10%, the rate of dwelling fires will also rise. It is predicted that the rate of dwelling fires will be 1.06 times the current national average rate. The rate of dwelling fire injuries is also predicted to rise if all predictor variables increase by 10%. It is predicted that the rate of injuries will be 1.09 the current national average rate.

If all the IMD predictor variables are reduced by 10%, the rate of dwelling fires is predicted to decrease. For example, the projected rate will be 0.9 times the current national average rate. The rate of dwelling fire injuries is predicted to be 0.88 times the current national average rate.

In summary, the projections based on the Census data suggest that the rate of fires and injuries will increase by 30-38% by 2010. The IMD projections suggest that if the deprivation score is reduced by 10%, the rate of fires and injuries is predicted to decrease by 10-12%.

Chapter 4

Discussion

4.1 Socio-demographic indicators of dwelling fire risk

4.1.1 Key socio demographic risk factors

The assessments consistently indicate that deprivation (such as unemployment) and being single is associated with dwelling fire risk. The census provides the strongest model explaining up to 69% of the variance in the data. The combined IMD and Census regression model and the individual IMD and Census regression models do produce similar predictions for FRSs.

Care must be taken in interpreting the finding that analyses of different sub-sets of England identify somewhat different sets of socio-demographic factors. These differences may simply reflect spurious differences arising from the use of smaller data sets. Also, there are some variables that are common across the majority of regression models, these include;

- Being single (either a single person or single parent);
- Never working.

These are similar to the factors identified in the 'all England' dataset.

The strongest model is provided for dwelling fires, as opposed to fire deaths or injuries. This is probably due to relatively higher rates of dwelling fires than injuries or deaths, leading to fewer areas with zero incidents. The regression model for dwelling fires may be the preferred model for targeting CFS.

4.1.2 The role of age and ethnicity in dwelling fire risk

This assessment has developed the understanding of the role of age in fire risk. It indicates that being single, sick disabled and deprived are factors. It is possible that being elderly is not in itself a factor. Rather it may be the combination of being single, sick/disabled and deprived is more common amongst elderly people. Multiple regression is intended to detect co-linearity between factors and isolate the main factors. Thus, it is possible that it is the commonality of being single, disabled and poor amongst elderly persons that has previously led to the identification of age being a factor.

Age and ethnicity are factors that do appear in the regression models however they do not appear consistently throughout. Some models include one type of ethnicity, while others include another. Therefore it is difficult to draw out any main conclusions from this. Some age groups also appeared in some of the regression models and were more evident in the Census regression models, again, it is hard to see a particular pattern in this and it is not consistent throughout the regression models.

It is also important to note that the main IMD and census regression model for dwelling fires indicates that Caribbean African and other black has a negative value (i.e. fewer fires in areas with more Caribbean African and other black persons).

4.2 Implications for FSEC

This study has produced updated and more powerful models that could replace those currently in the FSEC toolkit. FSEC contains a regression formula to predict the rate of casualty. The exploratory census regression for dwelling fire injuries could replace the one within FSEC without any additional data being added to FSEC. If the IMD is loaded into FSEC, having being 'read down' to output areas, the combined census-IMD regression formula for dwelling fire injuries could be applied, but this would not increase the predictive power of FSEC.

FSEC also used four socio-demographic factors to group output areas. The Potential Risk Factors used for grouping risk areas could also be updated. If FSEC is limited to the census, we would advise that grouping is achieved using only four factors to avoid excessive computation, namely; single parents, never worked, Caribbean/African and other black and single adult household. If the IMD is loaded onto FSEC the employment score could also be used for grouping.

4.3 Currency of IMD and census

Both the census and the IMD suffer from the disadvantage of being rarely updated, once every 10 years for the census. The IMD uses a mixture of data sources such as the DWP data on income support and Inland Revenue working families tax credit. The IMD 2000 was updated in 2004 using 2001 and 2002 data, which is the most recent version identified. Accordingly, neither of the census nor the IMD offer an advantage in respect of currency.

MOSAIC is provided at a household and post code level and is reportedly updated every year. The accuracy of these datasets has not been established in this study. As MOSAIC categorises areas rather than providing a rating of each it is not amenable to regression analysis. Hence it is not possible at this time to produce a regression based predictive model using MOSAIC. However, through judgement its categories can be used to identify areas that share features of the 'at risk' members of the community and hence may be of some use in targeting CFS.

4.4 Benchmarking FRS performance

The finding that dwelling fire risk varies greatly according to socio-demographic factors is thought to have potential implications for target setting and benchmarking. Firstly, it indicates that there are great (four fold) differences in the rate of dwelling fire/casualty arising from differences in socio-demographic factors such as deprivation, disability, being single and unemployment. It could be argued that targets for reducing dwelling fire and casualty should recognise this social inequality in risk.

Secondly, a simple comparison between FRSs of rates of fire and casualty would not take account of the impact of their socio-demographic profiles. A FRS whose predicted rate of fire casualty is, for example, twice the national average may be 'performing' well if the reported rate is 1.5 of the national average.

These findings support the notion of risk weighted (socio-demographic risk) targets and performance measures.

Chapter 5

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Appendix A: Correlation of census with three fire variables

The table below presents the correlations of a reduced set of census variables against the three fire variables.

Census variable	Fires	Injuries	Deaths
Population density	0.423764	0.329354	0.209467
Brigade	0.247046	0.238107	0.143797
Males	–0.15296	–0.17897	–0.12253
Females	0.271559	0.250071	0.159393
Age 0 – 9	0.192439	0.187658	0.101993
Age 10 – 19	0.305099	0.319559	0.111472
Age 20 – 29	0.428254	0.32411	0.18092
Age 30 – 39	0.150679	0.083221	0.061114
Age 40 – 49	–0.40461	–0.36153	–0.24081
Age 50 – 59	-0.5411	-0.4383	-0.23807
Age 60 – 69	-0.27555	-0.21124	-0.13369
Age 70 – 79	-0.18042	-0.13577	-0.0596
Age 80 +	-0.18632	-0.1547	-0.02478
No dependent children	-0.60054	-0.48719	-0.27983
One dependent child	0.455775	0.460055	0.251443
2 or more dependent child	-0.13627	-0.06617	-0.08831
Single never married	0.55225	0.425153	0.22963
Married (1st)	-0.67249	-0.56285	-0.33403
Re-married	-0.45565	-0.33224	-0.14389
Sep (still married)	0.55314	0.472619	0.2631
Divorced	0.338722	0.354673	0.226009
Widowed	0.065228	0.096709	0.089627
British	-0.27915	-0.18165	-0.17075
Irish	0.265376	0.190333	0.11955
Other white	0.107489	0.007002	0.09905
White and black Caribbean	0.332007	0.248094	0.128419
White and black African	0.352911	0.260427	0.174834

Census variable	Fires	Injuries	Deaths
White and Asian	0.212346	0.114068	0.134733
Other mixed	0.233726	0.133939	0.129321
Indian	0.133011	0.078696	0.116777
Pakistani	0.347403	0.29196	0.199004
Bangladeshi	0.168543	0.11819	0.037982
Other Asian	0.132025	0.080869	0.126212
Caribbean	0.241058	0.168029	0.130016
African	0.230528	0.161808	0.137634
Other black	0.250015	0.166281	0.159937
Chinese	0.277696	0.186217	0.082606
Other ethnic group	0.196699	0.092952	0.154335
Good health	-0.43272	-0.43185	-0.27683
Fairly good health	0.217928	0.237314	0.172989
Not good health	0.609362	0.570645	0.343612
No qualifications	0.375432	0.385943	0.222637
level1	-0.28287	-0.1428	-0.14828
level 2	-0.5398	-0.43052	-0.31264
level 3	0.131672	0.059751	0.034072
level 4/5	-0.03134	-0.13215	-0.04518
Other qualifications	-0.21811	-0.09399	-0.05021
In employ	-0.57412	-0.52513	-0.31954
not employed since 2001	0.415502	0.309734	0.162433
not employed since 2000	0.493116	0.411124	0.247447
not employed since 1999	0.552394	0.481939	0.319418
not employed since 1998	0.408708	0.373499	0.253048
not employed since 1997	0.281453	0.268482	0.165676
not employed since 1996	0.249083	0.270381	0.124019
not employed since 1991-1995	0.232381	0.242576	0.114878
not employed since before 1991	0.289829	0.28756	0.15941
Never worked	0.614338	0.483012	0.306642
Part-time	-0.39314	-0.27357	-0.20555
Full-time	-0.26949	-0.26024	-0.18929

Census variable	Fires	Injuries	Deaths
Unemployed	0.670805	0.554186	0.322846
FT Student	0.332859	0.261924	0.09313
Retired	-0.24456	-0.17562	-0.10538
Student	0.41837	0.322816	0.191414
Looking after home/family	0.138399	0.099939	0.119554
Sick disabled	0.650423	0.602202	0.323989
Other	0.616984	0.492586	0.320268
1-2 hours worked	-0.44436	-0.4341	-0.23503
3-5 hours worked	-0.47145	-0.42706	-0.2741
6-15 hours worked	-0.64826	-0.57489	-0.34129
16-30 hours worked	-0.30498	-0.19662	-0.15835
31-37 hours worked	0.298999	0.278976	0.076904
38-48 hours worked	-0.41441	-0.37082	-0.24082
49-59 hours worked	-0.54838	-0.54395	-0.25778
60+ hours worked	-0.46199	-0.47019	-0.19104
Detached	-0.6384	-0.53312	-0.30302
S-detached	0.001532	0.071352	0.00633
Terraced	0.502001	0.457353	0.240206
Purpose flats	0.279044	0.162514	0.087088
converted or shared house	0.262608	0.147876	0.190868
commercial build	0.077908	-0.00153	0.089451
Caravan	-0.3803	-0.34409	-0.21001
shared dwelling	0.291256	0.193473	0.204232
Owns outright	-0.4437	-0.36181	-0.1247
owns	-0.51648	-0.3938	-0.21215
all people living in households	0.040392	0.045498	-0.02133
Owns (mortgage)	-0.38084	-0.27426	-0.19676
shared ownership	0.051241	0.040676	0.034603
Social renter	0.565114	0.471099	0.178423
rented from council	0.510103	0.460563	0.12191
other social rented	0.126872	0.035528	0.117892
Private landlords	0.302167	0.185659	0.215775

Census variable	Fires	Injuries	Deaths
Private rented	0.227832	0.11813	0.170338
employer of household member	-0.29996	-0.293	-0.17316
relative or friend of a household member	0.239856	0.14159	0.219269
other	-0.1772	-0.18627	-0.1238
living rent free	-0.04526	-0.09193	0.013929
pen-owned	-0.31357	-0.24558	-0.09644
pen-rented from council	0.395151	0.367189	0.075739
pen-other social rented	0.082868	-0.00221	0.100073
pen-private rented and living rent free	0.004259	-0.02577	0.101779
Single adult household	0.607173	0.477332	0.261095
Other	-0.50431	-0.44474	-0.26662
AB	-0.35908	-0.39207	-0.22026
C1	-0.35836	-0.33156	-0.14837
C2	-0.13329	-0.0472	-0.03528
D	0.507002	0.496868	0.263764
E	0.518247	0.465477	0.243878
Household – 1 person	0.482719	0.356288	0.221806
Household – 2 people	-0.44039	-0.36981	-0.19802
Household – 3 people	0.121919	0.165315	0.069493
Household – 4 people	-0.43236	-0.33131	-0.24178
Household – 5 people	0.107659	0.102397	0.014286
Household – 6 people	0.383218	0.290385	0.203487
Household – 7 people	0.419707	0.340636	0.222881
Household – 8 + people	0.381435	0.317366	0.193016
1 room	0.242461	0.119684	0.106832
2 rooms	0.280532	0.157603	0.108584
3 rooms	0.389086	0.26655	0.160317
4 rooms	0.410469	0.333682	0.251861
5 rooms	0.225496	0.283542	0.118181
6 rooms	0.002481	0.089215	-0.00794
7 rooms	-0.55266	-0.46971	-0.2824
8 + rooms	-0.57289	-0.53208	-0.28831

Census variable	Fires	Injuries	Deaths
0.5 pp room	-0.16988	-0.15787	-0.07942
0.5 – 1 pp room	0.460379	0.379889	0.18891
1 – 1.5 pp room	0.396607	0.30375	0.223499
1.5 + pp room	0.287682	0.183996	0.168968
pensioner	0.158922	0.135913	0.126509
other	0.473998	0.340734	0.191603
all pen	-0.41041	-0.32332	-0.18702
no children	-0.61265	-0.49962	-0.27412
1 dependent child	-0.47231	-0.36453	-0.19383
2 + dependent child	-0.6168	-0.51281	-0.31869
all children non- dependent	-0.2718	-0.17503	-0.16578
no child	-0.04859	-0.09995	-0.04325
all student			
all pensioner	0.004368	-0.02558	0.03725
other	0.272896	0.157054	0.132694
1 person household	0.482719	0.356288	0.221806
1 adult pensioner no child	0.158922	0.135913	0.126509
1adt non-pensioner no child	0.473998	0.340734	0.191603
other HH	-0.56179	-0.43546	-0.26865
1 adult 1+ child	0.758294	0.694133	0.362606
1 adult non-pensioner + 1 adult pensioner no child or 2 adults pen	-0.37442	-0.29399	-0.16644
2 adults + 1or 2 child	-0.48588	-0.37372	-0.22168
2 adults non-pensioner no child	-0.47755	-0.4552	-0.22647
2adults + 3+ child or 3+ adults + 1+ child	0.133522	0.128394	0.050132
3+ adults + no child	0.052823	0.034035	-0.01946
married couple with dependent child(ren)	-0.58256	-0.48025	-0.27524
married couple no dependent child(ren)	-0.56823	-0.44951	-0.26416
cohabiting couple with dependent child(ren)	0.30036	0.342375	0.161276
cohabiting couple with no dependent child(ren)	0.016259	-0.04899	-1.3E-05
Lone parent with dependent child(ren)	0.767478	0.687477	0.361237

Census variable	Fires	Injuries	Deaths
Lone parent no dependent child(ren)	0.607014	0.516545	0.26598
One person HH	0.482719	0.356288	0.221806
Multi person HH – student	0.389887	0.285926	0.144522
Multi persons HH – all other	0.323105	0.197195	0.15046
Psychiatric hosp/home	-0.1063	-0.12592	-0.10268
Other hosp/home	0.127898	0.074206	0.0094
Children's home	0.01843	0.017204	-0.05534
Nursing home	-0.05996	-0.0504	-0.14749
Residential care home	-0.05087	-0.03277	0.074627
Other home	-0.1576	-0.15696	0.0579
Home or hostel	-0.02768	-0.01637	-0.12428
Other medical care home	-0.13148	-0.11143	-0.03328
Defence est.	-0.24552	-0.18579	0.050157
Prison service est.	-0.21381	-0.20126	0.01335
Probation/ Bail hostel	-0.15188	-0.09181	0.119241
Educational est.	0.157373	0.152561	0.063945
Hotel; Boarding/guest house	-0.01116	-0.02608	0.047535
Hostel	0.217378	0.089795	0.054188
Other comm. est.	0.072978	0.05272	0.024877

Appendix B: Assessment of dwelling fires

B.1 Introduction

This following section presents the results of the analysis of dwelling fires only. The regression analysis covered the following areas:

- All England data;
- Metropolitans;
- Non-Metropolitans;
- 5 FRS family groups;
- Greater Manchester FRS.

Analysis of each data set was carried out for the IMD data at Lower Super Output Area level (LSOA), and at Local Authority (LA) level and also for the 2001 Census data.

B.2 IMD data at local authority level

B.2.1 Introduction

The initial analysis of the IMD data used the data at Super Output area. However, this meant that there were several instances where the rate of dwelling fires would be zero due to looking at such a small geocoded area. Therefore, to ensure that the presences of zeros did not overly influence the regression model the regression analysis was repeated for the IMD data, however, this time looking at a much more condensed data set of local authorities. This ensured that the regression model was not influenced by zeros. This following section presents the findings of the analysis from looking at the IMD data at local authority level for rate of dwelling fires per million people.

B.2.2 Analysis of IMD for all England data set

Correlations

A Pearson r correlation was used to examine the relationship between the number of dwelling fires per million people and the IMD score. The results revealed that the IMD score was quite highly positively correlated with the rate of dwelling fires per million people ($r = .779$, $p < .001$).

IMD regression model for dwelling fires pmp

A regression model was run initially using the IMD score against rate of dwelling fires per million people. The results of the regression model explained 60% of the variance in the data and the model is significant at the 1% significance level {$F = 541.876(1, 353)$, $p < .001$}. The results are presented in Table 10.

Table 10: Regression model of Local Authority IMD data only

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	158.122	31.718		4.985	.000
	IMD Score	35.197	1.512	.779	23.278	.000

IMD regression model with proportion of alarms

A regression model was run using two factors, proportion of dwelling fires with alarms and the IMD score. These factors were then regressed against the dependent variable 'rate of dwelling fires per million people'. The results from the regression model revealed that the model explained 64% of the variance in the data and was significant {$F = 306.704\ (2, 352)$, $p < .001$}. The results from the regression model are presented in Table 11. The Beta values indicate that the proportion of dwelling fires with alarms is the most influential factor in this regression model.

Table 11: Regression model of Local Authority IMD data and proportion of dwelling fires with alarms

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	76.514	34.757		2.201	.028
	Proportion of dwelling fires with alarms	530.182	104.970	.167	5.051	.000
	IMD Score	33.426	1.487	.743	22.480	.000

B.2.3 Assessment IMD Local Authority data for Mets vs. Non-Mets

The data was divided into two sets, data from the Metropolitans and data from Non-Metropolitans. Separate analysis was then carried out on each data set and the results of which are presented in the following section.

Correlations

A Pearson r correlation was used to examine the relationship between the number of dwelling fires per million people and the IMD score for the metropolitan FRSs and then for non-metropolitan FRS. The results revealed that both the IMD scores for Metropolitans ($r = .703$, $p < .001$) and Non-Metropolitans ($r = .733$, $p < .05$) were positively correlated with rate of dwelling fires per million people.

Regression of IMD score at Local Authority Level for Mets vs. No-Mets

Mets – The regression model for Metropolitans explained 49% of the variance in the data and was significant at the 1% level of significance {$F = 65.353(1, 68)$, $p < .001$}.

Non-Mets – The regression model for Non-Metropolitans explained 54% of the variance in the data and was significant at the1% significance level {$F = 328.365(1, 283)$, $p <.001$}.

Table 12: Regression model for Mets and Non-Mets for IMD local authority data

	Mets			Non-Mets		
Element	**B coefficient**	**Std Error**	**T value**	**B coefficient**	**Std Error**	**T value**
Constant	134.612	138.917	.969	208.393	31.858	6.541**
IMD score	37.976	4.698	8.084**	31.534	1.740	18.121**

** Significant at the .001 level
* Significant at the .05 level

B.2.4 Assessment IMD Local Authority data for FRS family groups

The analysis of the IMD at local authority level was repeated for each of the FRS family groups

Correlations

The table below presents the correlations for each family group between IMD score and rate of dwelling fires per million people. All of the correlations are positive, the highest correlation being for family group 3 ($r = 0.818$**) and the lowest for family group 1 ($r = 0.609$**).

Table 13: Correlations for FRS family group of IMD score against rate of dwelling fires per million people	
FRS family group	**R^2**
Group 1	0.609**
Group 2	0.721**
Group 3	0.818**
Group 4	0.761**
Group 5	0.703**

Regression of IMD data at Local Authority Level for FRS family groups

A regression model was run for each of the FRS family groups. The results are displayed in Table 14 and Table 15. The results reveal that the regression model for FRS family group 3 explains the largest amount of variance in the data. The factors included in each regression model are presented in Table 15.

Table 14: Percentage of variance explained in the data together with significance		
FRS family group	**Percentage of variance explained in the data**	**F value or significance**
Group 1	35%	{F = 19.470(1,34), p < .001}
Group 2	51%	{F = 84.300(1,79), p < .001}
Group 3	66%	{F = 72.662(1,37), p < .001}
Group 4	58%	{F = 177.641(1,130), p < .001}
Group 5	49%	{F = 65.353(1, 68), p < .001}.

Table 15: Regression models for each FRS for IMD at local authority level

	Group 1			Group 2			Group 3			Group 4			Group 5		
Element	**B**	**Std error**	**t**	**B**	**Std error**	**t**	**B**	**Std error**	**t**	**B**	**Std error**	**t**	**B**	**Std error**	**t**
Constant	214.5	105.9	2.026	307.4	52.78	5.825**	131.9	74.81	1.763	166.4	48.64	3.421**	134.6	138.9	.969
IMD score	25.3	5.735	4.412**	28.39	3.093	9.181**	34.57	4.056	8.524**	34.22	2.568	13.32**	37.97	4.698	8.084**

B.2.5 Assessment IMD Local Authority data for Manchester

The analysis was repeated focusing on Manchester FRS only. This section of the report details the results of this analysis.

Correlations

A Pearson r correlation was used to examine the relationship between the number of dwelling fires per million people and the IMD score for Manchester FRS only. The results revealed that the IMD score was quite highly positively correlated with the rate of dwelling fires per million people ($r = .881$, $p < .001$).

Regression of IMD data at Local Authority Level for Manchester

A regression model was run to explore the IMD score for Manchester FRS. The results reveal that the model explains 75% of the variance in the data and is significant at the 1% significance level {$F = 27.717(1, 9)$, $p < .001$}. The results are presented in Table 16.

Table 16: Regression model at local authority level for Manchester FRS

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	–315.323	391.593		–.805	.444
	IMD Score	65.771	12.493	.881	5.265	.001

B.3 Analysis of the IMD at Lower Super Output Area Level (LSOA)

This following section of the report presents the findings from the regression analysis for the IMD (LSOA) and rate of dwelling fires per million people.

B.3.1 Correlations between fire data at LSOA

A series of correlations were carried out between the three fire data variables at the level of Lower Super Output Area. The results reveal that at the lower super output area level the only variables that are correlated with each other are dwelling fires and injuries. Fires deaths were not correlated strongly with either dwelling fires or injuries using the lower super output area data.

Table 17: Correlations between measures of dwelling fire using lower super output area data				
		Dwelling fires	**Injuries**	**Deaths**
Dwelling fires	Correlation	–	.572	.098
	P value	–	.000	.000
Injuries	Correlation	–	–	.097
	P value	–	–	.000

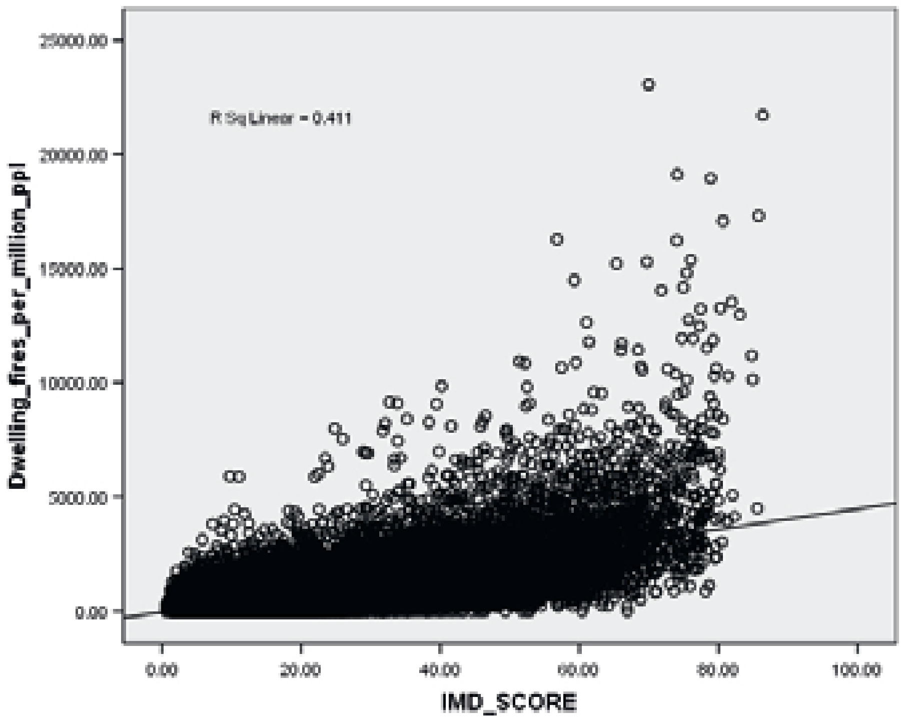
B.3.2 Analysis of IMD for all England data set

Correlations

A Pearson r correlation was used to examine the relationship between the rate of dwelling fires and the IMD score. The results revealed that there was a significant positive relationship between the rate of dwelling fires and the IMD score ($r = .641$, $p < .001$). This suggests that generally as the IMD score increases then so to does the rate of dwelling fires per million people.

Figure 16 below displays the IMD score against the number of dwelling fires per million people. The graph is positively correlated, indicating that as the IMD score increases then so does the dwelling fires per million people. This is graphically presented in Figure 16.

Figure 16: IMD score against dwelling fires per million people



IMD regression model for dwelling fires pmp

A regression model was run for IMD at Lower Super Output Area Level using only the IMD over score for rate of dwelling fires per million people. This model explains 41% of the variance and the overall model is significant {$F = 22690.442(1, 32481)$, $p < .001$}.

Table 18: IMD score by dwelling fires pmp

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	–40.488	8.046		–5.032	.000
	IMD_SCORE	45.249	.300	.641	150.633	.000

IMD sub groups regression model for dwelling fires pmp

The seven sub factors that make up the IMD score including the IMD score were checked for Col-linearity. The results of this revealed that several factors were col-lineated therefore, the overall IMD, income score, health deprivation were removed from the model. A stepwise regression model was run to investigate whether the sub groups that make up the IMD score could be an accurate predictor of dwelling fires per million people. The results reveal that this regression model explains 43% of the variance in this data and is significant at the 1% significance level {$F = 6175.522(4, 32481)$, $p < .001$}. The model is displayed in Table 19. The results of the regression model revealed that employment was the largest influential factor.

Table 19: Sub groups of IMD by dwelling fires pmp

	Unstandardised Coefficients		Standardised Coefficients	t	Sig.
	B	Std. Error	Beta		
(Constant)	–55.868	11.063		–5.050	.000
Employment score	9443.948	105.906	.620	89.173	.000
Living environment score	5.117	.346	.077	14.793	.000
Crime and disorder score	124.592	7.468	.094	16.684	.000
Education skills and training score	–4.992	.386	–.084	–12.924	.000

IMD sub groups regression model including proportion of dwelling fires with smoke detectors for dwelling fires pmp

A stepwise regression model was repeated for the factors in the regression model previously, however, this time the 'proportion of fires with alarms' factor was included in the model. This model explained 44% of the variance in the model and was significant at the 1% significance level {$F = 5043.333(5, 32481)$, $p < .001$}. As above the largest influential factor in the model was 'employment'.

Table 20: Sub-groups of IMD including alarms

	Unstandardised Coefficients		Standardised Coefficients		
	B	Std. Error	Beta	t	Sig.
(Constant)	–98.334	11.290		–8.710	.000
Proportion of dwelling fires with alarms	285.966	16.715	.072	17.109	.000
Employment score	9269.949	105.923	.609	87.516	.000
Education skills and training score	–4.906	.385	–.083	–12.758	.000
Crime and disorder score	120.826	7.438	.091	16.245	.000
Living environment score	5.170	.344	.078	15.011	.000

B.3.3 Assessment of IMD for metropolitans vs. non-metropolitan FRSs

Correlations

A Pearson r correlation was used to examine the relationship between the number of dwelling fires per million people and the IMD score for the metropolitan FRSs and then for non-metropolitan FRS. The results revealed that:

- There was a significant correlation ($r = .621$, $p < .001$) for metropolitan FRS;
- The results revealed that there was a significant correlation ($r = .632$, $p < .001$) for non-metropolitan FRS.

IMD sub-groups model for Mets vs. Non-Mets for dwelling fires per million people

The data was divided into two sets, data from the Metropolitans and data from Non-Metropolitans. Separate analysis was then carried out on each data set and the results of which are presented in the following section.

Two separate regression models were run (Mets and Non-Mets) to investigate if the variables displayed below are good predictors of dwelling fires, as follows:

- The metropolitan regression accounts for 43% of the variance ($F = 2270.964(4, 11827)$, $p < .001$).
- The non-metropolitans regression accounts for 41% of variance ($F = 3500.953(4, 20494)$, $p < .001$).

The results are presented in the Table 21 and suggest that:

- All the factors included in the model are significant
- The employment score is the largest factor in the model for both Mets and Non-Mets
- The majority of the B values indicate that as the deprivation levels increase so too do the number of dwelling fires for both Mets and Non-Mets
- However, for education skills score, as the scores increase then the number of dwelling fires decreases.

Table 21: Dwelling fires regressed against IMD score plus IMD score elements for metropolitans

	Mets			Non-Mets		
Element	**B**	**Std error**	**t**	**B**	**Std error**	**T**
Constant	–287.605	23.301	–12.343**	6210.183	119.421	5.378**
Employment score	11734.986	197.367	59.458**	7210.183	119.421	60.376**
Education skills and training score	–8.887	.751	–11.827**	-2.636	.417	–6.327**
Crime and disorder score	246.509	17.703	13.925**	120.865	7.453	16.216**
Living environment score	2.650	.642	4.130**	8.786	.406	21.662**

** Significant at the .001 level

B.3.4 Assessment of IMD for FRS families

The FRSs displayed in Table 22 have been divided into 5 family groups specified by Communities and Local Government. The 5 family groups each represent FRS with similar characteristics. The FRS family groupings are displayed in Table 22. The following section looks at each of the separate groups in turn by correlating their IMD scores against the number of dwelling fires per million people and then calculating a regression model for each FRS family group using the sub factors that make up the IMD score.

Table 22: FRS family groupings

Group 1	Group 2	Group 3	Group 4	Group 5
Cornwall	Oxfordshire	Cumbria	Cleveland	London
Gloucestershire	Buckinghamshire	Devon	South Wales	Strathclyde
Isle of Wight	Bedfordshire	North Yorkshire	Avon	Tyne and Wear
Northumberland	Berkshire	Hereford and Worcester	Cheshire	West Yorkshire
Shropshire	Cambridgeshire	Lincolnshire	Derbyshire	Gr. Manchester
Somerset	Central	Mid and West Wales	Essex	Merseyside
Warwickshire	Dorset	North Wales	Hampshire	South Yorkshire
	Dumfries and Galloway		Hertfordshire	West Midlands
	Durham		Humberside	
	East Sussex		Kent	
	Fife		Lancashire	
	Norfolk		Leicestershire	
	Northamptonshire		Nottinghamshire	
	Suffolk		Staffordshire	
	Tayside		Surrey	
	West Sussex			
	Wiltshire			

Correlations

A Pearson r correlation was used to examine the relationship between the number of dwelling fires per million people and the IMD score for each of the FRS families.

FRS family group	Pearson correlation	P value
Group 1	.568**	.000
Group 2	.606**	.000
Group 3	.656**	.000
Group 4	.647**	.000
Group 5	.621**	.000

** Significant at the .001 level
* Significant at the .05 level

IMD sub group regression model for each FRS family group

Five separate regression models were run to examine the predictive powers of the IMD score with Income score and Employment score on the number of dwelling fires. Table 23 presents the R squared values for each of the regression models. The models explain between 35% and 46% of the variance in the data.

Table 23: R squared and F value for each FRS family group			
FRS family group	R^2	F	P value
Group 1	.35	341.043	.000
Group 2	.37	1121.181	.000
Group 3	.46	509.087	.000
Group 4	.44	2042.795	.000
Group 5	.43	2270.964	.000

Table 24: IMD regression model for each FRS family group

	Group 1			Group 2			Group 3			Group 4			Group 5		
Element	**B**	**Std error**	**t**	**B**	**Std error**	**t**	**B**	**Std error**	**t**	**B**	**Std error**	**t**	**B**	**Std error**	**t**
Constant	84.49	34.73	2.432*	282.7	19.08	14.8 **	10.02	33.55	.299	–115.6	17.60	–6.56 **	–287.6	23.30	–12.3 **
Employment score	6274.	288.4	21.75**	5200	164.3	31.64**	7411.	338.7	21.88**	8660	171.6	50.44**	11734	197.3	59.458**
Education skills and training score	–	–	–	–	–	–	–2.884	1.100	–2.62*	–4.492	.610	–7.36 **	–8.887	.751	–11.8 **
Crime and disorder score	162.5	19.28	8.428**	195.2	12.20	15.99**	132.6	16.79	7.899**	26.25	12.33	2.128*	246.5	17.70	13.92**
Living environment score	4.276	1.092	3.915**	10.39	.780	13.31**	8.747	.893	9.793**	10.78	.621	17.36**	2.650	.642	4.130**

** Significant at the .001 level

* Significant at the .05 level

B.3.5 Assessment of IMD for Greater Manchester FRS

Correlations

A Pearson r correlation was used to examine the relationship between the number of dwelling fires per million people and the IMD score for Greater Manchester. The results revealed that there was a significant correlation ($r = .683$, $p < .000$).

IMD sub groups regression model against dwelling fires

A regression model was run to examine the predictive power of the IMD score together with two of its sub-groups income score and employment score. This model is presented in Table 25. This model explained 51% of the variance in the data and was significant to the 1% level {$F = 420.871(4, 1645)$, $p < .001$}. Employment score was the largest influential factor in the regression model. From the B value we are able to infer that as the percentage of employment deprived people increases in Manchester, then so too does the number of dwelling fires.

Table 25: IMD regression model for Manchester FRS only

Element	B coefficient	Std Error	T value
Constant	–818.979	86.690	–9.447**
Employment score	15372.177	769.738	19.971**
Education skills and training score	–11.567	3.062	–3.778**
Crime and disorder score	577.112	78.829	7.321**
Living environment score	6.216	2.709	2.295*

** Significant at the .001 level
* Significant at the .05 level

B.4 Assessment of the census for dwelling fires

B.4.1 Introduction

The census data factors were reduced initially by correlating each factor against the dwelling fire data. The correlations are given in Appendix A. Any correlations that were less than 0.6 were excluded automatically. This left a greatly reduced set of variables; however certain variables such as age and ethnicity were initially retained.

The next step was to run a correlation matrix on the remaining variables. Factors correlating higher than 0.8 suggested that certain factors would potentially co-lineate if put in a regression model together. Therefore one of these two variables could be included in regression models but not the other. This data set was used to carry out exploratory analysis of the census data.

A second piece of analysis conducted for the census data was investigating previously identified factors which are detailed later in this section of the report.

B.4.2 Analysis of Census data for all England data

Exploratory census analysis

This regression model explained 69% of the variance in the dwelling fire rate data {$F = 157.146(5, 353)$, $p < .001$}. The results of the regression model are presented in Table 26. The results indicate that the largest influential factor in the model is 'lone parent with dependent child(ren).

Table 26: Exploratory regression model for census data

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	–695.574	97.149		–7.160	.000
	Age_70	1277.732	570.585	.077	2.239	.026
	Caribbean/ African/Other black	–4404.823	472.225	–.390	–9.328	.000
	Never worked	8506.565	1351.385	.321	6.295	.000
	Single adult household	3069.902	739.926	.185	4.149	.000
	Lone parent with dependent child(ren)	32799.640	2463.503	.642	13.314	.000

Previously identified factors

Previous research into dwelling fires has revealed that there are several factors that are considered good predictors of dwelling fires. These include:

- Population density
- Single person households
- Lone Pensioners
- Sick/disabled
- Rented accommodation
- Single person families.

Therefore a linear regression model was run to examine the predictive power of each of these factors as indicators of dwelling fires. The main results of the regression models are presented in Table 28. The beta values for each of the factors indicates that as the number of, for example, single person households increases, then so too will the number of dwelling fires. Table 27 presents the R squared value, the larger the number the more variance is explained by the model. The results indicate that the regression model for single person families explains the most variance with 57% of the variance being explained. The regression model for lone pensioner explains the least variance with only 2% of the variance explained in that model.

Table 27: R squared, F and P values for each regression models of the previously identified factors

	R^2	F	P value
Population density	.17	77.046	.000
Single person household	.37	205.543	.000
Lone pensioner	.02	9.120	.003
Sick disabled	.42	258.105	.000
Socially rented	.31	165.155	.000
Privately rented	.05	19.272	.000
Single person families	.57	476.254	.000

Table 28: Regression models for each of the previously identified factors

	Element	B	Std error	t
Population density	Constant	713.727	24.897	28.667**
	Population Density	8.964	1.021	8.778**
Single person household	Constant	–65.368	65.558	–.997
	Single person household	10068.982	702.319	14.337**
Lone pensioner	Constant	447.365	131.498	3.402**
	Lone pensioner	6437.031	2131.459	3.020*
Sick disabled	Constant	201.236	43.219	4.656**
	Sick disabled	17657.800	1099.103	16.066**
Socially rented	Constant	327.787	43.895	7.467**
	Socially rented	3217.596	250.372	12.851**
Privately rented	Constant	634.718	51.402	12.348**
	Privately rented	2334.782	531.846	4.390**
Single person families	Constant	–190.298	49.391	–3.853**
	Single person families	53275.282	2441.218	21.823**

** Significant at the .001 level
* Significant at the .05 level

Further analysis into previously identified factors

From the individual regression models run to explore the predictive power of previously identified factors is was possible to identify the factors that explain the largest variance in the data. These were combined into one regression model. The factors included were:

- Single person households:
- Sick disabled
- Single person families.

The regression model explained 63% of the variance in the data and was significant at the 1% level {$F = 204.230(3, 353)$, $p < .001$}. The results of this regression model are presented in Table 29. The beta values reveal that single person families is the largest influential factor in this regression model. It is pertinent to note that in this case that sick-disabled has a positive co-efficient.

Table 29: Regression model of more influential previously identified factors

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	–349.754	52.943		–6.606	.000
	Sick disabled	7957.337	1274.340	.293	6.244	.000
	Single adult household	4261.167	729.645	.257	5.840	.000
	Single parent families	26848.104	4115.741	.382	6.523	.000

B.4.3 Assessment of census for Metropolitans vs. Non-Mets

Exploratory analysis

Two regression models were run, one for Mets and one for Non-Mets. The regression model for Mets revealed that the model explained 54% of the variance in the data {$F = 17.076, (5, 68)$, $p < .001$}. The regression model for Non-Mets explained 67% of the variance in the data {$F = 114.065(5,283)$, $p < .001$}.

Table 30: Exploratory analysis of the Census data for Mets vs. Non-Mets						
	Mets			Non-Mets		
Element	**B**	**Std error**	**t**	**B**	**Std error**	**t**
Constant	172.895	626.961	.276	–590.902	69.423	–8.512**
Age 50-59	–5410.34	2576.062	–2.100*			
Irish and other white				1747.246	853.775	2.046*
Caribbean/ African and other black	–3729.55	1230.693	–3.030*	–8289.876	1954.902	–4.241**
Not good health	9978.17	3659.716	2.726*			
Never worked				8830.314	1688.157	5.231**
Single adult household	3424.29	1292.920	2.881*	5596.205	1597.358	3.503**
Lone parent with dependent child(ren)	24910.36	9772.937	2.549*	24846.797	4193.527	5.925**

** Significant at the .001 level
* Significant at the .05 level

Previously identified factors for dwelling fires (Mets vs. Non-Mets)
The following section compares the Mets and Non-Mets for each individual factor. The results from the regression model are presented in Table 31 and Table 32. Key points are:

- The regression model for population density indicates that the model was significant for Non-Mets only.
- The regression model for single person households was significant for both Mets and Non-Mets, more so for Non-Mets. The beta value from both suggests that as the number of single person households increases then so too will the number of dwelling fires.
- The regression model for lone pensioners was significant for both Mets and Non-Mets however, more so for Non-Mets. The beta value for both Mets and Non-Mets suggests that as the number of lone pensioner's increases then so too does the number of dwelling fires.

- Both sick/disabled and socially rented were significant for Mets and Non-Mets. The beta value for both of these factors suggests that as the number of sick/disabled people increases or the number of socially renting people increases then so too will the number of dwelling fires.
- The regression models for privately rented indicated that this was significant for Non-Mets only. The beta value here also suggested that as the number of privately rented households increases then so too do the number of dwelling fires.
- The regression models of single person families was significant for both Mets and Non-Mets and the beta values for both indicated that as the number of single person families increases so too does the number of dwelling fires.
- Table 32 also suggests that the regression models for single person families accounts for 28% of the variance in the data for Mets and 60% of the variance in the data for Non-Mets which is the highest off all the factors.

Table 31: Previously identified factors for Mets and Non-Mets

	Mets			Non-Mets		
	R^2	F	P value	R^2	F	P value
Population density	–.01	.066	.798	.20	72.306	.000
Single person household	.05	4.849	.031	.54	338.147	.000
Lone pensioner	.06	5.043	.028	.04	12.905	.000
Sick disabled	.37	41.640	.000	.37	164.289	.000
Socially rented	.18	15.883	.000	.20	74.710	.000
Privately rented	–.01	.347	.558	.07	22.892	.000
Single person families	.28	27.915	.000	.60	431.036	.000

Table 32: Table of previously identified factors for Mets and Non-Mets

		Mets			Non-Mets		
	Element	**B**	**Std error**	**t**	**B**	**Std error**	**T**
Population density	Constant	1199.128	102.943	11.648**	628.456	22.731	27.647**
	Population Density	.544	2.120	.257	14.918	1.754	8.503**
Single person household	Constant	808.777	196.514	4.116**	-604.131	74.804	-8.076**
	Single person household	3516.136	1596.821	2.202*	16251.505	883.773	18.389**
Lone pensioner	Constant	284.581	420.999	.676	352.957	111.980	3.152*
	Lone pensioner	15795.657	7033.980	2.246*	6472.495	1801.777	3.592**
Sick disabled	Constant	321.847	147.813	2.177*	274.510	40.266	6.817**
	Sick disabled	19777.154	3064.827	6.453**	13985.521	1091.123	12.818**
Socially rented	Constant	707.296	140.696	5.027**	309.268	53.876	5.740**
	Socially rented	2164.950	543.221	3.985**	3145.549	363.922	8.643**
Privately rented	Constant	1154.803	127.453	9.061**	507.396	54.023	9.392**
	Privately rented	615.654	1045.534	.589	2941.482	614.785	4.785**
Single person families	Constant	60.987	225.732	.270	-271.187	50.713	-5.347**
	Single person families	31977.851	6052.449	5.283**	41045.087	1976.990	20.761**

** Significant at the .001 level

* Significant at the .05 level

B.4.4 Assessment of census for FRS Families

Exploratory analysis

Exploratory analysis was carried out on the reduced data set of census variables for each FRS family group. The results are presented in Table 33 and Table 34. From looking over the results it is apparent that not all the same factors were in each regression. This is presumably because each family has different socio-demographics factors that make it up; therefore not all the same factors will appear in each regression model. The regression models for Group 1, Group 2 and Group 3 each explain over 70% of the variance. The remaining groups each explain over 50% of the variance.

From looking over the regression models it is apparent that:

- One factor was common in all four of the regression models, this was 'lone parents with dependent child(ren)'
- The other factors were not consistent across the regression models.

The B co-efficient for each model indicates that as the number of lone parents with dependent children increases so too does the rate of dwelling fires per million people.

Table 33: R squared, F and P value for each regression model of the exploratory analysis

FRS family group	R^2	F	P value
Group 1	.71	29.144	.000
Group 2	.71	51.105	.000
Group 3	.74	52.494	.000
Group 4	.65	123.657	.000
Group 5	.54	17.076	.000

Table 34: Exploratory analysis of the census data for each FRS family group

	Group 1			Group 2			Group 3			Group 4			Group 5		
Element	**B**	**Std error**	**T**	**B**	**Std error**	**t**	**B**	**Std error**	**t**	**B**	**Std error**	**t**	**B**	**Std error**	**t**
Constant	–125.55	126.347	–.994	–385.24	84.255	–4.5**	–641.51	146.710	–4.37**	–423.38	78.460	–5.39**	172.895	626.961	.276
Population Density	14.113	4.245	3.325*												
Age 50-69													–5410.3	2576.06	–2.100*
Irish and other white				2821.72	867.081	3.254*									
Asian	–10046	1995.70	–5.03**												
Caribbean/ African and other black				–7541.8	2106.43	–3.58**							–3729.5	1230.69	–3.030*
Never worked				6494.59	2166.71	2.997*				11151.5	3064.63	3.639**			
Not good health							5017.70	1716.78	2.923*				9978.17	3659.71	2.726*
Single adult household							11864.2	1651.68	7.183**				3724.29	1292.92	2.881*
Lone parent with dependent child(ren)	34461.2	5527.50	6.234**	38602.3	3362.14	11.48**				32793.8	4321.15	7.589**	24910.3	9772.93	2.549*

** Significant at the .001 level

* Significant at the .05 level

Previously identified factors

The following section presents previously identified factors for each FRS family group. The results are presented in Table 35 and Table 36. The results indicate that the regression models for single person households have a high percentage of variance explains for all FRS groups apart from Group 5 which is the Metropolitans. Again this is similar for single parent families where the regression formula explains a quite high percentage of the variance in all FRS groups apart from Group 5.

Table 35: Previously identified factors by family group (R squared, F and P value)

	Group 1			Group 2			Group 3			Group 4			Group 5		
	R^2	F	P value	R^2	F	P value	R^2	F	P value	R^2	F	P value	R^2	F	P value
Population density	.21	10.128	.003	.30	33.991	.000	.25	13.574	.001	.15	24.478	.000	–.01	.066	.798
Single person household	.39	22.548	.000	.63	132.491	.000	.68	79.739	.000	.54	152.205	.000	.05	4.849	.031
Lone pensioner	–.001	.976	.330	.03	3.510	.065	.01	1.375	.249	.08	12.888	.000	.06	5.043	.028
Sick disabled	.35	19.029	.000	.22	23.171	.000	.48	35.765	.000	.49	127.208	.000	.37	41.640	.000
Socially rented	.26	12.664	.001	.31	36.227	.000	.23	12.207	.001	.16	25.848	.000	.18	15.883	.000
Privately rented	–.03	.111	.741	.10	9.855	.002	–.03	.000	.989	.16	25.591	.000	–.01	.347	.558
Single person families	.49	33.954	.000	.64	140.509	.000	.61	58.733	.000	.62	213.809	.000	.28	27.915	.000

** Significant at the .001 level

* Significant at the .05 level

Table 36: Previously identified factors by family group

		Group 1			Group 2			Group 3			Group 4			Group 5		
Element		**B**	**Std error**	**t**	**B**	**Std error**	**t**	**B**	**Std error**	**t**	**B**	**Std error**	**t**	**B**	**Std error**	**t**
Population density	Constant	608.0	39.98	15.20**	637.5	35.64	17.88**	681.7	39.59	17.21**	606.4	44.19	13.72**	1199.	102.9	11.64**
		17.45	5.485	3.182 *	15.38	2.639	5.830**	14.85	4.031	3.684**	15.07	3.047	4.948**	.544	2.120	.257
Single person household	Constant	–406.4	229.9	–1.768	–409	103.9	–3.94 **	–388	130.110	–2.98*	–838	131.5	–6.375 **	808.	196.5	4.116**
		13028	2743	4.748**	14064	1221	11.51**	14198	1590.	8.930**	19001	1540.	12.33**	3516	1596	2.202*
Lone pensioner	Constant	415.4	266.5	1.559	494.9	146.7	3.373**	398.1	308.3	1.291	–87.2	237.8	–.367	284.5	420.9	.676
		3967	4016	.988	4343	2318	1.873	5558	4740	1.173	14382	4006	3.590**	15795	7033	2.246*
Sick disabled	Constant	233.3	106.0	2.200*	492.3	63.63	7.736**	198.7	97.49	2.038*	102.8			321.8	147.8	2.177*
		12086	2770	4.362**	8738.	1815.	4.814**	15568	2603	5.980**	18996	1684.	11.27**	19777	3064	6.453**
Socially rented	Constant	192.3	139.8	1.376	242.1	90.95	2.662*	354.6	120.1	2.952*	342.8	87.61	3.914**	707.2	140.6	5.027**
		3510.	986.5	3.559**	3603.	598.6	6.019**	3151.	902.0	3.494**	2942	578	5.084**	2164	543	3.985**
Privately rented	Constant	720.9	140.4	5.134**	503.0	88.71	5.671**	758.3	127.5	5.947**	332.4	89.93	3.696**	1154	127.4	9.061**
		–488.2	1467.	–.333	2967.	945.3	3.139*	–16.9	1276.	–.013	5861.	1158	5.059**	615	1045	.589
Single person families	Constant	–194.8	151.9	–1.283	–173.	81.54	–2.125*	–145.8	120.3	–1.21	–394	81.68	–4.83 **	60.987	225.7	.270
		36371	6241	5.827**	38979	3288	11.85 **	38053	4965	7.664**	44438	3039	14.62**	31977	6052	5.283**

** Significant at the .001 level

* Significant at the .05 level

B.4.5 Assessment of census for Greater Manchester FRS

Previously identified factors

The regression results for Greater Manchester are shown in Table 37. Single person households (77% of variance explained), single parents (80% of variance explained) and social renters (82% of variance explained) are particularly strong factors. The results in Table 38 indicate that as each of these factors increases then so too does the rate of dwelling fires in Manchester per million people.

Table 37: R squared, F, and P value for Manchester's previously identified factors

	R^2	F	P value
Population density	.29	4.680	.062
Single person household	.77	31.440	.001
Lone pensioner	–.07	.415	.537
Sick disabled	.19	3.053	.119
Socially rented	.82	42.538	.000
Privately rented	.68	19.690	.002
Single person families	.80	36.073	.000

Table 38: Regression models of each previously identified factors for Manchester FRS

	Element	B	Std error	t
Population density	Constant	216.540	710.366	.305
	Population Density	73.989	34.202	.062
Single person household	Constant	–1610.581	599.701	–2.686*
	Single person household	31072.075	5541.495	5.607**
Lone pensioner	Constant	–331.773	3158.314	–.105
	Lone pensioner	32653.803	50651.682	.645
Sick disabled	Constant	–23.659	1005.991	–.024
	Sick disabled	31183.712	17845.822	1.747
Socially rented	Constant	–172.554	301.886	–.572
	Socially rented	9328.110	1430.230	6.522**
Privately rented	Constant	381.701	322.766	1.183
	Privately rented	18547.295	4179.811	4.437*
Single person families	Constant	–1346.534	516.913	–2.605*
	Single person families	114462.5	19057.740	6.006**

** Significant at the .001 level

* Significant at the .05 level

Exploratory analysis

A regression model was run on the factors selected for the exploratory analysis for Manchester only. Due to the sample size from Manchester being relatively small it was not possible to include all the census variables in the regression model. Therefore a few variables that had been identified in other regression models as being particularly influential in the regression model were selected and included in a stepwise regression model for Manchester FRS.

The results from the regression model are presented in Table 39. This model explains 91% of the variance in the data and is significant at the 1% significance level $\{F = 93.878(1,9), p < .001\}$. A stepwise regression model was used and eliminated all factors apart from 'never worked'. The regression formula indicates that as the number of people who never worked increases then so too do the number of dwelling fires.

Table 39: Exploratory regression model for Manchester for Census data

		Unstandardized Coefficients		Standardized Coefficients		
Model		**B**	**Std. Error**	**Beta**	**t**	**Sig.**
1	(Constant)	–217.754	208.559		–1.044	.327
	Never worked	44069.413	4548.367	.960	9.689	.000

B.5 Assessment of Joint IMD AND Census

B.5.1 All England dataset

The IMD data and Census data were combined at local authority level and a regression model was run. The regression model that was produced explained 69% of the variance in the data and was significant at the 1% significance level $\{F = 156.306(5, 353), p = .000\}$. The results of the regression model are presented in Table 40. The most influential factors in this regression model are; Lone parents with dependent child(ren) and never worked.

Table 40: Regression model for IMD data and Census data for dwelling fires						
		Unstandardized Coefficients		Standardized Coefficients		
Model		**B**	**Std. Error**	**Beta**	**t**	**Sig.**
1	(Constant)	–448.355	66.319		–6.761	.000
	Caribbean/ African Other black	–4074.408	542.586	–.360	–7.509	.000
	Never worked	6405.573	1548.577	.242	4.136	.000
	Single adult household	3072.483	741.444	.185	4.144	.000
	Lone parent with dependent child(ren)	27000.036	3915.829	.529	6.895	.000
	IMD score	6.769	3.516	.146	1.925	.055

B.5.2 Assessment of census and IMD for Mets vs. Non-Mets

Mets – the regression model for Mets explained 56% of the variance in the data and was significant at the 1% significance level {$F = 29.713(3,68)$, $p < .001$}.

Non- Mets – the regression model for Non – Mets explained 66% of the variance in the data and was significant at the 1% significance level {$F = 136.021(4,283)$, $p < .001$}.

Table 41: Regression models for Mets vs. Non-Mets for census and IMD combined						
	Mets			Non-Mets		
Element	**B**	**Std. error**	**t**	**B**	**Std. error**	**t**
Constant	–1401.269	433.156	–3.235*	–685.383	93.445	–7.335**
Age 70+	10020.558	2861.544	3.502**	1376.563	481.100	2.861*
Never worked				8059.435	1659.211	4.857**
Single adult household	3905.611	1329.659	2.937*	5384.673	1446.263	3.723**
Lone parent with dependent child(ren)				23597.605	3667.770	6.434**
IMD score	40.668	4.700	8.653**			

B.5.3 Assessment of census and IMD for FRS family groups

A regression model was run for the combined data sets of Census and IMD for each FRS family group. The results of which are presented in Table 42 and Table 43. The regression models explain between 56% and 80% of the variance in the data and are all significant at the 1% significance level.

Table 42: Combined regression model for Census and IMD values for R squared and F and T values

FRS family group	R^2	F	P value
Group 1	.79	26.755	.000
Group 2	.69	87.774	.000
Group 3	.80	49.789	.000
Group 4	.67	67.172	.000
Group 5	.56	156.306	.000

Table 43: Combined regression models for Census and IMD for each FRS family group

	Group 1			Group 2			Group 3			Group 4			Group 5		
Element	**B**	**Std. error**	**T**	**B**	**Std. error**	**t**	**B**	**Std, error**	**t**	**B**	**Std, error**	**t**	**B**	**Std, error**	**t**
Constant	–461.82	147.625	–3.128*	–381.37	95.139	–4.00**	–313.6	106.803	–2.937*	–781.99	133.671	–5.85**	–1401.2	433.156	–3.235*
Population Density	12.893	3.704	3.480*												
Age 70+													10020.5	2861.54	3.502 **
Irish and other white										5249.86	1692.15	3.102*			
Asian	–12843	2021.30	–6.35**							1184.92	556.234	2.130*			
Chinese and other ethnic	53018.8	14550.7	3.644**												
Not good health	4657.53	1995.70	2.334*							6815.75	1793.84	3.800**			
Single adult household				7271.36	2006.75	3.623**	14536.2	3318.98	4.380**				3905.	1329	2.937*
Lone parent with dependent child(ren)	25349.8	6689.34	3.790**	22403.	5501.37	4.072**	–23647.	11285.8	–2.095*	30809.9	4584.54	6.720**			
IMD score													40.66	4.700	8.653**

B.5.4 Assessment of census and IMD for Manchester FRS

A stepwise regression model was run for Manchester FRS only using the combined Census and IMD data. The results revealed that the model explained 77% of the variance and was significant at the 1% significance level {$F = 31.440(1, 9)$ $p = .001$}. The only factor that remained in the regression model was 'single adult household'.

Table 44: Regression model using combined census and IMD data for Manchester FRS

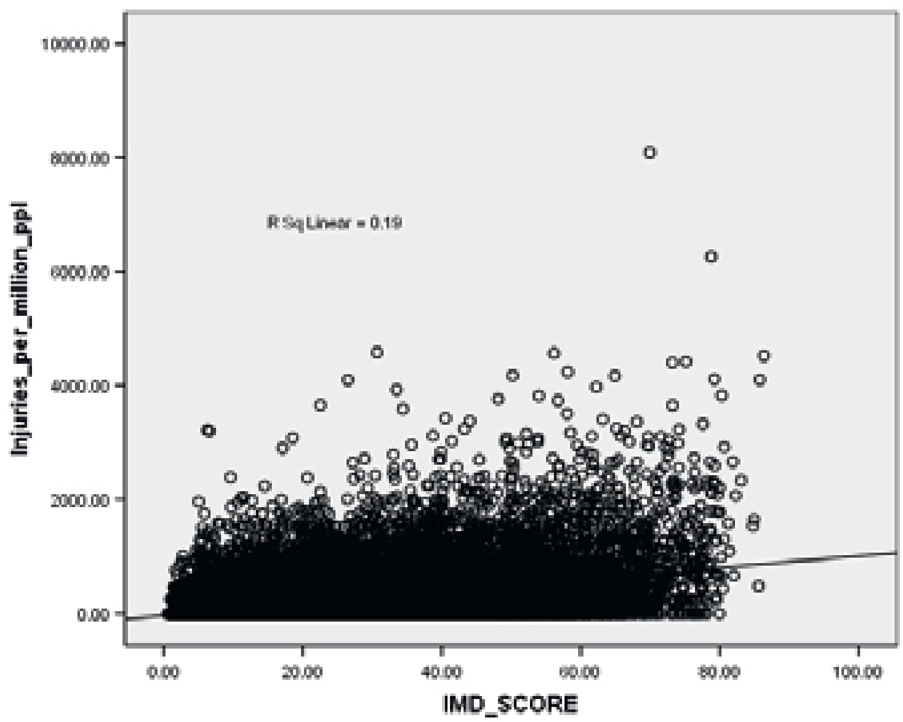
Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	–1610.581	599.701		–2.686	.028
	Single adult household	31072.075	5541.495	.893	5.607	.001

Appendix C: Assessment of dwelling fire injuries

C.1 Analysis of IMD score at Lower Super Output Area

A Pearson r correlation was used to examine the relationship between dwelling fire injuries and the IMD score. The results revealed that there was a significant positive correlation between dwelling fire injuries and IMD score ($r = .436$, $p < .001$) Figure 17 displays IMD score against number of dwelling fire injuries per million people. The graph indicates that the two are positively correlated so that as the IMD score increases as too does the number of dwelling fire injuries per million people.

Figure 17: IMD score against number of injuries per million people



IMD model for dwelling fires injuries

A regression model was run to investigate whether the IMD score is an accurate predictor of dwelling fire injuries. This model explains 19% of the variance {F = 7608.501(14, 32481), p = .000}. The results from the regression are shown below.

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	–37.809	3.218		–11.750	.000
	IMD score	10.479	.120	.436	87.227	.000

IMD sub-group model for dwelling fire injuries

A regression model was run for dwelling fires injuries against several of the sub-groups that make up the IMD score. The results of this regression model reveal that it explains 20% of the variance (F = 2708.820 (4, 32481), p < .001). The results are presented in the table below. Employment score was the most influential factor in this model and the results suggest that as the number of unemployed people increase so too does the rate of dwelling fires per million people.

Table 45: Sub groups of IMD by dwelling fire injuries

Model		Unstandardised Coefficients		Standardised Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	–33.695	4.474		–7.531	.000
	Employment score	1950.773	31.844	.376	61.259	.000
	Living environment score	.959	.139	.042	6.880	.000
	Crime and disorder score	35.147	2.978	.078	11.802	.000

IMD sub-group model including alarms for dwelling fire injuries

A regression model was repeated, however, ‘proportion of dwelling fires with alarms’ was included. This regression model explains 22% of the variance in the data and is significant at the 1% significant level {F = 3002.957(3, 32481), p < .001}. The results revealed again that ‘employment’ score is the most influential factor in the model.

Table 46: Sub groups of IMD including alarms by dwelling fire injuries

Model		Unstandardised Coefficients		Standardised Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	–47.440	3.858		–12.295	.000
	Employment score	1896.386	31.009	.365	61.156	.000
	Crime and disorder score	41.713	2.678	.092	15.575	.000
	Proportion of dwelling fires with alarms	184.517	6.719	.137	27.462	.000

C.2 Analysis of IMD Local Authority data

Correlations

A Pearson r correlation was used to examine the relationship between the number of dwelling fire injuries per million people and the IMD score. The results revealed that the rate of dwelling fires was positively correlated against the IMD score ($r = 0.696$, $p < .001$).

IMD regression model

A regression model was run using only the IMD score regressed against the fire variable rate of dwelling fires per million people. The results from the regression model revealed that the model explained 48% of the variance in the data and was significant {$F = 330.086(2, 352)$, $p < .001$}. The results from the regression model are presented in Table 48.

Table 47: Regression model for IMD score local authority data for rate of dwelling fire injuries

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	–.675	9.972		–.068	.946
	IMD score	8.636	.475	.696	18.168	.000

IMD and proportion of dwelling fires with smoke detectors

A regression model was run using two factors, proportion of dwelling fires with alarms and the IMD score. These factors were then regressed against the dependent variable 'rate of dwelling fire injuries per million people'. The results from the regression model revealed that the model explained 52% of the variance in the data and was significant {$F = 194.259(2, 352)$, $p < .001$}. The results from the regression model are presented in Table 48.

Table 48: Regression model for IMD score and proportion of dwelling fires with alarms at local authority data for rate of dwelling fire injuries

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	–29.207	10.932		–2.672	.008
	Proportion of dwelling fires with alarms	181.925	33.015	.208	5.510	.000
	IMD score	8.040	.468	.649	17.192	.000

C.3 Analysis of Census at Local Authority Level

Exploratory analysis

A regression model was run on the census data to explore the factors that combine to produce the most accurate predictors of dwelling fire injuries. This model explains 54% of the variance in the data {$F = 138.257(3,353)$, $p < .001$} and the results are presented in Table 49. The beta values from the output suggest that the variable 'lone parents with dependent children' has the largest influence over the model and suggests that as the number of lone parents with dependent child(ren) increases then so too does the rate of dwelling fires per million people.

Table 49: Exploratory regression model for dwelling fire injuries

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	–146.597	16.021		–9.150	.000
	Caribbean/African Other black	–1106.940	152.169	–.357	–7.274	.000
	Never worked	1236.730	435.128	.170	2.842	.005
	Lone parent with dependent child(ren)	10620.448	743.440	.758	14.286	.000

Previously identified factors

As with dwelling fires, the analysis looked at previously identified factors and regressed each factor individually against dwelling fire injuries. The results are presented in Table 50 and Table 51. Results indicate that the regression model for single person families explains the most variance in the data (48%). All the regression models were significant apart from 'lone pensioner'.

Table 50: Previously identified factors for dwelling fire injuries

	R^2	F	P value
Population density	.10	42.829	.000
Single person household	.23	103.868	.000
Lone pensioner	.02	6.625	.094
Sick disabled	.36	200.285	.000
Socially rented	.22	100.404	.000
Privately rented	.01	4.982	.000
Single person families	.48	327.302	.000

Table 51: Regression models for previously identified factors for dwelling fire injuries				
	Element	**B**	**Std error**	**t**
Population density	Constant	138.850	7.120	19.502**
	Population Density	1.911	.292	6.544**
Single person household	Constant	–29.486	19.890	–1.482
	Single person household	2171.593	213.078	10.192**
Lone pensioner	Constant	73.681	36.200	2.035*
	Lone pensioner	1510.243	586.769	2.574*
Sick disabled	Constant	3.579	12.462	.287
	Sick disabled	4485.053	316.916	14.152**
Socially rented	Constant	48.651	12.875	3.779**
	Socially rented	735.854	73.437	10.020**
Privately rented	Constant	136.485	14.381	9.491**
	Privately rented	332.107	148.797	2.232*
Single person families (with one child)	Constant	–92.913	14.962	–6.210**
	Single person families	13378.745	739.505	18.091**

Further analysis into previously identified factors

From the individual regression models run to explore the predictive power of previously identified factors is was possible to identify the factors that explain the largest variance in the data. These were combined into one regression model. The factors included were:

- Sick disabled
- Single parent families (with one child).

The regression model explained 50 percent of the variance in the data and was significant at the 1% level {$F = 180.155(2, 353)$, $p < .001$}. The results are presented in Table 52. The beta values indicate that single parent families are the largest influencing factor in this regression model and as the number of single parent families and the number of sick/disabled increase then so too do the number of dwelling fires.

Table 52: Regression model of previously identified factors for dwelling fire injuries

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	–94.139	14.624		–6.437	.000
	Single parent families	10345.083	1022.539	.537	10.117	.000
	Sick disabled	1656.965	395.123	.222	4.194	.000

C.4 Analysis of the combined data sets of Census and IMD

The census and IMD data were combined together at the local authority level. A stepwise regression model was run. The model that was produced explained 54% of the variance in the data and was significant at the 1%. The model suggests that 'lone parent with dependent child' is the most influential factor in this model.

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	–110.890	18.557		–5.976	.000
	IMD score	3.219	1.001	.254	3.217	.001
	Lone parent with dependent child(ren)	8384.445	1234.568	.599	6.791	.000
	Caribbean/ African and other black	–760.003	140.477	–.245	–5.410	.000

Appendix D: Assessment of dwelling fire deaths

D.1 Introduction

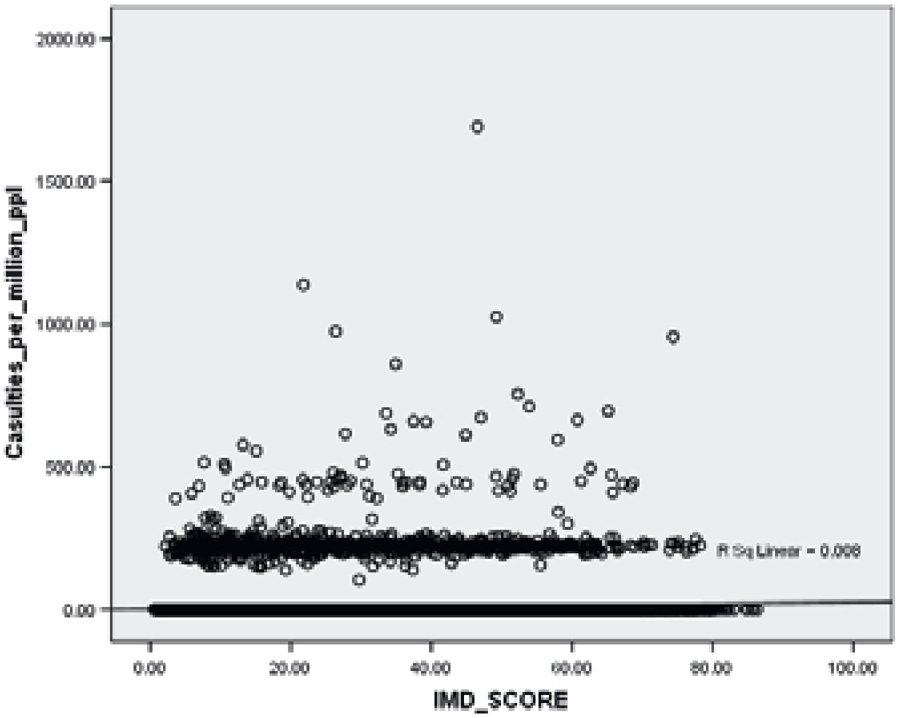
This section of the report presents the findings of the analysis from looking at dwelling fire deaths for the IMD (LSOA). The regression models only explained 8% of the variance in the data. This analysis revealed that due to the relatively low number of dwelling fire deaths, further analysis of the dwelling fire deaths would provide no insight. Therefore it was decided to exclude further analysis of dwelling fire deaths.

Analysis of Census for dwelling fire injuries revealed that the regression model only explained 55% of the variance in the data and that further analysis of dwelling fire deaths would explain even less. Therefore a decision was made not to analysis dwelling fire injuries for the Census data.

D.2 Analysis of IMD score at Lower Super Output Area

A Pearson r correlation was used to examine the relationship between dwelling fire deaths and the IMD score. The results revealed that there was not a positive correlation between dwelling fire deaths and IMD score ($r = .087$, $p < .001$) Figure 18 displays the IMD score against the number of fire deaths per million people. The graph indicates that there is not a correlation between the IMD score and the number dwelling fire deaths per million people.

Figure 18: IMD score against number of dwelling fires per million people



IMD model for dwelling fire deaths using LSOA

A regression model was run to investigate whether the IMD score together with a couple of the sub-groups that make up the IMD score (income and employment) are accurate predictors of dwelling fire deaths. This model explains 8% of the variance {F = 83.954(3, 32481), p = .000}. The table below presents the output from the regression model. The beta value indicates for income score that as the percentage of people income deprived decreases then the number of dwelling fire deaths increases, however this factor was not significant. This goes against some of the other findings in this study that have found that as the percentage people income deprived increases so to does the number of dwelling fires.

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	.788	.422		1.866	.062
	IMD_SCORE	.269	.066	.100	4.097	.000
	INCOME_SCORE	–9.214	7.071	–.025	–1.303	.193
	EMPLOYMENT_ SCORE	7.250	9.240	.012	.785	.433

IMD sub-group model for dwelling fire deaths

A regression model was run to investigate whether the sub groups that make up the IMD score could be an accurate predictor of dwelling fire deaths per million people. The regression model of fire deaths only predicts 8% of the variance in the data {$F = 40.336(7, 32481)$, $p = .000$}. The regression model is presented in the table below. The results reveal that only employment score, health deprivation and disability score, education skills and training and living environment score were significant.

Table 53: Sub groups of IMD by dwelling fire deaths

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	–1.469	.891		–1.648	.099
	IMD_SCORE	.197	.111	.073	1.772	.076
	INCOME_SCORE	–4.212	8.079	–.011	–.521	.602
	EMPLOYMENT_SCORE	35.655	11.969	.061	2.979	.003
	HEALTH_DEPRIVATION_AND_DISABILITY_SCORE	–1.915	.614	–.040	–3.118	.002
	EDUCATION_SKILLS_AND_TRAINING_SCORE	–.051	.024	–.023	–2.093	.036
	CRIME_AND_DISORDER_SCORE	.590	.433	.012	1.363	.173
	LIVING_ENVIRONMENT_SCORE	.057	.023	.023	2.466	.014

Appendix E: Qualitative analysis of mosaic data

Type	Name	Description	Fire risk rating	Identifying risk factor
F38	Tower Block Living	Young people in public sector high rise tower blocks with high levels of deprivation	High	Deprivation
F39	Dignified Dependency	Settled older couples and pensioners with low income renting small flats and maisonettes	High	Older people, renting
I48	Old People in Flats	Single pensioners in small, publicly rented flats, many of which were built for this age group.	High	Single person households, pensioners, rented accommodation
I49	Low Income Elderly	Elderly people living in low rise council housing, often on low incomes.	High	Low incomes, elderly
E32	Dinky Developments	Singles and childless couples in cul de sacs of small, often Brownfield-site, newly built town houses	Medium High	Single people
F35	Bedsit Beneficiaries	Childless couples and singles renting in city centres from private or public landlords	Medium High	Single people
I50	Cared for Pensioners	Old people in specially constructed accommodation mostly managed by local authorities, many with a resident warden.	Medium High	Elderly people
J51	Sepia Memories	Very elderly people of independent means who have moved to modest apartments suitable for their needs	Medium High	Elderly people
A04	Golden Empty Nesters	Families in later life-stages, many retired following successful careers, in select neighbourhoods	Medium	Older people.

Type	Name	Description	Fire risk rating	Identifying risk factor
D21	Respectable Rows	Younger service workers enjoying a reasonably prosperous lifestyle in relatively small terraces	Medium	Terrace housing
D23	Industrial Grit	Self-sufficient families traditionally reliant on industrial employment, living in older terraces	Medium	Older terrace housing
D24	Coronation Street	Young families with limited incomes living in cheap terraced housing.	Medium	Limited income, terraced housing
D25	Town Centre Refuge	Young, unattached people in small flats above shops and older housing close to small town centres	Medium	Flats, older housing
D26	South Asian Industry	Larger families, many of South Asian origin, in high-density terraces	Medium	Ethnic groups, terraced
E29	City Adventurers	High-salaried, twenty-something singles in smart flats in inner urban areas.	Medium	Single people
E33	Town Gown Transition	Students and academics mix with young professionals in terraces relatively close to universities	Medium	Terrace housing
F37	Upper Floor Families	Low income young families with children in small, hard to let blocks of public sector purpose built flats	Medium	Low income, purpose built flats
F40	Sharing a Staircase	Young children in mid-rise, walk-up council flats with poor social and housing conditions.	Medium	Poor social and housing conditions
G41	Families on Benefits	Disadvantaged families with children on very low incomes, typically living in low rise council estates	Medium	Deprivation, low income
G42	Low Horizons	Tenants reliant on city councils for housing and transport, where few neighbours have bought their homes	Medium	Renting

Type	Name	Description	Fire risk rating	Identifying risk factor
G43	Ex-Industrial Legacy	Settled but poor older people in low-rise social housing, often found in declining industrial areas	Medium	Low income
H44	Rustbelt Resiliance	Workers reliant on manufacturing employment living in low value terraced houses.	Medium	Terrace housing
H45	Older Right to Buy	Low income older workers in manufacturing jobs, some may have bought their council terraces.	Medium	Low income.
E31	Caring Professionals	Well qualified singles and couples in caring professions renting lower quality inner terraces	Medium Low	Single people, terrace housing
J53	High Spending Elders	Well-off early retirees enjoying affluent and active lifestyles in pleasant locations	Medium	Older people
J54	Bungalow Retirement	Better-off, relatively active pensioners who favour bungalows often in traditional retirement areas	Medium	Pensioners
J55	Small Town Seniors	Lower income pensioners and middle income workers who live in small, semi-rural communities and resorts	Medium	Low income, pensioners
F36	Metro Multiculture	Tenants of public housing in inner city areas, with a high proportion belonging to minority communities	Medium	Renting
E30	New Urban Colonists	Younger, high-achieving professionals, enjoying a cosmopolitan lifestyle in a gentrified urban environment	Medium Low	Urban environment
H46	White Van Culture	Younger owners, many in good quality ex-council properties, take advantage of local economic opportunities	Low	–

Type	Name	Description	Fire risk rating	Identifying risk factor
H47	New Town Materialism	Young families with local light industry or factory jobs have confidently exercised their right to buy	Low	–
A01	Global Connections	Very affluent, cosmopolitan sophisticates found in extremely expensive housing.	Low	–
A02	Cultural Leadership	Well-to-do professionals, living in traditional family units in exclusive suburbs	Low	–
A03	Corporate Chieftains	Top business people returning late at night to their big houses in extensive grounds	Low	–
A05	Provincial Privilege	Well-educated older professionals living in established suburbs	Low	–
A06	High Technologists	Corporate high-fliers living in spacious, often modern, detached houses	Low	–
A07	Semi-Rural Seclusion	Higher income families living on the outskirts of commutable metropolitan areas	Low	–
B08	Just Moving In	The occupants of very recently built housing	Low	–
B09	Fledgling Nurseries	Very young couples in recently developed housing working in intermediate jobs	Low	–
B10	Upscale New Owners	Younger professionals and managers who have bought expensive modern housing	Low	–
B11	Families Making Good	Upper middle income families in good quality housing, many with school age children	Low	–
B12	Middle Rung Families	Mortgaged owner occupier families with middle income	Low	–
B13	Burdened Optimists	Young couples and families of modest education striving for an aspirational standard of living	Low	–

Type	Name	Description	Fire risk rating	Identifying risk factor
B14	In Military Quarters	Servicemen and their families who live in military accommodation	Low	–
C15	Close to Retirement	Older couples and families reaping the benefits of their industrious working lives.	Low	–
C16	Conservative Values	Better off older couples living in bungalows and houses with large gardens, conservative in values and tastes	Low	–
C17	Small Time Business	Local professionals and small business proprietors in quiet residential areas	Low	–
C18	Sprawling Subtopia	Middle aged, middle income owner occupiers in repetitive, semi-detached housing	Low	–
C19	Original Suburbs	Upper white collar owners in established suburban housing	Low	–
C20	Asian Enterprise	Well-qualified minority groups, many from Asia, living in semi-detached suburban areas.	Low	–
D22	Affluent Blue Collar	Older manual workers with a good standard of living in comfortable semis where traditional working class values are held	Low	–
D27	Settled Minorities	Young families and singles of varied ethnic decent, in high density, pleasant urban terraces.	Low	–
E28	Counter Cultural Mix	Young, mobile population in a mix of jobs either in the service economy or in professional employment, in run-down urban areas.	Low	–
E34	University Challenge	Undergraduate students living in halls of residence or close to universities	Low	–

Type	Name	Description	Fire risk rating	Identifying risk factor
J52	Childfree Serenity	Well-educated couples and wealthy older people in smart private flats or older town houses	Low	–
J56	Tourist Attendants	People living in seaside resorts and small inland towns who cater for the needs of visitors.	Low	–
K57	Summer Playgrounds	Incoming visitors and locals in places of great natural beauty	Low	–
K58	Greenbelt Guardians	Farmers and wealthy commuters in rural areas accessible to towns	Low	–
K59	Parochial Villagers	Village dwellers living well away from major population centres	Low	–
K60	Pastoral Symphony	Scattered farmers, many of whom are owner managers of medium sized operations, in sparsely populated locations	Low	–
K61	Upland Hill Farmers	Farmers in more isolated areas of mostly upland agriculture who manage small farm holdings	Low	–

Appendix F Specific FRS Results

F.1 Dwelling fires

Table 54 shows the IMD and Census predicted rates of dwelling fires, and also the reported rate for each FRS:

Table 54: IMD and Census predicted and reported rates of fires per FRS

National average rate = 932		IMD predicted rate of dwelling fires pmp	Census predicted rate of dwelling fires pmp	IMD and Census combined predicted rate of fires pmp	FRS reported rate of dwelling fires pmp
FRS					
50	London	1037	1078	1019	964
47	West Yorks	1165	1155	1182	949
46	West Midlands	1264	1162	1202	1310
45	Tyne & Wear	1302	1370	1417	1861
44	South Yorks	1209	1043	1028	1038
43	Merseyside	1485	1813	1969	1723
42	Manchester	1258	1436	1517	1737
39	Wiltshire	598	607	490	693
38	West Sussex	577	647	760	760
37	Warwickshire	909	649	681	350
36	Surrey	424	505	692	622
35	Suffolk	688	595	870	594
34	Staffordshire	886	844	678	707
33	Somerset	713	705	964	644
32	Shropshire	781	803	895	733
31	Oxfordshire	537	606	1507	640
30	Nottinghamshire	1087	1048	1417	963
29	Northumberland	929	846	766	876
28	Northants	720	806	733	894
27	North Yorks	656	649	782	607
26	Norfolk	620	643	739	603

Table 54: IMD and Census predicted and reported rates of fires per FRS

National average rate = 932		IMD predicted rate of dwelling fires pmp	Census predicted rate of dwelling fires pmp	IMD and Census combined predicted rate of fires pmp	FRS reported rate of dwelling fires pmp
FRS					
25	Lincolnshire	762	695	648	663
24	Leicestershire	772	790	769	643
23	Lancashire	1005	1200	1126	1393
22	Kent	733	794	765	649
21	Isle of Wight	901	922	912	829
20	Humberside	1079	960	912	1074
19	Hertfordshire	537	655	645	664
18	Hereford/Worc	686	647	442	659
17	Hampshire	635	760	757	646
16	Gloucestershire	634	651	614	763
15	Essex	710	739	670	450
14	East Sussex	865	924	1044	1198
13	Durham	1136	1184	1043	936
12	Dorset	728	693	775	671
11	Devon	867	872	868	848
10	Derbyshire	916	784	812	674
9	Cumbria	919	790	884	1034
8	Cornwall	933	824	747	689
7	Cleveland	1316	1355	1400	1422
6	Cheshire	799	883	864	869
5	Cambridgeshire	659	710	621	769
4	Buckinghamshire	530	631	576	692
3	Berkshire	560	632	638	687
2	Bedfordshire	731	784	865	695
1	Avon	775	874	967	668

F.2 Dwelling fire injuries

Table 55 shows the IMD and Census predicted rates of dwelling fire injuries, with the reported rate for all FRSs:

Table 55: IMD and Census predicted and reported rates of dwelling fire injuries per FRS

National average rate = 188		IMD predicted rate of dwelling fire injuries pmp	Census predicted rate of dwelling fire injuries pmp	IMD and Census combined predicted rate of injuries pmp	FRS reported rate of dwelling fire injuries
FRS					
50	London	215	206	191	185
47	West Yorks	246	251	275	218
46	West Midlands	271	262	261	187
45	Tyne & Wear	280	284	294	280
44	South Yorks	257	212	227	204
43	Merseyside	325	403	440	377
42	Manchester	269	313	358	550
39	Wiltshire	107	119	129	121
38	West Sussex	102	128	138	153
37	Warwickshire	124	120	118	70
36	Surrey	65	79	77	140
35	Suffolk	129	110	94	118
34	Staffordshire	178	164	169	126
33	Somerset	135	134	153	80
32	Shropshire	152	164	127	62
31	Oxfordshire	92	115	117	141
30	Nottinghamshire	227	228	224	254
29	Northumberland	188	151	137	174
28	Northants	137	176	150	163
27	North Yorks	122	122	130	132
26	Norfolk	154	112	134	151

Table 55: IMD and Census predicted and reported rates of dwelling fire injuries per FRS					
National average rate = 188		**IMD predicted rate of dwelling fire injuries pmp**	**Census predicted rate of dwelling fire injuries pmp**	**IMD and Census combined predicted rate of injuries pmp**	**FRS reported rate of dwelling fire injuries**
FRS					
25	Lincolnshire	159	128	120	157
24	Leicestershire	150	164	143	106
23	Lancashire	207	255	249	316
22	Kent	140	170	141	78
21	Isle of Wight	182	190	154	188
20	Humberside	225	221	183	243
19	Hertfordshire	92	130	117	131
18	Hereford/Worc	129	122	119	90
17	Hampshire	116	160	159	132
16	Gloucestershire	116	125	102	104
15	Essex	135	151	127	106
14	East Sussex	173	179	209	199
13	Durham	239	227	209	191
12	Dorset	139	129	159	131
11	Devon	173	173	176	191
10	Derbyshire	185	154	164	124
9	Cumbria	186	143	171	150
8	Cornwall	189	147	152	146
7	Cleveland	283	298	269	252
6	Cheshire	157	172	173	173
5	Cambridgeshire	122	137	112	163
4	Buckinghamshire	90	124	94	123
3	Berkshire	98	115	106	89
2	Bedfordshire	140	152	153	71
1	Avon	151	183	210	94

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