The impact of introducing a National Minimum Wage for 16 and 17 year olds on employment and education outcomes

A report for the Low Pay Commission

20th January 2004.

Christine Frayne
Alissa Goodman

Acknowledgements

We would like to thank the LPC for funding this project, and for their very helpful comments on previous drafts. We would also like to thank the DfES for granting permission to use the EMA dataset for this work. Thanks also to many of our colleagues at IFS for very detailed and helpful discussions, including Erich Battistin, Mike Brewer, Carl Emmerson, Amanda Gosling, Howard Reed, and Costas Meghir.

Table of Contents

Executive Summary

1. We cannot know with certainty what the impact of a NMW for 16 and 17 year olds would be. Its effects would depend both on the structure of the labour market for this group of workers, how far up the wage distribution any new minimum would bite, and on how responsive firms and young people are to changes in the financial incentives facing them.
2. In this report we have attempted to set bounds on the possible effect of the minimum wage, by describing how much employment might fall if labour markets are competitive, and how much it might rise in the monopsonistic case. The true outcome is likely to lie between these two.
3. We used data consisting of a large sample of 16 and 17 year olds living in relatively deprived urban areas collected for the evaluation of the Education Maintenance Allowance to estimate these possible bounds.
4. Our estimates of the elasticity of labour demand suggest that in a competitive market, every 1 per cent increase in the 16/17 year old wage results in a 3.6 per cent decrease in employment hours amongst this group. This estimated elasticity is large, suggesting that this age group can be easily substituted for other workers. For example, at a higher wage firms may choose to employ more expensive but also more highly skilled and productive 18 year-olds. For particularly low skilled jobs, part time work among 15 year-olds is a possible substitute.
5. If a minimum wage were introduced at £3 this suggests that employment hours amongst 16/17 year olds could be cut by around 6 per cent. It is important to remember that this is not a prediction of the reduction that will occur if a NMW is introduced. Rather it is a bound on the reduction that could occur if labour markets are fully competitive. If firms are able to absorb even part of the costs of higher wages the effects will be far more moderate.
6. If the labour market for 16 and 17 year olds is not competitive, but is instead characterised by market power on the part of the firms, then the introduction of a NMW may also affect the employment and schooling choices of young people by increasing the benefits of working relative to not-working.
7. Our estimates suggest that an increase in the wage tends to lead to a shift out of school and into the labour market, and also towards combining school and employment. However the number of people who would alter their behaviour in this way as a result of the introduction of the NMW does not appear to be significant.

Chapter 1. Introduction

General overview

This report sets out our estimates of the impact of an extension of the National Minimum Wage (NMW) to 16 and 17 year olds on their labour market and education choices. Our key priority has been to provide a range of robust estimates of the possible impact of an extension of the NMW to 16 and 17 year olds, taking into account possible labour demand as well as labour supply responses.

In order to identify the impact of introducing a National Minimum Wage for 16 and 17 year-olds, it is necessary to take into account how the NMW will affect the decisions of both employers and young people. We therefore need to look at the changes in both labour demand and labour supply. The change in labour demand tells us by how much employers would reduce the number of people they would want to hire if the wage went up. The change in labour supply tells us how many more young people would want to work if the wage was increased. Chapter 2 looks at how these effects are determined.

The report uses data from the evaluation of the Education Maintenance Allowance (EMA), a subsidy which has been paid to 16 and 17 year olds from low income backgrounds in a number of LEAs across England in order to encourage them to remain in full-time education. The EMA dataset contains a longitudinal sample of approximately 19,000 young people in both the EMA pilot areas and specially selected control areas. The data was collected in the first autumn after their compulsory education ended, providing us with a unique sample of 16 and 17 year-olds. The experimental nature of the EMA gives us a powerful tool for assessing how changes in financial incentives affect the labour market for this group and we are able to exploit this variation to estimate the impact that a NMW could have. A summary of the main features of this data set, and a description of the activities and characteristics of the young people in our sample (including earnings and hours of work for those in work in the sample) is set out in Chapter 3.

Chapter 4 then concentrates in more detail on the labour demand effect. It considers the fact that in a perfectly competitive market it is the slope of the labour demand curve that will determine the change in employment that may result from the introduction of a minimum wage for 16 and 17 year-olds. By estimating the demand elasticity for labour, chapter 4 shows that if the market were perfectly competitive we would expect the demand for employment among young people to fall by 2% if the NMW were introduced at a level of £2.50 per hour, or around 6% if it were introduced at £3.00 per hour.

Chapter 5 looks at the labour supply effect of introducing a NMW for 16 and 17 year-olds. It estimates that introducing a NMW at £3 or £3.50 per hour would make little difference to the number of young people wanting to work, either by leaving school and joining the labour market, or by combining school and part-time work. This finding is interesting in the light of the EMA evaluation results, which show that young people's work and schooling decisions *are* sensitive to changes in financial incentives (Ashworth et al 2002). However, as we point out in Chapter 5, the operation of the NMW would be different to the EMA, and so we would not necessarily expect to see the same sort of effects.

Chapter 6 looks at how these two effects might be reconciled, and presents bounds on the likely effects of the introduction of the minimum wage for 16 and 17 year-olds in terms of employment and concludes.

Chapter 2. Estimating the effect of the National Minimum Wage for 16-17 olds

The effect of an extension of the National Minimum Wage (NMW) to 16 and 17 year olds will depend on young people's and employers' responses to the wage and on the exact structure of the labour market. A higher wage will tend to increase the number of people who wish to work, as work becomes a more attractive option than it previously was. In parallel the higher wage will usually decrease the number of people that employers wish to employ as workers become more costly.

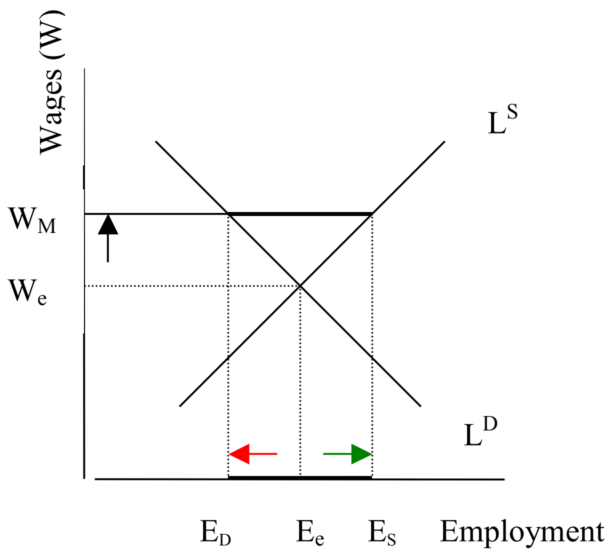
2.1 The labour market under perfect competition and monopsony

Figure 2.1 shows a stylised picture of the labour market. It plots the labour demand curve (L^D), which shows how many people employers wish to employ at any given wage, and the labour supply curve (L^S) which shows how many people would like to work for any wage. The labour demand curve is downward sloping as higher wages are associated with firms wanting to employ fewer individuals. The labour supply curve is upward sloping as, other things being equal, higher wages lead to more individuals wanting to work, so labour supply rises. In the absence of a minimum wage employment and wages are determined by where demand equals supply so we have employment E_e and wage W_e.

The imposition of a minimum wage immediately raises the wage to the new minimum W_M. Under perfect competition, at this higher wage, labour demand shrinks to E_D while labour supply rises to E_S, as both firms and individuals adjust their choices. The result is employment at level E_D which is lower than in the absence of the minimum wage, and unemployment equal to the difference between E_S and E_D. Under this scenario, in order to estimate the effect that the minimum wage will have on the employment of 16 and 17 year-olds we need to know the slope of the labour demand curve. The slope then gives us the employment elasticity – that is the percentage change in employment for a 1% change in the wage. We can then estimate the change in employment that will result from the introduction of the minimum wage.

If firms by contrast have some market power in the labour market, then they may choose to employ more workers when faced with a higher wage. Such market power could occur in any labour market where the firms are in a position to pay their employees a wage below the marginal product of their work – this might, for example, occur if employees are constrained to working in a particular geographical location for personal reasons giving the firms operating in those areas market power over these individuals. If firms have a degree of market power in the labour market being considered, the level of employment under a minimum wage could lie anywhere on the bold line between E_D and E_S. At the extreme, in a monopsonistic labour market (where there is only one employer) the resulting employment level would be determined by the labour supply responses of individuals rather than by the labour demand responses of firms (see Box below). The new employment level would thus be E_S and the new equilibrium would result in both higher wages and higher employment. In this case, the effect of imposing a minimum wage can be estimated by estimating the slope of the labour supply curve.

Figure 2.1 – The effect of the minimum wage on employment under different market structures



Explaining Monopsonistic labour markets

Figure 2.2 shows how the equilibrium wage and employment level are determined in a monopsonistic labour market. As before the L_S curve represents the labour supply decisions by individuals. The MP_L represents the marginal product of labour and is the same as the L_D curve as in the perfectly competitive case. It represents the benefit to the firm of a hiring an additional unit of labour. Unlike the perfectly competitive case the marginal cost of labour is not equal to the labour supply curve. Instead it is also depicted on the graph (MC_L). The marginal cost curve represents the marginal cost of an additional unit of labour to the firm. In the perfectly competitive case the marginal cost curve is the same as the labour supply curve because the cost of employing an additional worker is the same as the wage paid to workers already in employment (as firms are considered too small to individually change the market wage). In the monopsonistic case, this assumption is relaxed and the firms are assumed to have market power. This means that when they employ additional workers, they cause the wage to increase and incur the cost of this. For this reason, in the monopsonistic case, the marginal cost of labour curve lies above the labour supply curve.

The firm will choose to employ people at the point where the marginal cost (MC_L) curve equals the marginal benefit to the firm (the MP_L curve), resulting in employment E_1. However, as the Labour supply curve lies below the intersection of the marginal cost of labour curve and the labour demand curve, the firm is able to employ people at wage W_1 which is the wage given by the labour supply curve at employment E_1.

Figure 2.2 Labour market equilibrium under monopsony

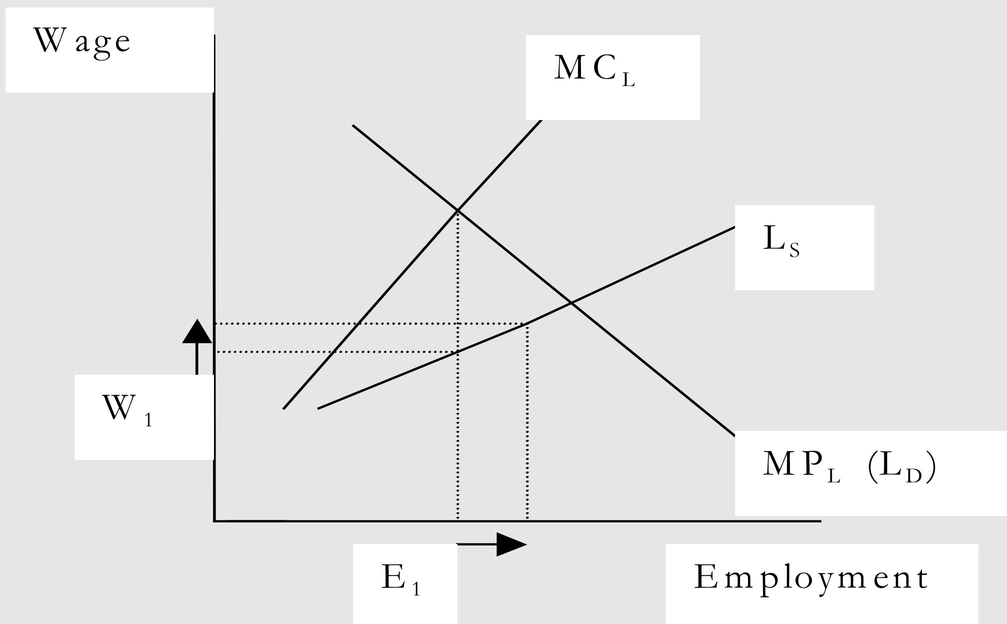
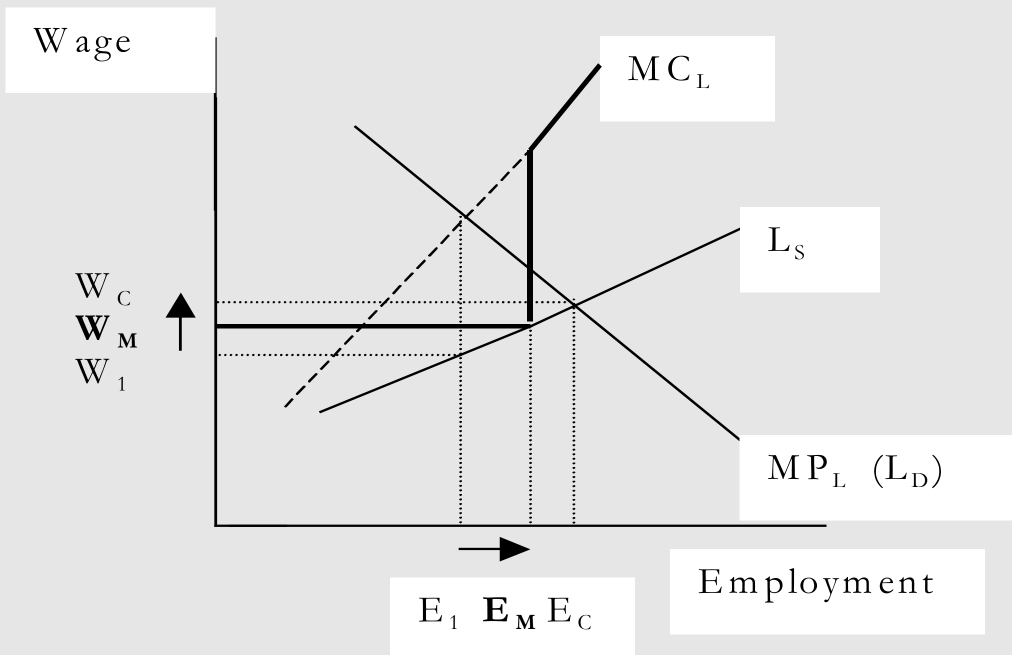


Figure 2.3 shows the effect of introducing a minimum wage W_M which lies between the wage under monopsony and the wage that would occur under perfect competition. At employment levels below the intersection of the minimum wage with the labour supply curve, the MC_L now lies horizontally at the level of the minimum wage. At these employment levels the marginal cost of employing an additional worker is $W_{M,}$ as there are unemployed individuals willing to work at this wage and there are no additional costs associated with already hired workers who already earn the minimum wage. Once employment reaches E_M the marginal cost curve jumps to the old MC_L as the wage that would be paid at employment levels above this is the same in the absence and in the presence of the minimum wage.

Figure 2.3 The effect of a minimum wage under monopsony



So what choice does the firm make under such a minimum wage? As before, it will choose the employment level where the MC_L equals the MP_L and pick the lower wage that is associated with the labour supply decisions of workers. Employment will equal E_M while the wage will be W_M. So for a minimum wage set between the monopsony wage and the competitive equilibrium wage, the minimum wage leads to an increase in both the wage *and* employment. This may seem counterintuitive. In particular, firms could still choose the same employment level as in the absence of the minimum wage (E_1), yet it seems to choose higher employment at a higher wage. The reason for this is that in the absence of the minimum wage the firm is paying a lower wage at E_1 and making a higher profit. In order to increase its employment it would incur a significant dent in its profit as it has to incur the costs of the increases in other wages. With the minimum wage the employer at E_1 already has reduced profits, but it can increase its employment levels much more cheaply as unemployed workers are willing to work at the same wage as those already employed. It therefore chooses to increase employment. It will have lower profits than in the absence of the minimum wage, but higher than if it stayed at employment level E_1.

For any minimum wage set at a level between W_1 and W_C, the employment level will be given by the labour supply curve. So in order to estimate the effect of the introduction of the minimum wage in a monopsonistic market, we need to know the labour supply curve.

So what happens if the minimum wage is introduced at a level above W_C? In this case the new MC_L curve is still flat where it intersects the MP_L curve and employment moves back up the labour supply curve to the left of the E_C point. With a minimum wage above the competitive market equilibrium, employment can be anywhere to the left of the E_C point.

2.3 Which approach is the correct one?

It is clear that the structure of the labour market for 16 and 17 year-olds will be key in determining the effect of the minimum wage for this group. Depending on whether the firms have any market power, the response to a minimum wage will either be a decrease or an increase in employment. At present there is little conclusive evidence on which of these effects is likely. In the USA, Card and

Krueger present evidence from the minimum wage reforms in the early 90s, that shows that the increase in the minimum wage in certain states increased employment in the fast food industry – an industry characterised by high teenage employment and market power on the part of the employers. Evidence from the UK from Dickens, Machin and Manning shows that the minimum wages set between 1975 and 1992 by the British Wages Councils did not have the effect of reducing employment. Again, this effect is thought to be the direct result of monopsony power on the part of employers. There is also little evidence that the introduction of the National Minimum Wage in 1999 for over 18s has had an adverse effect on employment rates (LPC 2003).

However, these are isolated studies and present us with evidence of the market structure in particular industries, for particular types of workers and at specific times. There are reasons to believe that the labour market for 16 and 17 year-olds is characterised at least in part by firms with some degree of market power. Teenagers are typically constrained in the geographical location of their work as they are unlikely to be able to afford to move out of the parental home and many are likely to work in low-skill industries with high turnover costs. It may be that the labour market for young people is characterised by market power in a small number of cases, or that market power is slight and only applies over a small part of the wage distribution.

As it is beyond the scope of this project to estimate the structure of the labour market for 16 and 17 year olds, we instead look at the two extreme cases - that of perfect competition and of a monopsonistic labour market – and use them to put bounds on the employment effect of a minimum wage. Chapter 4 looks at the responses of the minimum wage in the case of perfect competition by estimating the labour demand curve. Chapter 5 then looks at the responses to the minimum wage if the market is characterised by market power on the side of the employer by estimating labour supply responses. The “true” effect will be bounded by our two results.

Chapter 3. The 16 and 17 year olds in the EMA dataset

The EMA data was collected to evaluate the impact of paying a subsidy (the EMA) on education choices. It contains a sample of young people collected in the first Autumn after their compulsory education ended, providing us with a unique sample of 16 and 17 year-olds. The data was collected for two cohorts of young people, the first cohort finishing Year 11 in summer 1999, and the second cohort finishing Year 11 one year later in 2000. The evaluation has followed up and re-interviewed each of these cohorts over a number of years. The second wave of each cohort contains information on young people who are now 17 and 18 years old. We are able to use the 17 year-olds thus increasing our sample size.

The EMA sample was collected by a random draw of child benefit records from the previous academic year in 21 local education authorities. Of these, 10 were offering a subsidy worth up to £40 per week during term time for young people from lower income families who remained in education past the age of 16[1]. Just over 60% of our sample reside in such an area. Of these just over 75% would have been eligible for some level of the subsidy had they remained in education.

The EMA pilot areas were chosen by the government as the trial areas for the Education Maintenance Allowance as they are relatively more deprived than the national average. The control areas were chosen by the consortium evaluating the EMA (of which the IFS formed part) to resemble the pilot areas as closely as possible. This was achieved satisfactorily in all the urban pilot areas. However, the rural pilot area, Cornwall, was dissimilar (partly due to size) to any other rural area and it was not possible to find anywhere else that closely resembled it. Cornwall and the rural controls have therefore not been used in any of the analysis contained in this report.

The EMA data contains rich information on the young people's personal and family characteristics, collected from a face to face interview with both the young people themselves and their parents. Where the individuals have chosen to work rather than continue with schooling, we have detailed information on their precise occupation, whether it contains training, the hours they work and their hourly wage. In terms of their personal and family characteristics we know their family composition including information on their siblings, parental income, parental occupation, parental education along with the young people's own GCSE results, experiences of early life and whether they have any special education needs. As the data was collected specifically to look at the decisions made at age 16, the information contained is ideal for this project.

3.1 Sample size

Our sample contains 16 and 17 year olds for whom we have information on in the EMA dataset, excluding the rural areas. Table 3.1 shows that we have in total 13,902 separate individuals in our urban sample – 6,838 from cohort 1 and 7,064 from cohort 2 (see Table 3.1).

For this project, we can exploit information about the sample members who enter the sample at age 16 both the first time that they are interviewed (wave 1), and also at follow-up interview a year later when they are 17 (wave 2). From cohort 1 we have 4,304 individuals who enter the sample at age 16 in wave 1. Sample attrition means that we observe 3,247 of them at age 17 in wave 2. From cohort 2 we have 4,399 16 year olds at wave 1, and retain 3,370 of them in wave 2.

For those who enter at age 17, we only exploit information about their activities and wages at wave 1, and then drop them from our sample at wage 2 when they are 18. Our sample contains 2,534 individuals from cohort 1, and 2,655 individuals from cohort 2 who

[1] Young people with parental gross income of under £13'000 p.a. were eligible for the full award. This was then tapered down to £5 per week for those with parental income of £30'000 p.a.

are 17 in wave 1. For our purposes we treat the same individual at different ages as separate observations (our statistical analyses take this into account when calculating standard errors). This means that our final sample consists of 20,519 observations.

Table 3.1: The sample – by age and cohort

	Age 16	Age 17	Total
Cohort1 wave1	4,304	2,534	6,838
Cohort1 wave2	0	3,247	3,247
Cohort2 wave1	4,399	2,665	7,064
Cohort2 wave2	0	3,370	3,370
Total	8,703	11,816	20,519

For the analysis set out chapters 4 and 5, we use different sub-samples from our main dataset, and distinguish the activities and labour market characteristics of the 16 and 17 year olds in pilot and control areas. In this chapter, however, we describe the activities and characteristics of the whole sample, to give an overview of the activities of this age group as a whole.

3.2. Activities of 16 and 17 year olds in the sample

Table 3.2 shows the different activities of the 16 and 17 year olds in the sample, broken down by their age and wave (these figures are also available separately for EMA pilot and control areas, but are not shown here).

Table 3.2: Activities of 16 and 17 year olds in the sample

Per cent	16 wave 1	17 wave 1	17 wave 2	Total
Pilot and control areas combined				
Not in education:				
FT job	6.4	7.1	13.8	8.9
Ft job with training	7.9	8.3	7.5	7.9
PT work	2.5	2.8	2.5	2.6
PT work with training	0.1	0.1	0.3	0.2
Self-employed	0.2	0.1	0.4	0.3
Unemployed	7.6	6.9	6.1	6.9

Other	2.7	2.9	2.0	2.5
In education:				
FT education + job	30.5	33.4	39.0	34.0
FT education no job	41.4	37.5	27.8	36.0
PT education	0.7	0.7	0.4	0.6
FT or PT education + self emp	0.2	0.2	0.2	0.2
Total	*100*	*100*	*100*	*100*

The table shows that around 20 per cent of the sample have left school and are in some sort of work-based activity (full-time work with or without training, part-time work, or self-employment). Around 70 per cent of the sample is still at school, and roughly half of these are combining school with part-time work. Around 10 per cent of the sample is either unemployed or inactive. Table 3.2 also shows that the proportion in work-based activities rises with both age and seniority, whilst the proportion solely in education or non-employment declines.

3.3 Weekly earnings, hours and hourly wages amongst workers in the sample

In this section we describe the hours and wages of those in work in the EMA sample. The derivation of the hourly wage variable within the dataset is of particular importance for the results contained in this report. This is because the hourly wage variable is used both to estimate the possible responses of employers (in chapter 4) and young people (chapter 5) to changes in the wage, and also to predict the possible changes in employment patterns on introduction of a NMW based on these responses.

The hourly wage variable for 16 and 17 year olds obtainable in the EMA data is, however, not the ideal measure of wages for our purposes. This is because it is a *derived* variable based on a number of questions from the young person's questionnaire. In all cases it measures *usual weekly take home pay, including overtime, divided by usual weekly hours, including overtime*. Some of the problems with this measure include the fact that:

- It is measured net of tax. Any minimum wage for this group will instead apply to the gross wage.
- It captures the effective hourly wage paid to the young person based on their reported weekly pay, and the number of hours per week they work. In practice the minimum wage will instead be based on the official hourly rate paid to the young person.
- It is subject to considerable measurement error, which may exaggerate the number of young people appearing at either tail of the distribution. This is because it has been derived from two separate variables, each of which are in turn subject to measurement error. Combining the two will mean that the potential measurement error is magnified.

Table 3.3 shows the mean weekly wage, hours worked per week, and hourly wage for the sample that have some employment activity. Here the descriptive statistics are presented separately for EMA pilot and control areas. The table shows that the average weekly take-home pay is highest for young people who work full-time, but that average *hourly* wages are highest for those combining school and work. More than half those in full-time work without training, and as many as 80% of those combining full-time work with training are on net hourly wages as measured in the EMA dataset below £3.50 per hour. This compares with around 40% of those still at school.

Table 3.3: Wages and hours of 16 and 17 year olds – by pilot and control area

	weekly wage	weekly hours	hourly wage	%<£2.50	%<£3.00	%<£3.50

control areas						
FT job	130.79	38.45	3.38	28%	39%	54%
Ft job with training	97.52	38.50	2.55	60%	71%	81%
PT work	75.51	20.49	3.76	12%	28%	41%
FT ed + job	47.06	12.08	3.88	7%	19%	40%
pilot areas						
FT job	130.29	38.41	3.40	27%	40%	57%
Ft job with training	103.67	38.68	2.69	52%	66%	78%
PT work	85.07	20.61	3.90	11%	24%	42%
FT ed + job	45.90	11.68	3.86	7%	22%	41%

Note weekly and hourly pay are net wages, expressed in Autumn 2003 prices. Uprating of pay has been done up to April 2002 using the average earnings index for 16 and 17 year olds from the NES. Between April 2002 and Autumn 2003 a 5% increase has been assumed, roughly in line with nominal average earnings growth over this time.

Given the drawbacks pointed out above of the derived hourly wage variable available in the EMA dataset, we also present evidence here on how the hourly wage compares to the measures available in the Labour Force Survey (LFS), including the basic hourly rate measure, asked of all those who are paid a fixed hourly rate in their job. Table 3.4 shows how the distribution of derived net wages in the EMA data compares to two different wage measures in the LFS: the first measure has been constructed to be as similar as possible to the measure available in the EMA data. The second is the basic hourly rate variable collected in the LFS. All are expressed in 2003 prices[2]. As can be seen from Table 3.4, the EMA and LFS derived net wage variables have a fairly similar distribution. EMA areas are more deprived than the national average, and the data was collected a number of years ago, during which time there may have been above-inflation earnings growth. For these reasons the average hourly rate is somewhat lower amongst EMA recipients. On the other hand, the basic hourly rate collected in the LFS is higher on average, and also less

[2] The EMA data has been uprated to Autumn 2003 prices, whilst the LFS data remains in Spring 2003 prices – see note to Table 3.4.

dispersed. Table 3.5 shows that the number of young people falling below a possible £3 minimum wage on the basic hourly rate measure is very much lower than on the derived wage variables[3].

[3] However it should also be noted that using the LFS for these purposes is not without its problems: in particular the very small sample sizes in the LFS mean that the sub-group analysis needs to be treated with some caution. In addition, there appear to be a considerable number of missing wage values in the LFS data.

Table 3.4. Average hourly wages in the EMA data and the Labour Force Survey

	Derived usual net hourly wage		Hourly rate
	EMA data	LFS	LFS
All in employment	3.61	3.85	4.04
Standard deviation	*(1.38)*	*(1.41)*	*(0.839)*
Number of obs	*10,613*	*287*	*285*
<u>By activity</u>			
FT job	3.39	3.15	4.03
	(1.436)	*(0.899)*	*(0.937)*
	1,708	*60*	*39*
Ft job with training	2.64	2.11	2.66
	(1.309)	*(0.670)*	*(1.105)*
	1,538	*10*	*4*
PT work	3.85	3.87	4.26
	(1.361)	*(1.129)*	*(0.997)*
	488	*17*	*17*
FT ed + job	3.87	4.15	4.05
	(1.252)	*(1.452)*	*(0.786)*
	6,731	*200*	*225*

Note: The EMA hourly pay variable is a derived net wage variable, which has been constructed as *usual weekly take home pay, including overtime, divided by usual weekly hours, including overtime* expressed in Autumn 2003 prices. Uprating of the EMA pay variable has been carried out up to April 2002 using the average earnings index for 16 and 17 year olds from the NES. Between April 2002 and Autumn 2003 a 5% increase has been assumed, roughly in line with nominal average earnings growth over this time. The LFS hourly pay and hourly rate variables are from the Spring 2003 Quarterly Labour Force Survey. They have not been uprated, and remain in Spring 2003 prices. Wages for those in FT jobs with training in the LFS only include those on government employment and training programmes (inecaca=3).

Table 3.5. Proportion of 16/17 year olds below £3 per hour

	Derived net hourly wage		Hourly rate
	EMA	LFS	LFS
All in employment	31%	23%	6%
By activity			
FT job	39%	38%	10%
Ft job with training	68%	90%	20%
PT work	25%	29%	0%
FT ed + job	21%	15%	4%

Note: see Table 3.4 notes.

Any National Minimum Wage for 16 and 17 year olds is likely to be applied to the basic hourly rate paid to individuals, rather than their effective hourly rate as measured in the EMA dataset (which is in any case, as we pointed out above, subject to some measurement error in the data). For this reason, our estimates in chapter 4 of the number of people who would be affected by the introduction of a NMW are based on the Labour Force Survey, rather than the EMA data.

3.4 Background characteristics of the young people in the sample

The EMA data is particularly suitable to the task of estimating labour market effects on 16 and 17 year-olds as it contains a wide range of personal characteristics. Table 3.6 shows the main personal characteristics of the young people in our sample while table 3.7 looks at their parents' characteristics. On average, the individuals in the pilot areas have lower socioeconomic characteristics than those in the control – with the exception of their GCSE results, which are marginally better than in the pilot area. This is unsurprising given that the pilot areas were chosen as testing areas for the EMA for the relatively high deprivation in those areas. Table 3.6 shows that average gross weekly family income is £417.45 for the whole sample (corresponding to £21'700 per annum). In the pilot areas this falls to £402.35 per week, while in the control areas it is higher at £440.79 per week. In addition individuals in the pilot areas are more likely to live in families in receipt of means tested benefits, less likely to live in owner occupied housing, more likely to live in council housing. They are less likely to have older siblings educated to 18, are less likely to be white and are less likely to have had at least one parent in work when they were very young. They also have lower English and maths GCSE scores on average, and are less likely to have attended more than one primary school.

Table 3.7 looks at their parents' characteristics in total and by pilot and control areas. Individuals in the pilot areas are less likely to have parents educated to A-level standard or higher and parents who work in managerial or professional jobs. Both their mothers and fathers are less likely to be in full time work. Overall, 81% of the fathers on whom we have detailed information are in full time work while 36% of mothers also work full time. The incidence of living with two parents or having father figure in the household is very similar across pilot and control areas.

Table 3.6: Personal characteristics by pilot/control area

Table 3.7: parental characteristics by pilot/control area

	Pilot Average	Control Average	Total Average
Weekly family income	402.35	440.79	417.45
Family in receipts of means tested benefits	0.24	0.20	0.22
Owner occupied housing	0.72	0.74	0.73
Council or housing association housing	0.23	0.19	0.21
Claimant count by local or unitary authority by month	3.88	3.45	3.71
Number of older siblings	0.93	0.94	0.93
Number of younger siblings	0.93	0.89	0.91
Any siblings educated to at least 18	0.31	0.33	0.32
White	0.91	0.94	0.92
Maths GCSE score	4.10	4.21	4.15
English GCSE score	4.50	4.60	4.54
Maths GCSE score missing	0.09	0.08	0.08
English GCSE score missing	0.09	0.08	0.09
Special needs or disabled	0.10	0.10	0.10
At least one parent in work when born	0.84	0.88	0.86
Attended 2 primary schools	0.26	0.30	0.28
Attended more than 2 primary schools	0.08	0.10	0.09
Received childcare as a child	0.92	0.92	0.92
Lived near one set of grandparents when child	0.33	0.33	0.33
Lived near two sets of grandparents when child	0.43	0.39	0.41
Grandparents provided care when child	0.29	0.30	0.30
Ill before the age 1	0.22	0.23	0.23
	Pilot Average	Control Average	Total Average
Mother's age	42.97	43.21	43.06
Father's age	46.36	46.42	46.36
Mother has A-levels of higher	0.29	0.34	0.31

Mother has O-levels of equivalent	0.26	0.28	0.27
Father has A-levels or higher	0.38	0.41	0.39
Father has O-levels or equivalent	0.27	0.28	0.27
Father manager or professional	0.28	0.33	0.30
Father’s occupation clerical or similar	0.38	0.35	0.36
Mother manager or similar	0.14	0.18	0.16
Mother’s occupation clerical or similar	0.32	0.32	0.32
Mother and father figure present in household	0.64	0.64	0.64
Father figure present in household	0.77	0.78	0.77
Father in full-time work	0.79	0.83	0.81
Father in part-time work	0.03	0.03	0.03
Mother in full-time work	0.35	0.38	0.36
Mother in part-time work	0.35	0.36	0.36
Information on father is missing	0.35	0.34	0.34

The EMA control areas were chosen to resemble the pilot areas as closely as possible, not just in terms of the people who lived there, but also in terms of the characteristics of the local areas and the opportunities they presented people with. Table 3.8 shows pre-reform ward-level indices of deprivation for our data alongside the average for England overall. An explanation of what these indices measure is given in Appendix A, but on all scores a higher value represents higher deprivation. On all measures apart from the one measuring the geographical access to services, our sample shows considerably higher deprivation than the English average and the pilot areas showed higher rates of deprivation than the control areas. The one exception, “geographical access to services” measures proximity to services such as shops, education and healthcare and is more favourable in our sample than the English average as our sample is based in densely populated urban areas which typically have more services in close proximity than more sparsely populated areas.

The fact that the local areas covered in our sample (both pilots and controls) are more deprived than the national average means that our estimates of likely labour demand and labour supply responses to the introduction a NMW for 16 and 17 year olds apply to the relatively deprived urban areas in our sample, and may not represent the average responses across the country as a whole. For example, if there are more readily available substitutes for 16 and 17 year olds amongst a workforce with relatively high unemployment rates, than the elasticity of labour demand across these areas may be higher than across the country at large.

Table 3.8: Local area characteristics by pilot/control area

	Pilot Average	Control Average	Total	England
Indices of multiple deprivation for the local area				
Index of multiple deprivation	35.53	30.75	33.66	21.70
Income	28.55	25.52	27.36	18.86
Employment	15.86	13.90	15.09	10.19
Health deprivation and disability	0.90	0.61	0.79	0.00
Education, skills and training	0.56	0.50	0.54	0.00
Housing	0.38	0.08	0.26	0.00
Geographical access to services	-0.35	-0.27	-0.32	0.00
Child poverty	41.57	36.70	39.66	26.74

Finally, Table 3.9 shows education outcomes in the local areas for our sample. The areas in which our pilot individuals live have fewer people staying in education beyond the age of 16 and fewer people going to university. The schools nearest are broadly similar in both our pilot and control areas – with pilot areas having slightly smaller class sizes and slightly lower GCSE results. The main difference is that the mean distance to the nearest year 12 provider is significantly lower for those in the pilot areas.

The local area characteristics are important as they allow us to control for the opportunities and characteristics of the small local area where our young people live. This ensures that we are not simply comparing similar people living in very different surroundings but that the opportunities they face are also similar.

Figure 3.9 Local school characteristics by pilot/control area

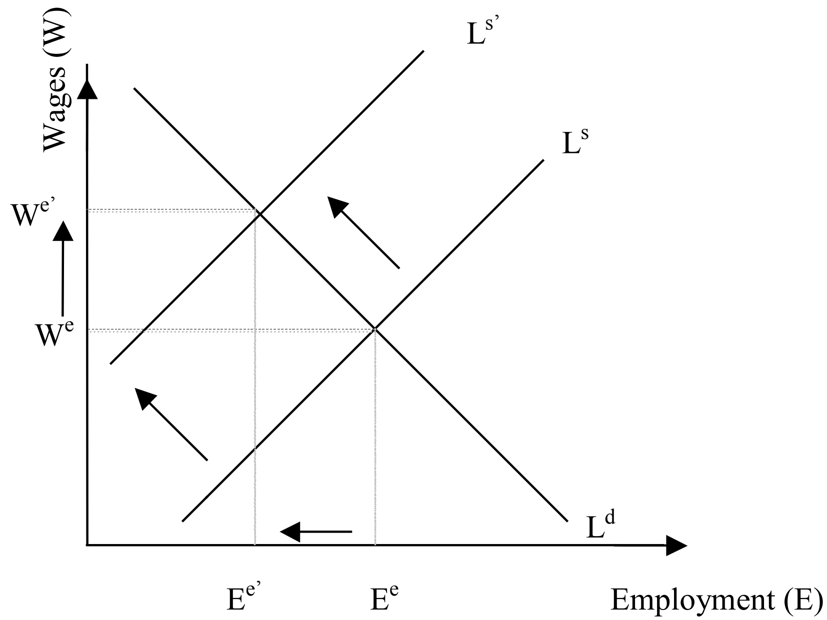
	Pilot Average	Control Average	Total
Pre-pilot education participation rates			
% not staying in education past 16 (proxy measure)	66.37	64.27	65.55
% not going to uni (proxy measure)	88.04	87.19	87.71

Nearest school data			
Class size in 1999	21.52	21.61	21.56
Authorised absences in 1999	8.51	8.53	8.52
% getting 5 GSCEs at A*-C in 1999	39.49	39.88	39.64
% getting no GCSEs at A-G in 1999	6.02	5.57	5.84
Does the school have a sixth form?	0.48	0.44	0.47

Chapter 4 The impact of the NMW under perfect competition - estimating Labour Demand

As we set out in chapter 2, in a perfectly competitive labour market the introduction of a minimum wage will lead to a decrease in employment due to a decrease in labour demand. In order to estimate the magnitude of this effect we need to estimate the slope of the labour demand curve. This is generally not directly observable – we usually observe only the equilibrium wage and employment level, so we only know where the labour supply and labour demand curve intersect. In order to identify the slope of the labour demand curve we need to observe a second point on it. This is possible if there has been a shift in the labour supply curve to give a second intersection point (the two points will be observed either at different times or simultaneously in different locations). Such a shift in the labour supply curve is shown in Figure 4.1, by observing curve $L^{s'}$. In this instance we have a new equilibrium point giving equilibrium wages $W^{e'}$ and employment $E^{e'}$.

Figure 4.1 – estimating the slope of the labour demand curve using shifts in the labour supply curve



The introduction of the Education Maintenance Allowance (EMA) in September 1999 will have shifted the labour supply in the Local Education Authorities where it was piloted. The EMA is a means tested benefit of up to £40 per week paid to 16 and 17 year-olds who remain in full-time education in the two years after it is compulsory for them to do so. By increasing the opportunity cost of being in work – that is, the value of the alternative activity that a young person can choose instead of going to work – there will be fewer young people willing to work at any given wage. This is equivalent to a left-ward shift in the labour supply curve, as shown in Figure 4.1.

Using the EMA data, which was collected in the 10 pilot areas along with 11 control areas that were specially chosen to resemble the pilot areas as closely as possible, we can compare the labour market equilibria in the EMA areas (with a labour supply curve $L^{s'}$ in our diagram) with those in the control areas (with a labour supply curve L^s). We therefore have simultaneous observations in two different locations. In order to be able to attribute the observed differences to the shift in the labour supply curve, we need to be confident that the areas are similar in terms of their labour market structure and that the personal characteristics of the young people are also similar. A similar labour market structure is necessary to ensure that the two labour supply curves are intersecting a similar labour demand curve, while similar personal characteristics will ensure that the labour being supplied/demanded is qualitatively similar. For example, two samples with young people with very different prior educational achievement will be very different from an employment point of view.

As discussed in section 3, the EMA control areas were selected to resemble the EMA pilot areas as closely as possible, in terms of the factors that will influence young people's education and by extension, labour market decisions. Both the pilot and control areas are relatively deprived and have similar pre-reform local labour market opportunities and education participation rates for 16 year olds. While the selection of the control areas was designed to choose young people in areas facing similar opportunities and choices, we still need to control for the distribution of personal characteristics for the young people in our sample to eliminate any possible composition bias. We do this using propensity score matching techniques.

4.1 Using matching as a methodology

In order to control for possible differences in the observable characteristics of our sample, we use propensity score matching – a semi-parametric econometric technique. Our aim is to find the equilibrium employment level and wage in the labour market for 16 and 17 year-olds in EMA areas, and the counterfactual equilibrium wage and employment levels in these areas had the EMA not been introduced.

To do this we construct a "matched sample" by selecting the individuals in our control area sample who are most like the individuals in our pilot area in terms of their characteristics. We then use this matched comparison sample to analyse the differences in the labour market equilibria in the presence and absence of the EMA.

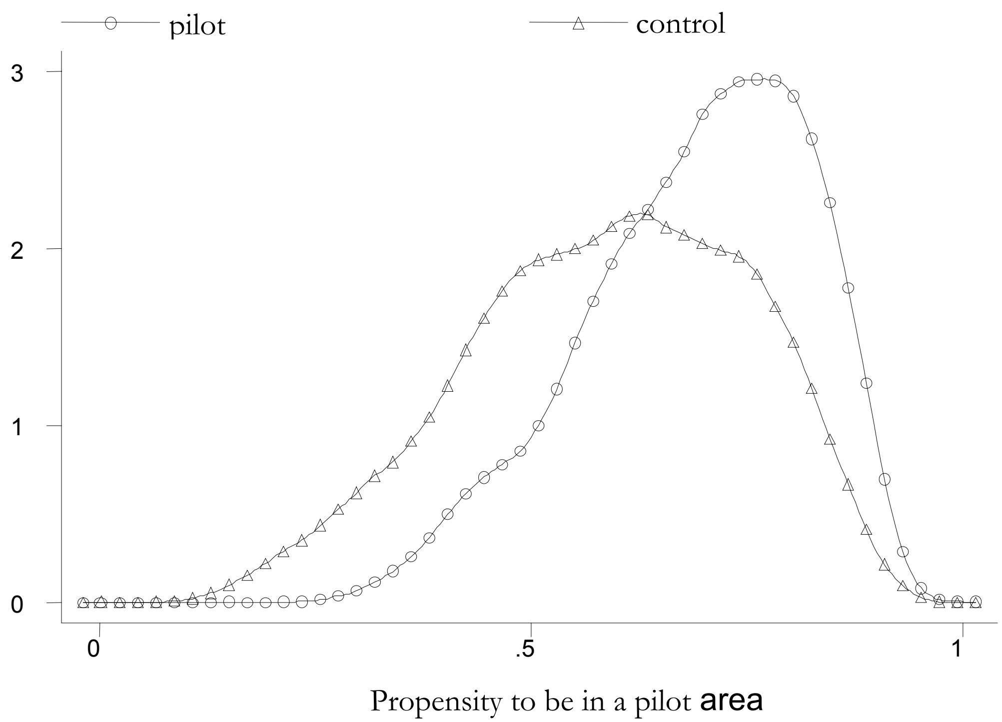
Our methodology is set out more formally in Appendix B. Our first step in implementing this methodology is to determine the propensity score for the young people in both our pilot and control areas. We do this by running a probit regression. This gives a propensity score which tells us what the probability a given individual has of being in the pilot area given their observable characteristics. For example, if there were a higher proportion of young men in the pilot than in the control areas, young men would have higher propensity scores than young women with otherwise identical characteristics. Figure 4.2 shows the distribution of propensity scores for individuals in the pilot and control areas. It shows that although the distribution of propensity scores is not the same in pilot and control areas, there are almost no individuals in the pilot areas who look different to at least some individuals in the control areas. This means that using the pilot individuals as our base, we are able to find individuals in the control areas who look like them for (nearly) the entire sample of pilot individuals. Incidentally, the converse is not true. There is a small but significant number of individuals in the control areas with propensity scores under 0.3, but almost no pilot individuals with such low scores.

Using these propensity scores, we construct an expectation for the outcomes we are interested in the control areas, by conditioning on the propensity scores and weighting individuals using a kernel. In this way the average outcomes of our "matched sample" are calculated. It is this "matched" sample that we use to compare the two labour market equilibria under different labour supply curves. Alternatively, we could have chosen not to weight the individuals, but weighting allows us to increase the precision of our estimates. In constructing the conditional expectations we use only the range of propensity scores that are present in our pilot sample. This allows us to avoid a major source of bias (Heckman, Ichimura and Todd, 1997). We then construct an overall average by weighting our sample according to the distribution of the propensity score in the pilot areas.

Figure 4.3 shows the new distribution of propensity scores once matching has taken place. It shows that the matched comparison sample has been chosen to be a near perfect match of the pilot area sample. This means that we can be confident that the results we obtain are not due to *observable* differences in the composition of our samples.

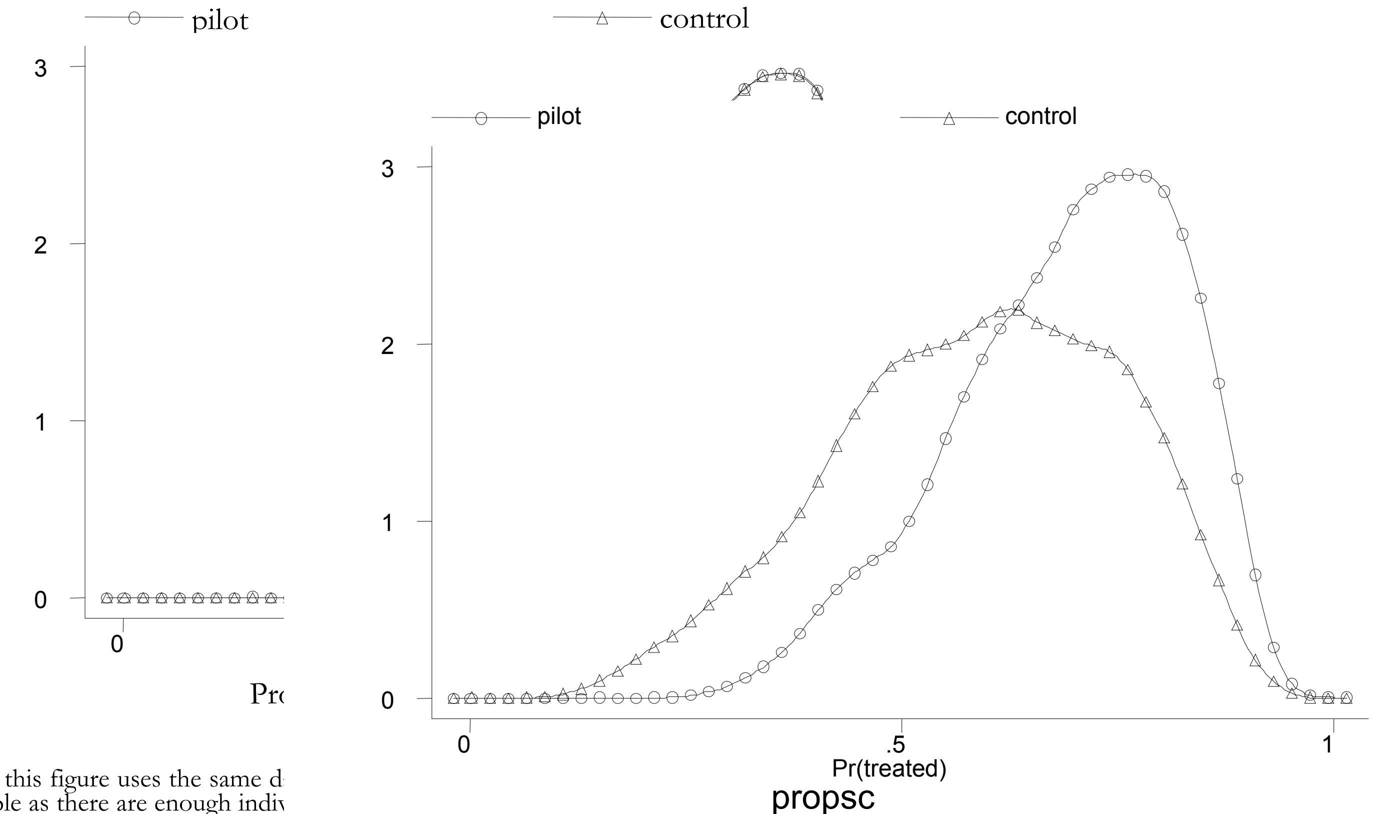
Our methodology specifically sets out to correct for any possible systematic difference due to observable characteristics – no matter how well two areas have been chosen to resemble each other there will be at least a small difference in the distribution of the characteristics of the people within those areas. What is potentially more problematic is the possibility of systematic differences between the pilot and control areas that are unobservable and relate young people's choices in terms of their activity at age 16. The existence of unobservables that affect young people's education/labour market decisions is undisputed and unproblematic – it is where these unobservables are systematically different between the pilot and the control areas that their existence becomes problematic. This could occur if, for example, families moved into EMA areas for their children to take advantage of the EMA or the effects of the EMA on the local labour market. For our first cohort, we can be confident that due to the late announcement of the policy there was little scope for such movement to have taken place amongst people in our sample. For those in the second cohort, the absence of selection into pilot or control areas on such unobservables is an assumption we believe is reasonable due to the to high cost of moving (particularly as most 16 and 17 year olds live with their parents) relative to the effects of the EMA (which is only available for two years) and to the fact that Local Education Authorities are large in area.

Figure 4.2 the distribution of the propensity scores by pilot and control areas



Note: this figure is a density graph using the entire sample to look at the propensity to be in a pilot area. A score nearer 1 represent a higher similarity to individuals in the pilot area. The mean score is over 0.5 reflecting the fact that the pilot area sample is larger than the control area sample, so the average individual is more likely to be in the pilot rather than in the control area.

Figure 4.3 the distribution of the propensity scores by pilot and control areas after matching



Note: this figure uses the same d… l weighted. The identical distribution is possible as there are enough indiv… nable us to select comparisons with the same background characteristics.

4.2 Results

Using the methodology described above we were able to derive the wage elasticity of the demand for labour in our areas. The wage elasticity is given by

$$\varepsilon = \frac{(dE / E)}{(dW / W)}.$$

It represents the proportional change in the demand for employment hours for a 1% change in the wage.
Table 4.1 shows the estimated wage elasticities for the demand for labour, according to the amount of EMA that the individuals were eligible for, and at the various stages of the analysis. Table 4.1 shows that once matching has been undertaken and the results have been weighted to represent the original pilot sample, the wage elasticity of demand ranges from –3.6 to –3.8 for the sample of those eligible for the EMA (depending on whether they are eligible for the full amount or any amount), indicating, as expected that an increase in the wage leads to a reduction in labour demand, as the elasticity of labour demand is negative. Although the two numbers are estimated for different groups and for a different shift in the labour supply curve (since the EMA entitlement is different across groups), we would expect the two elasticities to be similar – as is the case. The fact that the two groups have a different amount of EMA and therefore have a different shift of the labour supply curve does not change the fact that we are estimating the slope of the same line. We are simply estimating its slope from different points[4].

Table 4.1 estimated elasticities of demand

	Fully eligibles	All eligibles
Unmatched	– 7.1	– 17.2
Matched	– 2.5	– 2.1
Pilot weighted	**– 3.8**	**– 3.6**

Table 4.2 shows the wage levels in the pilot and control areas along with the changes in employment that were used to derive the elasticities in Table 4.1. It shows that the reason for such large elasticities is that the change in employment between the pilot and control areas was particularly large. For fully eligible individuals, there was a reduction in employment hours of 20%. The change in the wage rate is much more modest, leading to a large elasticity.

Table 4.2 estimating elasticities of demand – underlying effects

	Fullv	All eligibles

[4] Assuming that the slope of the labour demand curve is linear.

	eligibles	
Pilot wage	3.30	3.38
Control wage	3.13	3.24
% change in employment	– 20.2%	– 15.5%

What do these results mean?

The elasticities shown in table 4.3 for the pilot weighted results are very high. A labour demand elasticity of –3.6, represents a 3.6% reduction in demand for employment hours for every 1% increase in the wage.

To gain a better understanding of the effect that the introduction of a National Minimum Wage would have on the whole of the UK we applied the elasticity derived using the EMA data to the LFS wage distribution - measured by the basic hourly rate - for 16 and 17 year-olds. We did this using the Labour Force Survey for Spring 2003[5]. Table 4.3 shows the effect of introducing the NMW at £2.50, £3.00 and £3.50 an hour on wages and employment. It shows that a minimum wage of £2.50 would represent an average increase in wages of 0.5% resulting in a decrease in employment hours of 2.0%. A NMW of £3.00 would reduce labour demand by 5.8% while the higher wage of £3.50 would lead to a reduction of 12.7% in employment hours.

Table 4.3 Possible change in employment resulting from introduction of NMW

	Labour Force Survey Spring 2003	
	% Increase in wages	% Decrease in labour demand
Minimum wage of £2.50	0.5%	2.0%
Minimum wage of £3.00	1.6%	5.8%
Minimum wage of £3.50	3.5%	12.7%

Note: change in labour demand is estimated using a labour demand elasticity of –3.6. The wage data used to derive the figures for this table does not exclude wages for jobs with training – however very few individuals who are in such jobs report a wage.

[5] Chapter 3 provided more details about the difference in the wage measures available in the Labour Force Survey compared to the EMA data, and how the distribution of wages compare.

How credible are these results?

Our analysis suggests that labour demand for 16 and 17 year-olds is very elastic – that is it responds highly to the wage – and points to potentially large effects if the market is perfectly competitive. A minimum wage of £3.00 per hours could lead to a reduction of labour demand of around 6 per cent.

Table 4.2 provided the intuition behind these results: the availability of the EMA resulted in a relatively large reduction in the number of young people seeking employment, but this reduction only led to a relatively small upward movement in the average wage. If we assume that these two changes represent a move from one labour market equilibrium to another, then the converse must also be true: i.e. a small change in the wage would lead to a relatively large change in employer demand for workers of this age.

One way of putting this large effect into context is to consider that workers from this age group are likely to have low skills and be hired due to their low cost rather than their particular suitability for a particular job. An increase in the wage therefore makes them less attractive to employers who are able to easily substitute them for other workers. For example, at a higher wage they may choose to employ the more expensive but also more highly skilled and productive 18 year-olds. For particularly low skilled jobs part time work among 15 year-olds is a possible substitute.

Whether this is or is not a major concern when introducing the minimum wage depends on a number of factors. If it is believed that the labour market for 16 and 17 year olds is characterised by market power on the part of the firms, then the analysis in this section has no predictive power. If firms are able to absorb even part of the costs of higher wages the effects will be far more moderate. Alternatively, one might consider that a loss of low pay and low productivity jobs for this age group is of no real concern as such jobs provide little opportunity of obtaining new skills. A reduction in labour market opportunities might work positively if those affected continue in education and gain from the experience. Conversely, if those affected remain unemployed, this should be of serious concern to policy makers. A combination of a minimum wage with support and help for additional training or education would be one way of guarding against the possibility of high youth unemployment.

Chapter 5 The impact of the NMW under monopsony

In this chapter we estimate the impact of the introduction of the NMW on employment and schooling choices if labour markets are monopsonistic. In this case, the impact of a biting minimum wage would be through the labour supply responses of young people (see Figure 2.3).

Our approach has been to use the EMA data to estimate an econometric model of work and schooling decisions amongst 16 to 17 year olds. Our model takes into account the fact that young people face a number of different decisions about their activity, which may be affected by a change in the wage. There are two, interrelated decisions we have considered: the first is the decision whether to remain in full-time education, or to leave education and enter the labour market; the second is the decision of whether or not to take a job. This latter decision applies whether the young person has remained in education (in which case they will be deciding whether to combine education and part-time work), or has left school. There are a number of possible extensions to our work in this area, including the estimation of the likely impact of the NMW on hours worked.

For the results from our model to be credible we need to be sure that we are fully controlling for all other factors that determine labour market and schooling decisions besides the wage. Most notably, young people who stay on at school are likely to be of higher ability and motivation than those who leave school at 16. We have taken great care to employ appropriate methodologies to take this into account. However, it is not clear that the data is sufficiently rich for us to have been successful in this. A useful extension to our research would therefore be to use more sophisticated methodologies than the simple ones used here and test the robustness of the results to them.

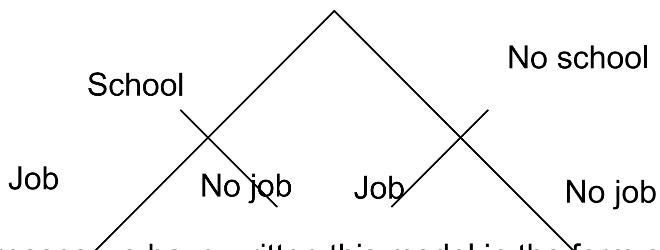
This chapter first sets out our econometric model and its underlying assumptions. We then describe the variables used within the model, and the sample on which the estimation is performed. Finally, we report results from our estimation of the model, including some simulations of how young people’s activities could change if various minimum wages were introduced.

It should be noted that for this part of the project we do not compare the EMA pilot areas to EMA controls: instead our focus is just on the EMA pilot areas, where young people will all be facing similar labour market conditions. This is because our finding from chapter 4 - that the EMA is likely to have affected both participation decisions, and the wage available - would make interpreting any results from this approach quite difficult.

5.1 A model of schooling and employment choices for 16 and 17 year olds

We base our results on a simple model of the labour participation decisions of young people, in which the decision to take up a job and the decision to remain in school depend upon the potential wage, as well as a range of other characteristics. These include gender, previous educational attainment, parental characteristics (including education, employment, income, local labour market conditions), and other financial incentives, such as EMA entitlement if in school.
There are a number of ways in which we could characterise such a model. Figure 5.1 sets out the decisions faced by the young person in the form of a decision tree: the first decision made is whether or not to stay on in school, the next decision is then whether or not to take on a job, given the prior schooling decision. All of these decisions depend on the potential wages offered to the young person.

Figure 5.1. A model of schooling and job decisions amongst 16 and 17 year olds



For our purposes we have written this model in the form of the following three equations, which form what we will later refer to as our structural model of wages, schooling and labour force decisions.

$$W_i = \beta_1 X_i + u_{1i} \qquad (1)$$

$$School_i = \delta_1 W_i + \beta_2 X_i + \gamma_2 Z_{1i} + u_{2i} \qquad (2)$$

$$Job_i = \delta_2 W_i + \beta_3 X_i + \gamma_3 Z_{2i} + u_{3i} \qquad (3)$$

In this structural model, individuals (each denoted by the subscript, $_i$) are characterised as having potential log wages W_i which are determined by a vector of exogenously determined personal, family, and neighbourhood characteristics, X_i, and a random error term $u_{1i.}$ (equation 1). In practice, the type of jobs available to people who are at school and working part-time are likely to differ from the jobs available to people who have left school. For this reason, we estimate two potential wages for each individual – one potential wage that they would command if they stayed in school and took a job, and the other they would command if they left school and took a job.

Individuals make the choice as to whether to remain in full-time education or to leave school (equation 2), and also whether or not to take a job (equation 3). These are the decisions set out in the tree in Figure 5.1. Each of these decisions is determined by the potential wage they could command, together with the vector of characteristics X_i, which also determine wages, and a set of additional exogenously determined characteristics (denoted Z_{2i} in the case of the schooling decision, and Z_{3i} in the case of the job decision)[6], as well as a random error term u_{2i} and u_{3i} respectively.

The parameters of most interest to us within the context of understanding the possible impact of introducing the NMW for 16 and 17 year olds is the responsiveness of individuals' participation decisions to changes in the potential wage, given by δ_1 in the case of the schooling decision, and δ_2 in the case of the decision whether or not to take a job.

There are a number of important issues to contend with in estimating this model. First, it is important to realise that many of the factors determining these decisions are unobserved in our data. These include unobserved individual ability[7], expected future wages, and individual discount rates (i.e. how much income a young person is willing to forgo to gain a higher income later). The unobservability of these variables means that without appropriate methods, the wage is likely to be endogenous with respect to both the decision of whether or not to stay on in school (equation 2), and whether or not to take a job (equation 3). The presence of such endogeneity[8] means that our estimates of δ_1 and δ_2 will be biased unless we can employ suitable methods to the data available to take this into account.

There are a number of approaches that can be adopted to estimate this model, in order to correct for this endogeneity, and to uncover estimates of δ_1 and δ_2. We have taken a simple approach of first predicting a wage for those who are currently not working, and then using this predicted wage as an explanatory variable in the subsequent participation choice model. Below we set out this approach in more detail, before discussing a number of improvements to this approach which could be implemented, in order to make sure that we have been successful in removing important sources of bias from our estimates.

---

[6] These variables Z are chosen such that they do not determine wages other than their impact through schooling and job decisions, i.e. they have no place in equation 1.

[7] Though we do have GCSE results in mathematics and English, which will be partially determined by ability, and are therefore important explanatory variables in our analysis.

[8] Formally, this implies that $E(X_i,\varepsilon_i)\neq 0$ for any independent variable X and error term ε.

5.2 Estimating the model: a "two-stage" approach

As stated above, we have carried out the estimation of the model in two stages. The first stage generates predictions of the potential wage for those who are not in work. The next stage then uses these predicted wages as an independent variable in the model of participation choice, thereby generating estimates for δ_1 and δ_2.

Stage 1: Obtaining wage predictions taking into account endogeneity and sample selection.

Our main task in predicting potential wages for non-working 16 and 17 year olds is to take into consideration two important factors, namely:

i) *Endogeneity of the decision to stay on at school:* young people are not randomly allocated between staying on in school and leaving. Instead, those that stay on at school are likely to be more able, and also discount future income less sharply than those who do not.

ii) *Sample selection:* those in work – whether they have decided to stay on at school, or to leave - are a selected sample who have decided to participate in paid work. Again, those that work may be different from those that choose not to in ways that we cannot observe. Unless we take this sample selection into account, we will not correctly estimate the potential wages that those out of work would earn if they chose to take a job.

To correct for these common problems we have used methods based on the Heckman selection model (see Heckman, 1979), extended to take into account that there are two-underlying decision processes we need to account for in estimating wages (see Fishe, Trost and Lurie, 1981, and Maddala, 1983). In effect, these methods allow us to predict the wages that non-workers would be offered, had they decided to work, taking into account the fact that their schooling/non-schooling decision, and their job/no-job decision may be driven by unobserved characteristics that are correlated with their potential wage. In implementing this model, we have estimated the following two wage equations:

$$W_{schooli} = \beta_{school}X_i + \gamma_{schoo1}Z_{1i} + \sigma_{school1}\lambda_{1i} + \sigma_{school2}\lambda_{2i} + u_{schoo1i} \quad \text{if school = 1}$$

$$W_{noschooli} = \beta_{noschool}X_i + \gamma_{noschool}Z_{1i} + \sigma_{noschool1}\lambda_{1i} + \sigma_{noschool2}\lambda_{2i} + u_{noschooli} \quad \text{if school= 1}$$

(4a and 4b)

where λ_{1i} is a selection correction term (often referred to an inverse Mills ratio) designed to correct for the endogeneity of the choice of whether or not to remain in school, and λ_{2i} is a selection correction term designed to control for selection into the sample due to the choice of whether or not to take a job. Appendix C explains the methodology used to implement this part of the analysis in more detail.

Once the wage equations set out in (4) have been estimated we obtain wage predictions for the out of work sample by calculating the expected value of the wage in school, and the wage in the labour market for each individual, conditional on the decisions that they have made with respect to work and schooling.

Stage 2: Estimating the change in participation choices associated with changes in the wage

The next stage is to use the wage predictions obtained above to estimate our structural model of school and labour market participation. Of course in order for the results to be interpreted as behavioural responses, we need to be sure that the wage predictions we have obtained do truly represent the wages those not in work would have earned had they chosen to be in work, and that all factors determining the choice between staying at school and leaving school have been taken into account. As we will show below, it is not clear that the data is sufficiently rich to take into account all factors determining the choice to stay or leave school at 16, despite our use of the selection methods set out above to account for this choice.

Bearing this in mind, we have used two different types of specifications of our main model. First, we have estimated a bivariate probit model, in which an individual chooses from between four different states, namely:

i) stay at school, no job

ii) stay at school, with job

iii) leave school, no job

iv) leave school, with job

By including the predicted wage in this model, we are able to simulate the change in behaviour which would be associated with various changes in the wage. In this specification it is the predicted wage in the labour market (i.e. the potential wage if the young person left school) which we take as the relevant explanatory variable in the model.

We also present results from an alternative specification, which holds the decision to stay in school or not constant. Here we examine how the decision to take a job is affected by a change in the wage for the in school, and out of school sample separately. In this specification we take the potential wage in school as the determinant of job decisions for the in school sample, and the potential out of school wage as the determinant of job decisions for the out of school sample.

Box 5.3 Improvements to the "two-stage" approach: estimation of the full structural model

The two-stage approach we have used is commonly adopted for estimating models such as the one set out here. However it can be open to criticism, since it contains some circularity. This is because the approach relies on the estimation of reduced form participation equations (the probits A1 and A2a and A2b in Appendix C), to arrive at predicted wages. These predicted wages are then placed back into very similar participation equations (equations (2) and (3)). The circularity of this procedure creates wage predictions that are highly correlated with the other regressors in the model. When regressors are nearly multi-collinear, this can lead to a number of statistical problems with estimation; in particular, small changes in the data can produce wide swings in parameter estimates, standard errors can be very large, and coefficients may have the wrong sign, or be of implausible magnitude. Though we have reduced the near multi-collinearity in the model sufficiently to avoid these problems, most of this is achieved through differences in functional form between the first stage reduced form participation probits and the eventual structural participation equations. Achieving identification of the parameter estimates this way can be criticised, since the parameters lack a clear economic interpretation.

For this reason a very fruitful extension would be to adopt two different approaches which allow the parameters of the structural model to be estimated simultaneously, without the need to predict wages first. These methods are:-

i) *A reduced form approach, using indirect least squares:* The parameters of the model δ_1 and δ_2 can be estimated directly by noting that the full model as set out in equations 1), 2) and 3) can be re-written as a reduced form model, from which the parameters δ_1 and δ_2 can be recovered, using simple estimation techniques.

ii) *Maximum likelihood estimation of the full structural model:* The likelihood of observing all the wage, employment, and schooling outcomes contained in the data, given our structural model, can be written as a log likelihood function[9]. The parameters of the model can then be found by finding the parameter values which maximise the value of the log likelihood function.

5.4 Variable definitions, and sample descriptives

The sample used for this part of the analysis consists just of young people in EMA pilot areas[10]. The sample consists of all those in the urban pilots, excluding individuals who are self-employed, and those with a job who do not report their wage. Our sample therefore consists of 13,081 16 and 17

[9] Available on request from the authors.

year olds, of whom 5138 (39.2%) are in school with no job, 4273 (32.8%) in school with a job, 1253 (9.7%) have left school and have no job, and 2417 (18.3%) have left school and have a job.

In our analysis we estimate the model of wages and participation by controlling for a range of personal, family, and local area characteristics, including age, gender, ethnicity, GCSE results, family income, parental education and work, family size and composition, local area unemployment. The full set of variables we use, including the variables chosen to be instruments in the model, are set out in Appendix C.

The characteristics of the sample are summarised in Table 5.1. Those in jobs who have left school are paid lower hourly wages than those still in school (echoing the data from the full sample described in Chapter 2). As we will see later, this difference in pay between those in school and those who have left school is not eliminated when we control for ability as measured by GCSE results, or when we control for unobserved ability through our selection model. The proportion of our sample working for less than £3 per hour is around 22 per cent of those in school, compared to 48% of those who have left school[11].

Table 5.1 also shows that the "no school, no job" group are clearly the most disadvantaged group in terms of personal characteristics and family background, with the lowest GCSE scores of any other group and the lowest family income (coming predominantly from the lowest family income deciles). This group is also the most likely to be living in council or social rented property, come from a single parent family, and have parents who have no qualifications and do not work. The most advantaged group, by contrast, are those who are combining full-time school with part-time work. These individuals have the highest GCSE scores, come predominantly from the top half of the family income distribution, and have older, higher qualified, and more frequently working parents.

It is also interesting to note that the labour market conditions in the local area also appear to make a difference to young people's work choices. Those with a job live in areas with lower unemployment claimant counts on average than those who are not working.

---

[10] Young people from the control areas have been excluded from the sample, so that the amount of EMA a young person is entitled can be used as a valid instrument (i.e. source of exogenous variation) for the school/non-school choice, and also the decision to take a job if the young person has stayed on in school. Chapter 4 showed that compared to the control areas, the availability of the EMA affects both participation decisions, and the wage. Hence it would not be a valid instrument were control areas included in the sample.

[11] This proportion is considerably higher than the number of people paid below a £3ph hourly rate in the Labour Force Survey – see Chapter 3.

Table 5.1 Sample characteristics

	School no job	School, job	No school, no job	No school, job
Wages, hours				
Hourly wage		3.863		3.176
Log hourly wage		1.305		1.059
Proportion < £3ph		0.223		0.484
Weekly hours		11.715		36.135
Personal characteristics				
Male	0.515	0.421	0.496	0.582
age 16, Y12	0.491	0.370	0.449	0.372
age 17, Y12	0.264	0.257	0.276	0.242
age 17, Y13	0.245	0.373	0.275	0.386
White	0.828	0.931	0.887	0.952
maths GSCE score	4.463	4.957	3.033	3.586
english GCSE score	4.929	5.391	3.703	4.102
special needs	0.104	0.052	0.144	0.087
Family background				
family income decile:				
Poorest	0.107	0.072	0.154	0.094
2nd	0.119	0.071	0.168	0.089
3rd	0.126	0.080	0.165	0.130
4th	0.112	0.072	0.140	0.103
5th	0.113	0.094	0.102	0.114
6th	0.089	0.098	0.080	0.098
7th	0.084	0.119	0.069	0.123
8th	0.082	0.131	0.057	0.106
9th	0.076	0.128	0.042	0.095
Richest	0.092	0.135	0.023	0.048
owner occupier	0.693	0.842	0.378	0.637
council/HA tenant	0.264	0.124	0.543	0.317

mother and father at home	0.641	0.705	0.437	0.612
has father figure	0.752	0.819	0.585	0.771
mother's age	43.179	43.172	41.287	41.476
Father's age	46.899	46.124	45.429	44.640
mother no quals	0.514	0.364	0.733	0.581
mother L1,2,3	0.282	0.360	0.093	0.172
mother L4,5	0.227	0.297	0.200	0.270
father no quals	0.598	0.468	0.804	0.671
father L1,2,3	0.363	0.454	0.157	0.222
father L4,5	0.240	0.279	0.260	0.293
father works full-time	0.720	0.876	0.603	0.797
mother works full-time	0.301	0.429	0.232	0.370
mother works part-time	0.317	0.391	0.229	0.350
father's social class I or II	0.263	0.325	0.122	0.160
father's social class III, IV, V	0.373	0.371	0.376	0.410
mother's social class I or II	0.134	0.180	0.047	0.089
mother's social class III, IV, V	0.303	0.374	0.208	0.307
has older sibling who stayed on past 16	0.335	0.350	0.172	0.185
Local labour markets				
local claimant count	4.13	3.89	4.10	3.94
N	5138	4273	1253	2417

Note: Maths and English GCSE scores 1 A* 7 A 6 B 5 C 4D 3 E 2 F 1 G 0 fail missing; Mother/Father L 1,2,3 represents mother/father having A-levels or higher qualifications; mother/father L 4,5 represents mother/father's highest qualifications being O-levels or equivalent;