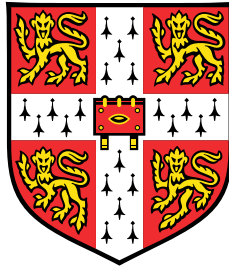


Empirical Essays on Inventors, Workers and Firms



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Summary

My research seeks to understand the behaviour of workers and firms and how their decisions affect labour market outcomes. My PhD dissertation consists of three separate Chapters that use detailed historical, census and administrative data to gain insights into the mechanisms at play when incentives for production and location decisions change.

Chapter 1 asks whether financial incentives can induce inventors to innovate more. I exploit a large reduction in the patent fee in the United Kingdom in 1884 to distinguish between its effect on increased efforts to invent, and a decrease in patent quality due to a lower quality threshold. For this analysis I create a detailed new dataset of 54,000 British inventors with renewal information for each patent. In the longer run high-quality patenting increases by over 100 percent, and the share of new patents due to greater effort accounts for three quarters of the pre-reform share of high-quality patents. To test for the presence of credit constraints I generate two wealth proxies from inventor names and addresses, and find a larger innovation response for inventors with lower wealth. These results indicate efficiency gains from decreasing the cost of inventing and in addition, from relaxing credit constraints.

In Chapter 2 we assess the effects of changes in ethnic neighbourhood composition in England and Wales. A change in social housing allocations in the 1990s serves as instrument for changes in the local ethnic composition. For the analysis we create a dataset of highly disaggregated census geographies for 1991-2011. The results imply that an exogenous increase in social housing minority share by 10 percentage points raises the minority share in private housing by 1.2 percentage points initially. This sorting effect is larger for privately rented than for privately owned housing. We further show that an increase in the minority share leads to higher local population growth and a small decrease in house prices in the longer run.

Chapter 3 proposes a new approach for analysing responses to comprehensive labour market reforms. Using detailed micro data we evaluate the German Hartz reforms that aimed at reducing unemployment. The timing of the reforms affects the model parameters, which are estimated using matched data on 430,000 workers in 340,000 firms. Contrary to previous findings, our analysis shows that the reforms marginally reduced unemployment at the cost of a pronounced decline in wages. Low-skilled workers suffered the largest wage losses. Furthermore, we decompose the contribution of each reform wave on employment and wages, and document a structural shift in the factors that govern overall wage dispersion.

Preface

The work on this dissertation was carried out between October 2011 and December 2016. This dissertation has not been submitted in whole or in part for the award of a degree at this or any other university and does not exceed 60,000 words in length. Except where specific reference is made to the involvement of others, the material contained in this dissertation is original and is the result of my own work.

The first Chapter greatly benefited from guidance by my supervisor Hamish Low. I thank Jason Lu, Miguel Morin and Mimi Tam for their generous support. Useful comments were provided by Toke Aidt, Michael Best, Teodora Boneva, Petra Geraats, Jeremy Greenwood, Walker Hanlon, Zorina Khan, Henrik Kleven, Stephen Machin, Kaivan Munshi, Pau Roldan, Claudia Steinwender, John Van Reenen and Guo Xu, and by seminar participants at the University of Cambridge, the London School of Economics, the Norwegian School of Economics, the University of Oxford, the University of Southampton, the Economic History Association Annual Meeting in Boulder, the Annual Cliometric Society Conference in Pittsburgh, the CESifo-Delphi Conference on innovation in Munich, and the NBER Summer Institute. I am very grateful to Lyndon Davies from the British Intellectual Property Office and Sue Ashpittel from the British Library for facilitating access to patent source files. Several short-term research assistants provided invaluable help with the data collection, in particular Maximilian Schinke, Lukas Fuchs and Juni Hoppe. I gratefully acknowledge financial support for this research by the Keynes Fund under project JHLT, without which this work would not have been feasible.

The second Chapter is joint work with Ghazala Azmat (Sciences Po Paris), Stephen Machin (London School of Economics) and Alan Manning (London School of Economics). We are grateful to Michael Amior, Stephen Gibbons, Christian Hilber, Hamish Low and Kaivan Munshi for valuable suggestions. Seminar participants at the IZA Institute of Labor Economics, Aalto University and the Centre for Economic Performance Conference provided helpful comments.

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The Faculty of Economics at the University of Cambridge provided a very supportive and cooperative environment during my PhD. Toke Aidt has been a mentor and provided opportunities where possible. I particularly thank Kaivan Munshi for his encouragement, helpful advice and effort during the job market. Thanks to Ghazala Azmat and Stephen Machin I could become part of the Centre for Economic Performance at the London School of Economics, where I spent a day a week from summer 2013 on and was exposed to a wide range of current empirical research. Throughout the ups and downs of our joint paper, Jake Bradley has impressed me with his enthusiasm, intelligence and patience.

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Chapter 1

The Responsiveness of Inventing: Evidence from a Patent Fee Reform

1.1 Introduction

Do inventors respond to an increase in financial incentives for inventing? Technological progress is a fundamental driver of growth and one of the most effective ways for combating challenges from diseases to climate change. Despite its relevance, we know little about the incentives and constraints inventors face. This Chapter exploits a large anticipated decrease in the patent fee in the United Kingdom in January 1884 to analyse the resulting increase in high-quality patents. The nineteenth-century fee change provides a rare policy experiment that allows a direct focus on the behavioural responses of inventors. These responses are of particular interest because inventors are high-skilled individuals who make choices with implications for the aggregate economy. I find large elasticities of high-quality patents in response to the fee reduction, which indicate significant efficiency costs of a high patent fee. The efficiency loss is even larger for inventors who are likely to be credit constrained before the reform.

This Chapter makes three main contributions. To study the behavioural responses to the patent fee reduction in 1884, I create an extensive new dataset of UK patenting for a ten-year window around the fee change. The resulting data includes detailed information on the names and addresses of 54,000 British inventors who applied for UK patents from 1879-1888 and obtained patent grants. In addition, I compile renewal information on each of these patents from over 60 volumes of printed journal publications of the UK Patent Office to construct a measure of patent quality. Patent renewals are widely used in the literature to gauge patent quality (Griliches, 1990; Lanjouw et al., 1998; Schankerman and Pakes,

1986)¹, and the cumulative fees for renewing a UK patent remained constant before and after the patent reform in 1884. A second quality measure is obtained by identifying British patents that subsequently also received patent protection in the United States. Both of these quality measures capture patent value because inventors only pay renewal fees or file for an additional US patent if the expected benefit exceeds the cost of doing so.² The patent reform in 1884 reduced fees by 84 percent from a high initial level, and this fee reduction led to a longer-run percentage increase in overall British patents of 141 percent. High-quality renewed patents increased by over 100 percent, with an elasticity of -1.25. This rise in high-quality patenting is also reflected in an increased number of UK patents that received protection in the US.

A second contribution of this work is to provide a framework for understanding the effects of the patent fee change on inventing effort exerted and on the quality of inventions patented. A lower patent fee raises efforts and investments in inventing due to higher payoffs. At the same time, the fee reduction leads to negative quality selection because of the resulting fall in the quality threshold for patented ideas. I approximate the relative importance of increased effort by comparing the high-quality share of the patenting increase to the pre-reform share. The share of new patents due to increased effort accounts for three quarters of the share of high-quality patents before the fee reduction. I identify these longer-run effects by exploiting the discontinuity arising from the fee reduction in January 1884.

In addition, the model describes the short-run trade-off between delayed patenting to pay the cheaper fee after the reform and the decaying value of an idea that is not patented. To analyse the shifting of patents observed in the months around the fee drop, I adapt the bunching approach developed by Kleven and Waseem (2013) and Best and Kleven (2016) for notched discontinuities in tax and duty schedules to the case of the downward patent fee notch in January 1884. The quality of patents increases just before the fee falls while patent numbers decline, and excess bunching of patents in the months after the reform amounts to over 250 percent. This short-run effect on quality shows that patent quality is not simply a function of the total number of granted patents. Inventors know about the quality of their ideas and choose the optimal date for patenting and effort accordingly. The short-run response is identified from the observed excess bunching over a counterfactual density of patenting.

¹For example, Brunt et al. (2012) adjust nineteenth-century agricultural patents in Britain for quality by using renewal information. Hanlon (2015) employs renewal data on UK textile patents to assess the effects of input prices on the direction of technological change in the 1860s.

²Another possibility is to construct quality measures from patent citations in contemporaneous publications (Hanlon, 2015; Nuvolari and Tartari, 2011) but to my knowledge a continuous publication with this information does not exist for 1879-1888. A frequently used measure for more recent patent quality are citations by later patents but only few British patents from the 1880s appear in later citation data.

The third contribution of this Chapter is to test for the presence of credit constraints. I generate two proxy measures for wealth and show that inventors with lower wealth respond to the fee reduction with a larger number of high-quality patents than high-wealth inventors. The first wealth measure captures the probabilistic share of inventor surnames at the county level among high-wealth individuals that were probated at death. This strategy of imputing rank from the likelihood of a surname appearing in high socio-economic status groups follows Clark (2014) and Clark and Cummins (2015). The resulting wealth measure is independent of individual ability and effort as well as of local education levels. I construct a second wealth measure from information on the employment of servants in inventor households. Information on the number of servants employed by household is available in the 1881 Census of Population, and I can match a subsample of inventors in the census data by using full inventor names and addresses.

This Chapter contributes to more recent evidence on the effectiveness of innovation policies. For example, Bloom et al. (2002) show that tax credits for research and development (R&D) are an effective innovation policy, with a long-run elasticity of around unity. In an analysis of a R&D tax credit reform in the UK in 2008, Dechezleprêtre et al. (2016) document an elasticity of R&D spending of around 2.6 in response to a cost reduction for smaller firms that are more likely to be financially constrained. Work by Lerner and Wulf (2007) finds an increased number of heavily cited patents in response to longer-run compensation incentives for research personnel in firms. Lach and Schankerman (2008) show that scientists in universities respond to stronger royalty incentives by increasing the quality rather than the quantity of inventions. In the presence of spillovers such positive effects of R&D investment further exceed their direct effects on firm productivity and employment (Bloom et al., 2013; Moretti et al., 2016). In one of the few studies on patent fee elasticities de Rassenfosse and van Pottelsberghe de la Potterie (2012) estimate a fee elasticity of around -0.30 from variation in recent cross-country data, compared to an elasticity of overall patenting of -1.68 found in this Chapter. Compared to more recent evidence, the quasi-experimental variation used in this Chapter allows an assessment of individual responses to the fee change, at a time when inventing was less reliant on large initial investments in education.

This Chapter is also related to the recent literature on misallocation. When a market for ideas exists, good ideas can be patented and sold in spite of initial credit constraints. Misallocation of ideas can arise if there are information frictions about the quality of ideas (Akcigit et al., 2016; Arrow, 1962). In a model with endogenous firm entry and exit Acemoglu et al. (2013) find that optimal innovation policies should support the R&D of new entrants while subsidies to incumbent firms reduce growth and welfare. Another aspect of the misallocation of talent is human capital formation (Bell et al., 2016; Celik, 2015; Hsieh

et al., 2013). For example, misallocation of talent arises for women and blacks in the US due to frictions in human capital accumulation (Hsieh et al., 2013). Bell et al. (2016) use administrative data on 1.2 million inventors in the US to show that lower-income children with comparable talent are less likely to become inventors. The analysis of entry barriers in this Chapter is limited to the static effects of credit constraints, which indicates significant misallocation even for given levels of human capital.

An extensive literature focuses on the related link between inequality and growth. In endogenous technological change models such as by Romer (1990), Grossman and Helpman (1991), and Aghion and Howitt (1992), individuals invest more in R&D if their payoff from innovating is higher. When credit constraints are present, a reduction in wealth inequality can foster growth by allowing constrained individuals to invest in good ideas (Aghion and Bolton, 1997; Banerjee and Newman, 1993). Work on entrepreneurship shows that the tightness of borrowing constraints determines the number of entrepreneurs (Cagetti and De Nardi, 2006; Evans and Jovanovic, 1989; Holtz-Eakin et al., 1994), and that the propensity of becoming a business owner is increasing in wealth (Hurst and Lusardi, 2004).

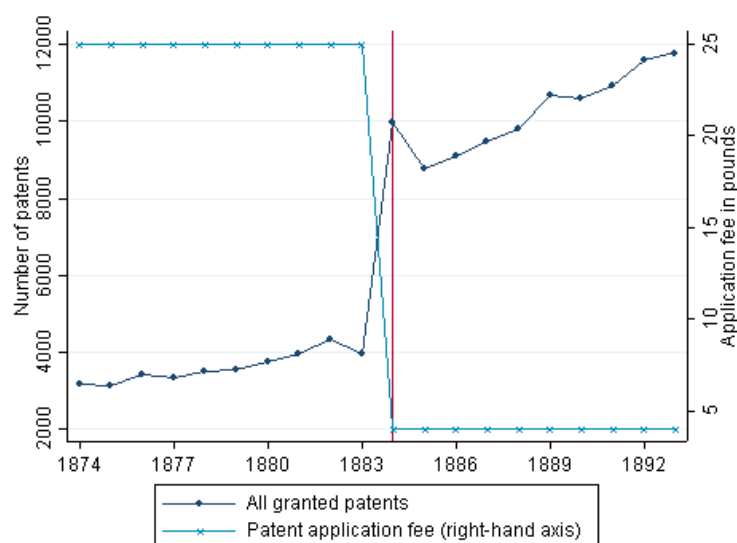
In debates preceding the 1884 patent reform, critics pointed to the detrimental effects of a high UK patent fee in a context when many inventors were credit constrained, and thus many good ideas were not patented (MacLeod et al., 2003). By comparison, low patent fees in the United States at that time ensured broad access to intellectual property rights (Khan, 2005; Lamoreaux and Sokoloff, 2007). To justify a high patent fee in the UK, proponents emphasised its role in deterring patent applications for low-quality inventions. In this Chapter I use detailed data to evaluate this trade-off between cheaper access to patent protection and a decrease in the quality of inventions. To my knowledge, Nicholas (2011) carries out the only previous study of the effects of the UK patent reform in 1884, by using a 20-percent annual sample of granted patents for 1878-1888. The main focus of the analysis by Nicholas is the geographic and sectoral composition of the longer-run increase in patents, which he finds evenly distributed. The work presented in this Chapter differs from the study by Nicholas by assessing the effects of the fee change on inventor effort and patent quality with detailed data gathered on all patents by date of their application.

This Chapter is organised as follows. Section 1.2 provides an overview of the patent reform and describes the procedures involved in obtaining a patent in the UK in the second half of the nineteenth century. A model of patenting decisions is presented in Section 1.3, which distinguishes between the lower quality threshold effect and increased effort in response to a fee drop. Section 1.4 describes the different data sources used and how the wealth proxy measures are generated. Section 1.5 presents the estimation and results, and Section 1.6 concludes.

1.2 Context of the Patent Reform in 1884

The Patents, Designs and Trade Marks Act of 1883 took effect on January 1 1884 and significantly lowered the patent application fee from a high initial level of £25 to £4. The reduction in fees is reflected in pronounced increases in total granted and renewed UK patents, as shown in Figures 1.1 and 1.2.

Figure 1.1 Number of UK patents 1874-1893

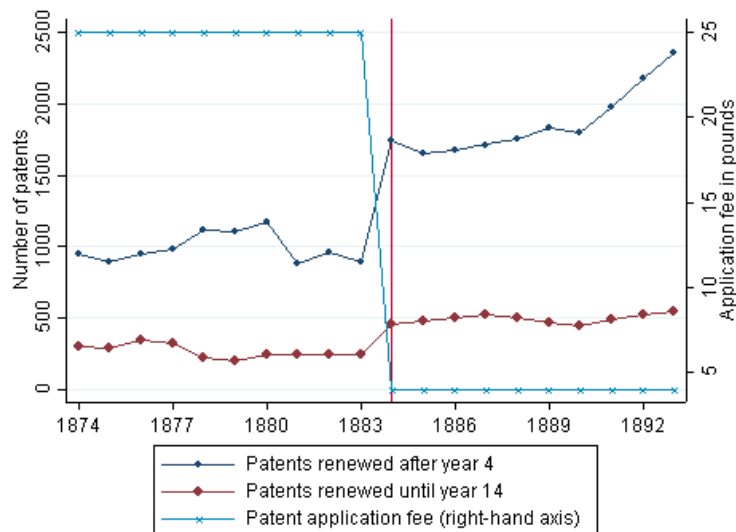


These yearly aggregate numbers are sourced from the Annual Reports of the Patent Office and include patents for British and for foreign residents. Before the reform, the costs involved in patenting in the UK were high in terms of average local living costs and impeded inventive activities (MacLeod et al., 2003). The pre-reform fee of £25 is approximately equivalent to £11,700 in 2016, when deflating by average earnings.³ To relate the fee to the earnings of a middle-class employee, the yearly salary of a clerk employed in the UK Patent Office was £177 in 1883 and that of a Patent Office draughtsman was £131. When introducing the new patent bill in 1883 Joseph Chamberlain, then the president of the Board of Trade, called the initial patent fee of £25 ‘an insurmountable obstacle in the way of the poorest inventors’.⁴ In addition, cumulative renewal fees of £150 had to be paid to keep the patent in force until a full patent term of 14 years. By contrast to the UK, the patent fee in the US in the 1880s was equivalent to only £7 for a full patent term of 17 years, and patenting fees were also

³This approximation was calculated on www.measuringworth.com. The present value varies by the method of conversion, and £25 are equivalent to about £2,300 in 2016 in terms of purchasing power.

⁴*Hansard*, 16 April 1883, col. 354, as cited in MacLeod et al. (2003).

Figure 1.2 Number of UK renewed patents 1874-1893



lower than in the UK in several other European countries. Frank Grierson, a naval architect, told the Society of Engineers in 1880 that a patent in the US ‘is within the reach of every mechanic; in England it is a venture for a capitalist’.⁵ One reason for the high patent fee was the explicit intention to deter patent applications for low-value inventions, so that the system could be self-policing (MacLeod et al., 2003). Overall, only a small proportion of inventions were patented in the UK in the second half of the nineteenth century (Brunt et al., 2012; Moser, 2005; Moser and Nicholas, 2013).

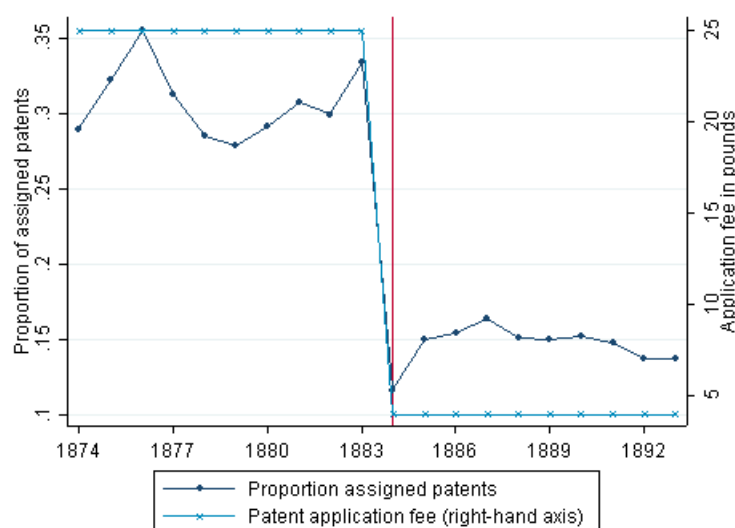
Figure 1.3 shows the marked fall in the proportion of assigned and licensed patents in the UK from around 30 to 14 percent after January 1884.⁶ Assignment information is one data source that gives some indication about credit constraints. In the presence of credit constraints, one option for constrained inventors is to obtain protection for their idea and then sell on their patent right in the form of an assignment or a license. Assignment data for this period is only available in the form of yearly aggregate data but not for individual patents.

The cumulative amount required to keep a patent to the full term of 14 years was £150 and remained the same before and after the reform in January 1884. Figure 1.4 provides a detailed overview of the renewal fee schedule before and after the reform.

⁵Frank Grierson (1880), A Paper on the National Value of Cheap Patents, *Transactions of the Society of Engineers*, as cited in MacLeod et al. (2003).

⁶Annual aggregate numbers of assigned and licensed patents are sourced from the Annual Reports of the UK Patent Office.

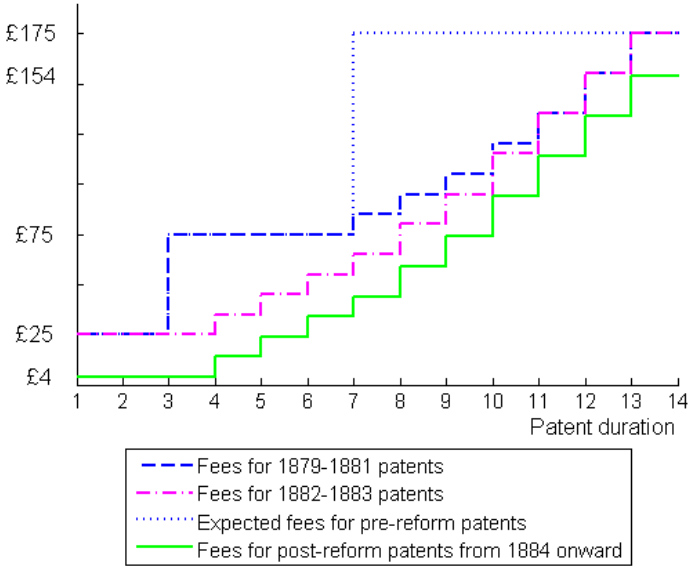
Figure 1.3 Proportion of assigned UK patents 1874-1893



The date of a patent refers to the date of application, after which a patent was granted within three to ten months on average. For renewals before 1884 a renewal fee of £50 had to be paid to keep the patent in force after the first three years. A payment of an additional £100 was required after seven years to maintain the patent until the full term of 14 years. For renewals of patents after the reform, the first renewal fee for patents applied for after January 1881 was only due from the fourth year onward and post-reform payments could be made annually. For estimating longer-run responses, I compare patents that were applied for in 1882 and 1885, for with the same fees applied for renewals between four and 14 years after the initial application.

The reduction in the patent fee by 84 percent in January 1884 followed several decades of public debate about the patenting system, which included pressure to abolish patents entirely. The British patent system was first reformed in 1852 as a result of the system being both ‘enormously cumbersome and prohibitively costly’ (Boehm and Silberston, 1967). The reform in 1852 reduced the initial costs of obtaining patent protection from about £300 to £25, created a single UK patent to replace the separate patents of England, Scotland and Ireland, and established the UK Patent Office. These changes did not satisfy critics and the patent system met severe opposition during the 1860s and 1870s, so that some even expected the collapse of the system (Machlup and Penrose, 1950). Between 1878 and 1883 eleven bills of patents for invention were discussed in Parliament that proposed a range of changes to the patenting procedure, including a lengthening of the patent term from 14 to 26 years. The Patents for Inventions Bill proposed in February 1883 mentioned a patent fee change.

Figure 1.4 Application and renewal fees payable by years of patent term



Notes: Cumulative renewal fees for keeping a patent in force to the maximum term of 14 years were £150 and remained the same after the reform in January 1884. Renewal fees payable for patents with application dates in 1882-1883 were the same as renewal fees after the reform, and only patents from 1879-1881 faced a different fee schedule for renewals before year 11. Until the reform was announced, the expectation was that renewal fees of £50 had to be paid after year 3 of patent term and of £100 in year 7. Patents from 1879-1881 that had paid the renewal fee of £50 in year 3 before the patent reform could be renewed in yearly instalments after year 7 from August 1 1884 onward.

The Patents, Designs and Trade Marks Act of 1883 was eventually passed in August 1883 as primary legislation that included the decrease in the patent fee from £25 to £4. The ensuing increase in patent applications from January 1884 on was unprecedented so that Boehm and Silberston (1967) describe the first eighty years of the nineteenth century as ‘the age of the patentless invention’.

In this Chapter I focus on the patent reform that took effect in 1884. A significant patent reform was also passed in 1852 but patent renewal fees were only introduced after the reform in 1852. Comparing patent renewals before and after the reform of 1852 is thus not possible. The patent reform in 1884 was also implemented with more institutional continuity, and a greater number of inventors already participated in the patenting system in the 1880s. After earning a profit of two million pounds between 1850 and 1880, a tenet of the reform was that the Patent Office should no longer operate at surplus income, and operating costs would mainly be covered with revenue from renewal fee payments. The cumulative amount of renewal fees remained the same after the reform in 1884, but the timing of renewal fee

instalments changed so that patents that were applied for in 1879-1881 faced a different fee schedule as explained above. In addition to the patent fee reduction, the Patent Act of 1883 reduced the administrative steps necessary for obtaining a patent from nine to six steps, extended the period from the application date to filing a full specification from six to nine months, and slightly extended the examinations of patent applications. After the reform, the Patent Office had to establish that a patent application contained only a single invention and that the invention was properly described, but the procedure still did not entail any examination for the novelty of an invention. Fewer administrative steps and a longer time for filing the full patent specification were further positive incentives for patenting. Extended examinations are likely to have dampened the incentive of inventors to file patents somewhat. While the Patent Act of 1883 was thus a reform package, the decrease in the patent fee was the main reform component affecting incentives to patent and to invent.

1.3 The Decision to Patent Close to a Fee Reduction

The model in this Section describes the decision of an inventor to patent in the context of a patent fee change. An inventor chooses to patent an idea when the patent value exceeds the value of not patenting, and a fall in the patent fee has two main effects on behaviour. On the one hand, a cheaper fee lowers the quality threshold at which it is profitable to patent an idea. On the other hand, inventors can respond to the fee drop by exerting more effort because of higher net payoffs.

1.3.1 A Selection Effect Due to a Lower Quality Threshold

An anticipated fall in the patent fee induces a trade-off between a lower patent fee in the future and the value decline of an ageing idea that is not patented when it is conceived. While a cheaper fee is always desirable for the inventor, a delay in patenting an idea is costly. If an idea is not patented for a long time, it can be imitated. An inventor maximises his utility from patenting an idea, which is a function of the quality of the idea q , the time when the idea is conceived s , and the time at which the idea is patented t , and $t \geq s$,

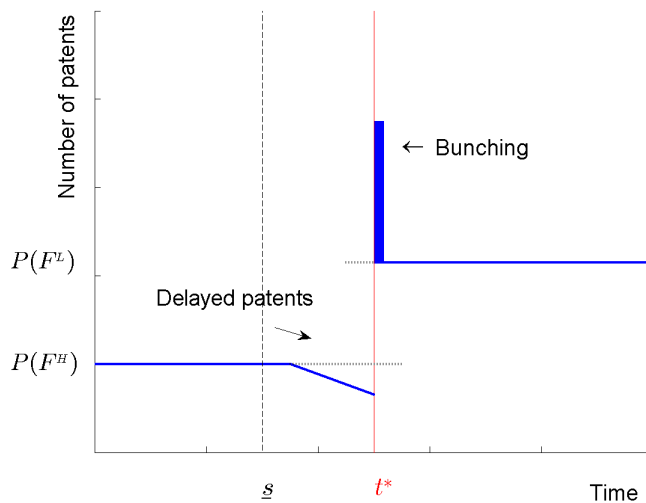
$$U(q, s, t) = (1 - \delta)^{t-s} M(q) - F(t). \quad (1.1)$$

The decay rate δ captures the hazard rate of imitation for an idea that is left unpatented. The proportion of the value that decays increases exponentially with the time delayed for patenting $t - s$. $M(q)$ is the immediate utility of an idea, which is a monotonically increasing and unbounded function of q , with $M(0) = 0$. I assume that the inventor has

perfect information about the quality of his idea, that other costs of inventing are abstracted from, and that discounting is constant with a zero discounting rate. The reservation utility of not patenting is set equal to zero.

The optimal timing of a patent depends on the decay rate of an idea and the profile of patenting fees $F(t)$. In the case of a sudden and anticipated fee drop at time t^* , the profile of fees can be written as $F(t) = F^H$ for $t < t^*$, and $F(t) = F^L$ for $t \geq t^*$ with $F^H > F^L$. In this case, it is only ever optimal to patent at time s or at t^* . Either the inventor patents in the current period, or waits the minimal amount of time before patenting at the lower fee. When the latter occurs an idea is patented at t^* and thus contributes to the bunching at the fee notch. The evolution of patent numbers P is illustrated in Figure 1.5.

Figure 1.5 Delayed patenting before a patent fee drop



Notes: This Figure shows the evolution of patent numbers P as a function of the fee regime over time with a patent fee drop at time t^* . The earliest time when it can be profitable to delay a patent to t^* is given by \underline{s} . Depending on the quality of an idea, some patents are delayed between \underline{s} and t^* , and the missing mass given by the triangle below a counterfactual distribution is a lower bound for mechanically delayed patents in period t^* .

The corresponding value function of an idea of quality q conceived at time s is given by

$$V(q, s) = \max_t U(q, s, t). \quad (1.2)$$

To explain bunching of patents at t^* , I first consider when it is optimal for an idea to be patented at time t^* . This is equivalent to maximising the value function above at $t = t^*$. If an idea conceived at time $s < t^*$ is delayed from patenting until t^* , the utility of patenting

at time t^* must exceed the reservation utility of zero. For each s , this defines a minimum quality of an idea $\underline{q}(s)$. For an idea to be delayed, it must be the case that $q \geq \underline{q}(s)$. This is summarised by

$$q(s) \geq M^{-1} \left(\frac{F^L}{(1-\delta)^{t^*-s}} \right), \quad (1.3)$$

such that the lower bound of the quality of an idea worth delaying is

$$\underline{q}(s) = M^{-1} \left(\frac{F^L}{(1-\delta)^{t^*-s}} \right). \quad (1.4)$$

As M is monotonically increasing and unbounded, M^{-1} is well-defined and also monotonically increasing. The minimum quality threshold $\underline{q}(s)$ is a decreasing function of s because a higher s represents a smaller delay time $t^* - s$. This means that an idea of lower quality is still worth patenting at time t^* if s is higher.

In addition, for an idea to be delayed optimally it must be the case that the inventor receives a higher utility for patenting at time t^* than at time s . This implies

$$(1-\delta)^{t^*-s}M(q) - F^L \geq M(q) - F^H, \quad (1.5)$$

which after rearranging leads to the following condition for the quality of an idea that is delayed

$$q(s) \leq M^{-1} \left(\frac{F^H - F^L}{1 - (1-\delta)^{t^*-s}} \right). \quad (1.6)$$

This condition defines an upper bound to the quality of an idea delayed from time s

$$\bar{q}(s) = M^{-1} \left(\frac{F^H - F^L}{1 - (1-\delta)^{t^*-s}} \right). \quad (1.7)$$

For an idea to be worth delaying, it must be the case that the idea is not too good. If an idea were of very high quality, then the decay of the idea is so costly that it is not worth delaying. In particular, $\bar{q}(s)$ is an increasing function of s . For greater s the amount of time needed for delaying is shorter, therefore the relative decay $(1-\delta)^{t^*-s}$ is smaller, and hence an idea needs to be of higher quality not to be worth delaying.

The above two bounds for the quality of an idea worth delaying solve the optimisation problem of the inventor. Whenever it is the case that $\underline{q}(s) \leq q \leq \bar{q}(s)$, then an idea is delayed for patenting until time t^* . There is a minimal time \underline{s} , before which an inventor would never want to delay patenting. The upper quality bound is an increasing function of s and the lower bound is a decreasing function of s . Defining \underline{s} by $\underline{q}(\underline{s}) = \bar{q}(\underline{s})$, then for periods $s < \underline{s}$ it is the case that $\underline{q}(s) > \bar{q}(s)$. It is thus never optimal for the inventor to wait until t^* with patenting

an idea conceived before \underline{s} . Such an idea would need to be both of very high quality for it to be still worth patenting at the later time of t^* , and yet still not be so good that one would prefer to simply patent it in the current period. It is impossible for both to occur for $s < \underline{s}$, and this establishes the earliest time at which a fee change can affect patenting decisions.

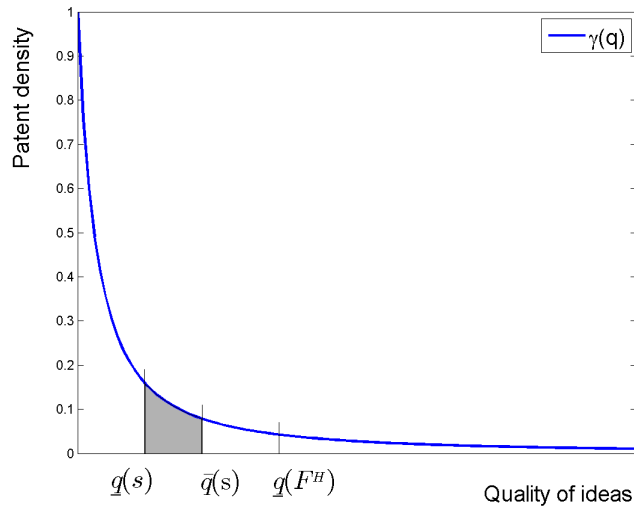
Knowing the optimal decision of when to patent an idea, it is possible to describe the size composition of bunching at time t^* . I assume that for each instantaneous moment in time, there is a continuum of measure 1 draws from a quality distribution of ideas. Suppose that the quality distribution of ideas follows a Pareto distribution, with a density function $\gamma(q)$ and a cumulative distribution $\Gamma(q)$. As there is a continuum of measure 1 of draws, the proportion of ideas drawn matches exactly that of the distribution.

Using this assumption, I can derive the exact measure of draws that is chosen to be delayed at each moment in time. For an idea to be delayed from time s , it must be the case that $\underline{q}(s) \leq q \leq \bar{q}(s)$. It follows that the measure of draws to be delayed must equal

$$d(s) = \Gamma(\bar{q}(s)) - \Gamma(\underline{q}(s)), \tag{1.8}$$

which is displayed in Figure 1.6.

Figure 1.6 Delayed patents that contribute to bunching



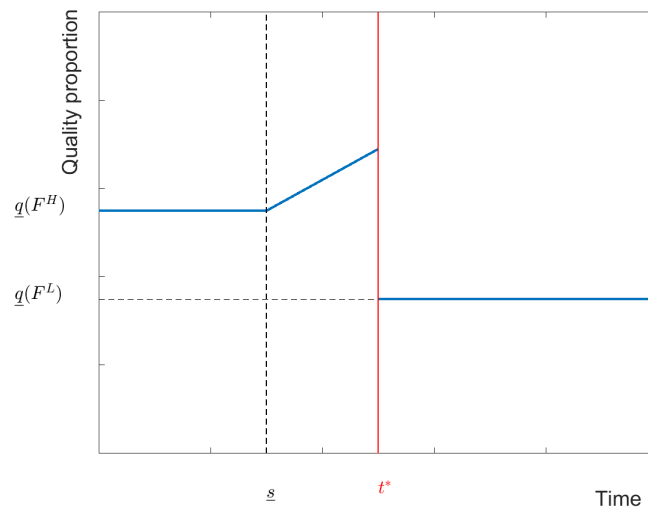
Notes: The distribution of the quality of ideas is denoted by Pareto density $\gamma(q)$. Ideas of age s are delayed if their quality falls between the minimum quality threshold $\underline{q}(s)$ and the upper quality bound $\bar{q}(s)$ for an idea of age s .

Finally, the size of the bunch is the accumulation of the above measures of draws,

$$B = \int_{\underline{s}}^{t^*} d(s)ds. \quad (1.9)$$

As shown in Figure 1.7, the minimum quality of an idea is higher before the fee reduction. It increases in periods $t > \underline{s}$, when patenting of some ideas is delayed, and falls to $\underline{q}(F^L)$ after the fee reduction in period t^* .

Figure 1.7 Selection affecting the proportion of high-quality patents



Notes: Only patents of higher quality are patented between periods \underline{s} and t^* because these incur a higher cost of decay if delayed. The quality threshold for ideas declines from $\underline{q}(F^H)$ to $\underline{q}(F^L)$ at t^* .

One measurement of the quality of an idea in the data is based on the decision to renew a patent. Unlike the fee for patenting the fees to renew a patent did not change at the threshold t^* . Therefore, a patent is renewed if the original idea is of a quality greater than the lower-quality bound for renewals, which does not vary across time. Based on this framework I can make the following prediction using renewals as a measurement of quality.

Prediction 1. The proportion of renewals among patents submitted at time s is increasing in s , where $\underline{s} \leq s < t^*$, because it is more and more costly to delay patents of higher quality between \underline{s} and t^* . The patents that appear in the bunch at the fee notch at t^* have a smaller proportion of renewals compared to the proportion of renewed patents that are submitted between \underline{s} and t^* .

1.3.2 A Behavioural Effect Due to Increased Effort

So far, only the optimal time to patent is considered. For a given time period, an important choice also arises with respect to the amount of effort to exert. With increased effort innovation can occur. To allow for innovation in the model, inventors also choose effort, so that effort is exerted in order to obtain a larger quantity of draws from the quality distribution of ideas. For this purpose I endogenise the size of the measure of draws. Instead of a measure 1 of draws from the same quality distribution of ideas, the measure of draws can now be generalised to d . Drawing more ideas is costly as, for example, research time is required to develop new ideas. I model this cost by introducing an effort function $e(d)$, where $e'(d) > 0$ is unbounded and $e''(d) > 0$. These two conditions ensure an interior solution, as the marginal cost of an additional draw is so high eventually that the number of draws is finite.

A representative inventor chooses d at time s to maximise the utility of patenting from a measure of d draws,

$$\max_d E_q d [V(q, s)] - e(d), \quad (1.10)$$

which generates the following first-order condition with respect to d ,

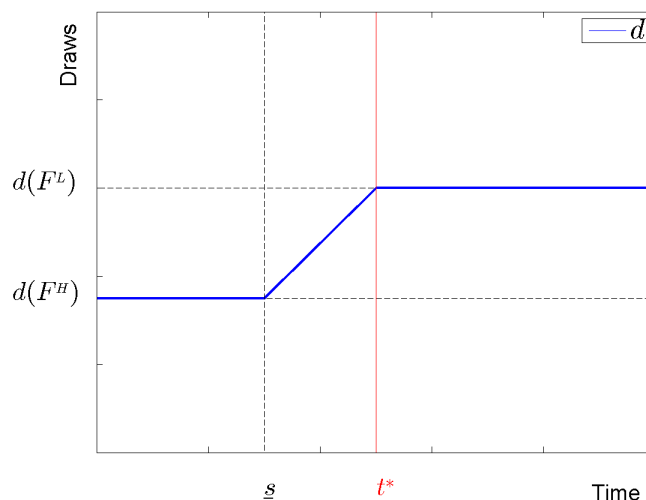
$$E_q [V(q, s)] = e'(d). \quad (1.11)$$

As effort is increasing in d , the optimal choice for d is increasing in the expected value function $E_q [V(q, s)]$. This expression can be used to analyse the effect of the fee change on innovation. If the absolute number of patents renewed is the measure for innovation, then a higher rate of innovation corresponds to more ideas of a quality that exceeds the minimum quality threshold for renewals. This happens when d is higher.

The fee change incentivises higher d , as shown in Figure 1.8. At the initial steady-state when $s < \underline{s}$, ideas have no additional value despite the option to delay. As s increases beyond \underline{s} , the value of an idea increases due to the increasingly less costly option of delaying. This causes the optimal level of d to increase. From t^* on, there is a new steady-state, where the value of an idea is at the new higher value. The optimal level of d is constant at the new higher level. The increases in d are reflected in a greater absolute number of high-quality patents, and hence a greater rate of innovation. Thus, the fee reduction has an effect of incentivising faster innovation.

Prediction 2. The absolute number of renewals following the fee change at t^* is higher than at the initial steady-state when $s < \underline{s}$.

Figure 1.8 The behavioural effect of a fee drop on effort exerted



Notes: The overall payoff from patenting increases after the fee falls to F^L , which incentivises inventors to exert more effort and take more draws from the quality distribution of ideas.

Prediction 3. The proportion of patents renewed relative to the total number of patents is lower following the fee change at t^* than at the initial steady-state when $s < \underline{s}$. This is the case because the quality threshold for renewals is constant while the selection effect lowers the quality of patented ideas.

As a result of these predictions, the relative importance of increased effort can be approximated by comparing the high-quality share of the overall patenting increase to the pre-reform share of high-quality patents.

1.3.3 Credit Constraints

Furthermore, I allow for the possibility that the effect of a fee change is not homogeneous across the population of inventors. Inventors who are credit constrained are likely to respond more strongly to a fee change than those who are unconstrained. The focus here is on credit constraints, but these are observationally equivalent to differences in preferences that lead constrained inventors to respond more strongly to a cheaper patent fee. To account for constraints in the model, I introduce a credit limit c for each inventor such that the inventor cannot patent whenever the fee $F(t)$ is greater than c .

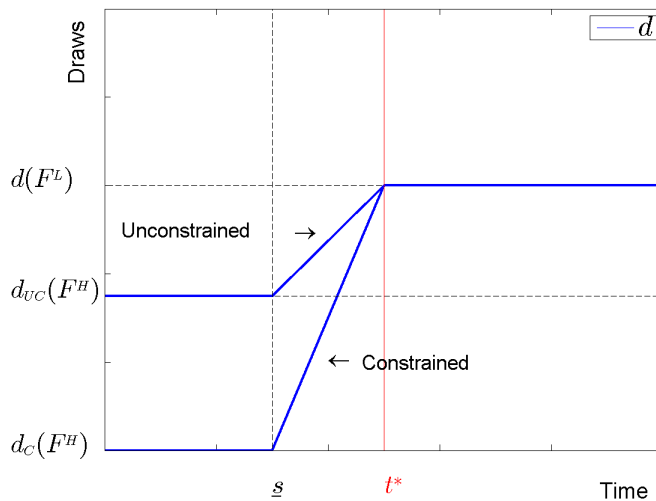
The optimal behaviour of an inventor subject to a credit constraint c depends on the relation of c to F^H and F^L . When $c > F^H > F^L$, the inventor is unconstrained and thus behaves as derived above. When $c < F^L < F^H$, the inventor can never patent. In the case

when $F^L < c < F^H$, the inventor cannot patent when the fee is high before the reform but is able to patent under the cheaper fee. Therefore after t^* , this inventor behaves the same as an unconstrained inventor. Before t^* , the constrained inventor can also delay ideas to patent in the bunch at t^* . The delaying behaviour of the constrained inventor differs from that of the unconstrained inventor because his decision to delay is not constrained by equation (1.5). There is a minimal quality for patenting but an upper bound as for the unconstrained inventors does not apply, so that only condition (1.3) is relevant. The proportion of draws that gets delayed for patenting is now

$$d_C(s) = \Gamma(\bar{q}(s)). \tag{1.12}$$

Before period \underline{s} the expected value of an idea is zero, and hence the optimal measure of draws for a constrained inventor is zero. As s increases beyond \underline{s} , the optimal measure of draws increases at a rate faster than that of the unconstrained inventor, which is illustrated in Figure 1.9. At t^* , the optimal measure of draws is the same as that of the unconstrained inventor at the new higher level. From t^* onwards, unconstrained and constrained inventors exert the same amount of effort if credit constraints are fully relaxed.

Figure 1.9 The effort increase for constrained and unconstrained inventors



Notes: Inventors who are credit constrained during the high fee regime exert zero effort before period \underline{s} , and increase draws faster than unconstrained inventors after \underline{s} . If constraints are fully relaxed as a result of the fee drop, effort exerted by the constrained catches up with that of the unconstrained inventors in period t^* .

The data only contains imperfect measurements of when an inventor is constrained, and the categories of constraints correspond to different distributions of c . The constrained group of inventors in the data are individuals with a lower distribution of c and hence are on average more likely to be constrained. Using this measure of constraints, the following prediction follows from the model.

Prediction 4. The innovation response, measured by the percentage increase in renewed patents, is stronger for the constrained group.

1.4 Data

The data used in this Chapter contains information on individual patentees and the date of their patent application. The patent dataset generated includes British patentees between 1879-1888, a ten-year window around the decrease in the patent fee on January 1 1884, and is composed of 54,000 British patentees who were granted a total of 42,500 patents. The term patentee is used for an inventor who was granted a patent. Table 1.1 shows summary statistics of the number of patentees and types of patents.

Table 1.1 Summary statistics for British patentees and patents

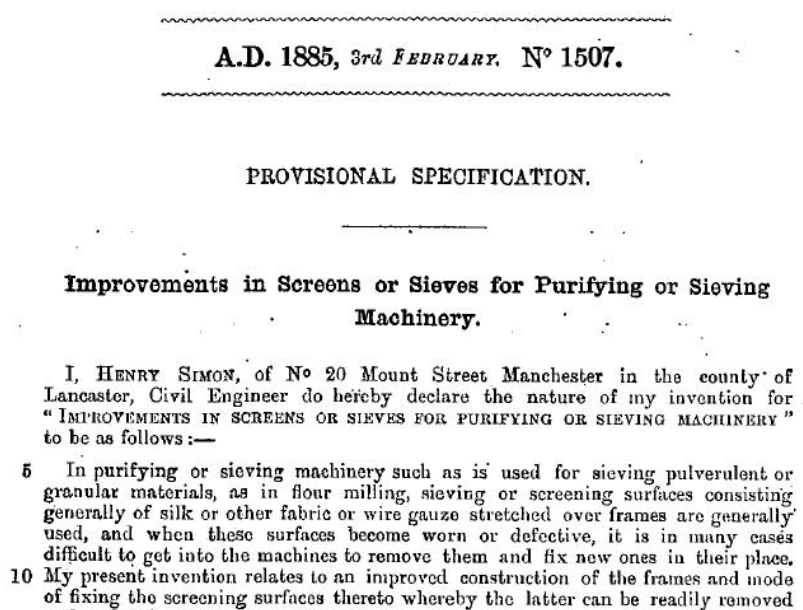
	1879-1888	1879-1882	1885-1888
Number of British patentees	53,873	11,114	31,354
Number of patents by British patentees	42,474	8,822	24,456
Proportion of single inventors	0.61 (0.49)	0.62 (0.49)	0.59 (0.49)
Average number of patentees if team	2.26 (0.57)	2.26 (0.57)	2.27 (0.59)
Proportion of patentees with more than one patent	0.55 (0.50)	0.52 (0.50)	0.55 (0.50)
Average number if multiple patents per patentee	4.90 (6.85)	4.73 (5.96)	5.04 (7.24)
Proportion renewed at four years	0.31 (0.46)	0.35 (0.48)	0.30 (0.46)
Proportion of patents renewed at 14 years	0.07 (0.25)	0.06 (0.25)	0.07 (0.25)
Proportion of patents patented in the US	0.06 (0.25)	0.09 (0.28)	0.06 (0.23)

Notes: British patentees are patentees who were resident in Great Britain. Multiple patentees named on a single patent are referred to as team. Standard deviations are reported in parentheses.

Over 60 percent of patents were granted to a single patentee, and the remaining 39 percent were patentees named on patents granted to more than one inventor. Of all patents applied for, 55 percent were granted.

Information on the patent date, name, address and often occupation of each patentee were extracted from individual patent specifications. Figure 1.10 shows an example abstract of a 1885 patent that includes the patentee's name, address and occupation, which were typically provided in patent abstracts.

Figure 1.10 Specification extract for patent number 1507 of year 1885



To analyse responses under the same incentive conditions, I focus on patentees who were resident in Britain, referred to as British patentees in this Chapter. The demographic information compiled from patent specifications enables distinguishing between foreign and British patents, and around two thirds of all UK patentees were British.⁷ Data did not previously exist that allows identifying granted patents of British residents only, who are likely to be more responsive to a UK fee change than foreigners who patent in the UK. Previously, patent data for this period was mainly available in the form of printed publications of the UK Patent Office, with only yearly aggregate data on patents applied for, granted patents and renewed patents. In the Annual Reports of the Patent Office from

⁷A distinction is drawn between foreign residents and British residents who both obtained patent protection in the UK. The patent data also includes around one percent of patentees resident in Ireland, who are not included in the sample of British patentees. Census data is not available for Ireland for the 1880s and wealth proxy measures can thus not be generated for patentees resident in Ireland.

1884 onwards, aggregate yearly figures are provided separately for patent applications by foreigners and by British residents but this breakdown is not available before 1884, nor for granted or renewed patents.

In addition, I digitised and compiled renewal information on the life cycle of patents with application dates between 1879-1888 from over 60 volumes of the Patent Office journal for 1879-1902. Information on whether a patent was granted and renewed at different years of term is only available in printed volumes of the Patent Office journal, which is called *Commissioners of Patents' Journal* until 1884, *Official Journal of the Patent Office* for 1884-1888, and *Illustrated Official Journal (Patents)* from 1889 onwards.

To generate a second quality measure for patents, I matched patents that were granted in the United States to British residents with the British patent data. By using information from the *American Annual Report of the Commissioner of Patents* for years 1879-1890, on average 230 UK patents per year pre-1884 and 430 patents per year from 1884 onward can be identified as British patents that also received patent protection in the US.

To test for credit constraints, I create two proxy measures for inventor wealth by using precise information on inventor names and addresses. Subsections 1.4.1 and 1.4.2 describe how the two proxy wealth measures are generated.

1.4.1 Ranking Inventor Surnames by Wealth

I use inventor surnames to construct a proxy measure of wealth, by making use of the relative probate frequency of an inventor's surname by county compared to the general frequency of the surname in a county. This approach follows Clark (2014), Clark and Cummins (2015) and Clark et al. (2015) who develop surname-based measures for estimating intergenerational wealth mobility. Olivetti and Paserman (2015) apply a similar strategy by indexing the relative occupational status of first names in the US over the last two centuries.

Probate was legally required for any estate value at death equal to £10 or above, and on average only 15 percent of adults in England had their estate probated at death between 1858-1887 (Clark and Cummins, 2015). Probate information is available in the records of the National Court of Probate for years after 1858, and was accessed through the genealogy website www.ancestry.co.uk to create a ranking of inventor surnames by county. While the National Probate Calendar indexes testators with information on full names, county, value of estate, and sometimes occupation, I only use county average occurrences of a surname among those being probated at death for the rank measure. This approach has the advantage of making the resulting wealth measure independent of individual achievement or talent, and of education levels in a county. The surname measure is constructed as the ratio of county

frequencies,

$$\frac{\text{Share of surname } z \text{ probated in county } j \text{ at } T \pm 10}{\text{Share of surname } z \text{ in county } j \text{ in the 1881 census}}$$

To approximate the age cohort of the inventor, the time range for the surname probate likelihood is defined as a 21-year range around T , the patenting year plus eleven years. With an average inventor age of 36, and accounting for the fact that inventors are likely to have an average life expectancy that is higher than the British population average of 43 years in the 1880s, this gives an average inventor age range of 37 to 57 for which corresponding probate years are searched. As the median patent in the sample is filed in 1886, I restrict the census surnames to individuals between the ages of 21 and 41 in the 1881 census. An example of relative counts and the corresponding ranking of inventor surnames for the county of Yorkshire is provided in Table 1.2.

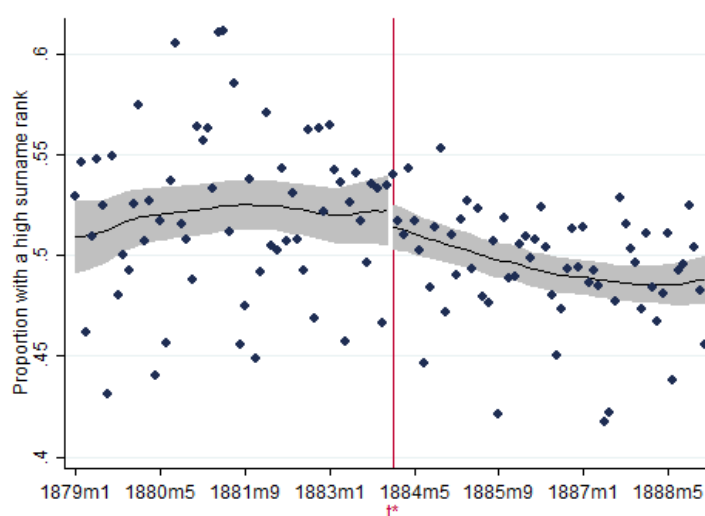
Table 1.2 Surname ranks for county Yorkshire

Lowest ranked surnames:			Highest ranked surnames:		
Surname	Probated N	Census N	Surname	Probated N	Census N
Hemmingway	1	107	Micklethwait	11	7
Maskell	1	37	Reffitt	4	3
Mullin	1	34	McIntock	5	3
Griffin	5	194	Whytehead	5	3
Beesley	1	31	Qualter	4	2
Balls	1	30	Cordeaux	4	2
Dodd	5	151	Middlemost	4	2
Duffy	8	232	Gallwey	2	1
Case	1	28	Bamlett	2	1
Sturgeon	1	28	Pollit	6	3
Average county N	122,565	885,509	Average county N	122,565	885,509

Notes: The frequency of surname occurrence within a county is denoted by N . Probated N refers to the number of surnames probated in a county over a 21-year period that is chosen to approximate a patentee's age cohort. Lowest ranked surnames are shown for non-zero ranks.

Using this surname ranking, it is possible to match around 83 percent of inventor surnames with probated surnames in the county of an inventor's residence. Figure 1.11 shows the evolution of the proportion of inventors with a high socio-economic surname rank from 1879-1888. Around nine percent of inventor surnames can be uniquely matched with a probate surname within a county and time period. I do not use unique matches, however, as a unique match does not necessarily include the inventor in question because the probate data only contains the small population subsample that was probated at death.

Figure 1.11 Proportion of patentees with high wealth ranking



Notes: Surnames are classified as high-rank if the probabilistic share of an inventor's surname being probated at death exceeds that of its frequency in the 1881 census at the county level. A 95-percent confidence interval is shown for polynomials fitted before and after the patent fee change at t^* in January 1884.

1.4.2 Census Information on the Employment of Servants

The 1881 Census of Population contains information on the number of servants employed in each household. I use this information on servants to construct a second proxy measure for wealth by merging the data on inventors with the 1881 census. The 1881 census includes full names and demographic information of each individual, and the 100-percent sample of the 1881 census with individual names was accessed through the North Atlantic Population Project.⁸ I match the data on inventors with census data based on an algorithm using the full names and addresses of inventors. Due to the increased digital availability of historic census data, studies that use similar matching of historical records with census data as implemented in this Chapter have become more frequent over the last years.⁹

By using data on names and addresses around 34 percent of patentees can be uniquely matched in the census data. While nearly all patentees have a match in the census data, many

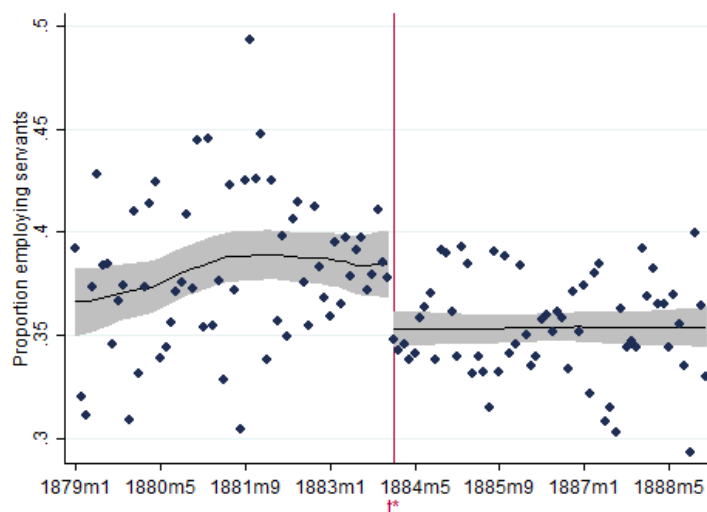
⁸The North Atlantic Population Project provides access to 1881 Census data for Great Britain, by K. Schürer and M. Woollard, *National Sample from the 1881 Census of Great Britain* [computer file], Colchester, Essex: History Data Service, UK Data Archive [distributor], 2003.

⁹For example, such matched census data is used in work on intergenerational mobility in the US and in Britain (Long and Ferrie, 2007, 2013), on intercontinental migration to the US (Abramitzky et al., 2012), or for analysing the cultural effects on language imposition in the US (Fouka, 2015).

of these matches are not unique. The resulting sample of uniquely matched patentees is not random and is likely to reflect socio-economic selection based on less frequent names and lower geographic mobility between the date of the 1881 census and the date of patenting. To locate patentees in the census data, I impose a labour force age range of 16 to 60 for each year of patenting and a corresponding age cohort in the 1881 census. For example, an inventor who patented in 1888 was on average younger in 1881 than one who patented in 1879, and is more likely to have moved from the county of residence since the census year.

The wealth proxy constructed from census data used in this Chapter is whether a patentee household employed servants or not. On average, 36 percent of matched patentees employed servants in their household compared to around 19 percent of the male census population aged between 16 to 60 years. The measure of servants employed in a household thus indicates that patentees are a subsample of the population with comparatively high wealth.

Figure 1.12 Proportion of patentee households employing at least one servant



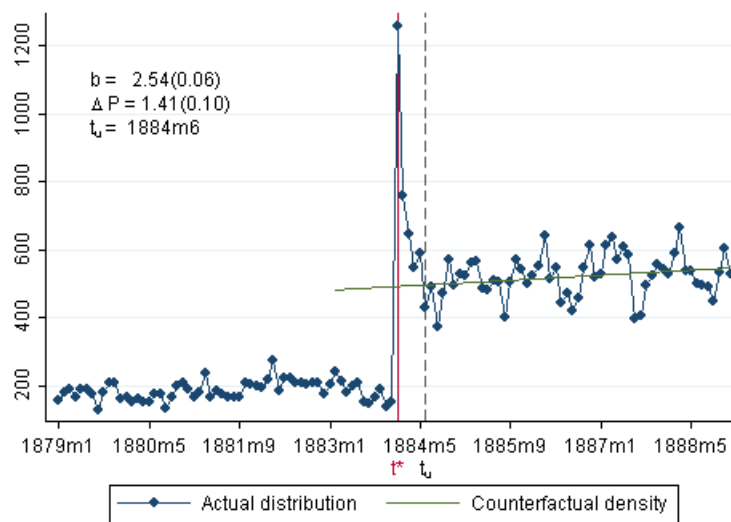
Notes: Information on servants employed is available for inventors that can be uniquely matched in the 1881 census. A 95-percent confidence interval is shown for polynomials fitted before and after the patent fee change at t^* in January 1884.

Figure 1.12 plots the proportion of matched patentees who employ at least one servant, showing a small downward shift after the patent fee reduction in January 1884. For an inventor household that employs servants, the average number of servants is 1.17 before 1884 and 1.09 from January 1884 onwards.

1.5 Estimation

The total number of patents increased strongly after the fee drop on January 1 1884, with significant bunching at and after the fall in the fee as depicted in Figure 1.13.

Figure 1.13 Number of British patents granted



Notes: The x-axis plots the application date of patents. Excess bunching over the counterfactual density after the fee reduction at t^* in January 1884 is denoted by b , and ΔP refers to the percentage change in average monthly patent numbers between years 1885 and 1882. Period t_U marks the upper bound for the months affected by bunching. Bootstrapped standard errors are reported in parentheses.

In this section, I first estimate the excess bunching observed in the months after the fall in the patent fee. The short-run responses are then compared to longer-run elasticities for periods from 1879-1888 that are not affected by the short-run shifts of patenting activity.

1.5.1 Bunching and Longer-run Elasticities

The downward notch in the patent fee in January 1884 introduces a discrete fall in patenting costs that leads to short-run bunching of patents. As described in Section 1.3, it is profitable to delay patenting in the periods just before the patent fee drops when the value of waiting exceeds the value of patenting before the fee change in t^* . Kleven and Waseem (2013) and Best and Kleven (2016) develop a bunching approach that uses the discontinuities in the choice sets of individuals created by the presence of a notch for identifying the reduced-form elasticity of an outcome variable in response to a tax or duty change. I apply this bunching

strategy to analyse the short-run response to the fall in the patent fee in the months from January 1884 onward.

Excess bunching in response to the fee drop is estimated as the total number of patents over a counterfactual density of patents. The counterfactual is here approximated by fitting a predicted linear trend in patenting numbers from the months exceeding the upper bound to the periods affected by bunching, $t > t_U$, to the months affected by bunching, $t^* \leq t \leq t_U$, and using bins of one month's width. The counterfactual is thus obtained from the predicted values of the regression

$$\hat{c}_t = \beta t P_t + \sum_{i=t_0}^{t_U} \gamma_i \mathbf{1}[P_t = i] + v_t, \quad (1.13)$$

when omitting the dummies in the excluded range, $t \leq t_U$, and excess bunching b is given by

$$b(t_U) = \sum_{i=t^*}^{t_U} (c_t - \hat{c}_t). \quad (1.14)$$

The upper bound t_U of the exclusion range is relatively sharp in the data, so that it can be chosen as the point marking the upper bound of the patents that are bunched. In Figure 1.13, a vertical dashed line indicates t_U in June 1884. Instead of one spike at t^* only, patents are bunched until several months after the fee notch, which is likely due to frictions in the processing of applications and in the application timing by inventors. For the estimates in this Chapter, I extend the exclusion range for estimating the counterfactual distribution to all months before t_U , instead of fitting a polynomial to both sides of the bunching period $t^* \leq t \leq t_U$. This avoids bias from behavioural responses affecting the alternative counterfactual distribution in the months before t^* because bunching at the fee notch can be a result both of delayed patents and increased effort in anticipation of the fee change. Standard errors for the bunching estimators are bootstrapped in a procedure following Chetty et al. (2011). Standard errors for the other parameters are obtained by pairwise bootstrapping.

The fee notch produces pronounced short-term shifting of patents to the periods after the fee drop when $t^* \leq t \leq t_U$. The magnitude of excess bunching b for British patents of all durations is 2.54. The corresponding short-term elasticity of patent numbers in response to the fee change is given as the ratio of excess bunching over the percentage change in the patent fee,

$$e_{SR} = \frac{b}{\Delta F}, \quad (1.15)$$

where ΔF is equal to $(F^H - F^L)/F^L$. The short-run elasticity for British patents of all durations corresponds to -3.02 and is reported in Table 1.3.

Table 1.3 Patent number responses to the 1884 patent fee reduction

	b	e_{SR}	ΔP	ε_{LR}
All patent types	2.54 (0.06)	-3.02 (0.07)	1.41 (0.10)	-1.68 (0.13)
Granted only	2.67 (0.06)	-3.18 (0.08)	1.62 (0.13)	-1.92 (0.08)
Renewed after four years	2.24 (0.05)	-2.67 (0.06)	1.05 (0.10)	-1.25 (0.06)
Renewed for 14 years	1.53 (0.08)	-1.82 (0.10)	1.13 (0.19)	-1.34 (0.13)
Patented in the US	7.42 (0.34)	-8.83 (2.04)	0.34 (0.17)	-0.41 (0.20)

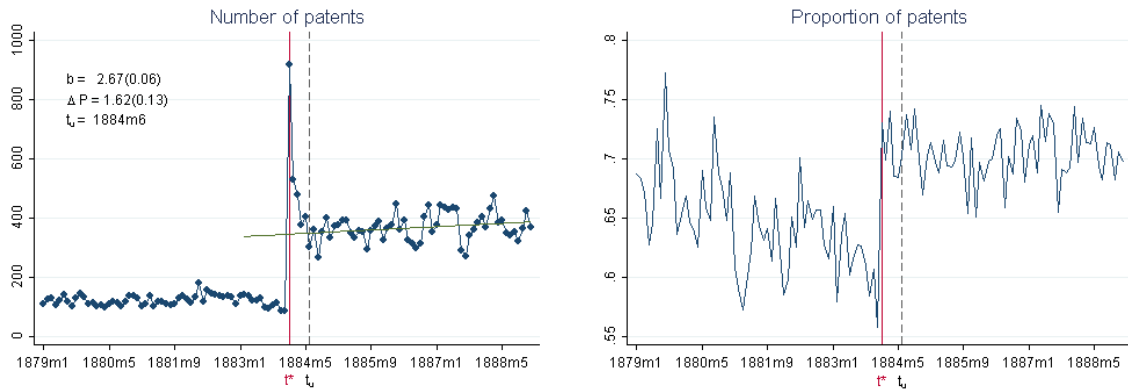
Notes: Short-run excess bunching is given by b , e_{SR} denotes the reduced-form elasticity estimated from bunching, $\Delta P = (P_{1885} - P_{1882})/P_{1882}$ is the percentage change in the monthly average number of patents in 1885 compared to 1882, and ε_{LR} gives the longer-run elasticity. Standard errors are reported in parentheses.

This short-run elasticity measures the combined response of existing delayed patents and patented new ideas in response to the fee reduction. Just before the fee notch patenting numbers show some decline, and this small area of missing mass to the left of the fee drop is a lower bound to all delayed patenting. In the absence of delays, this reduced-form elasticity would measure a Frisch elasticity.

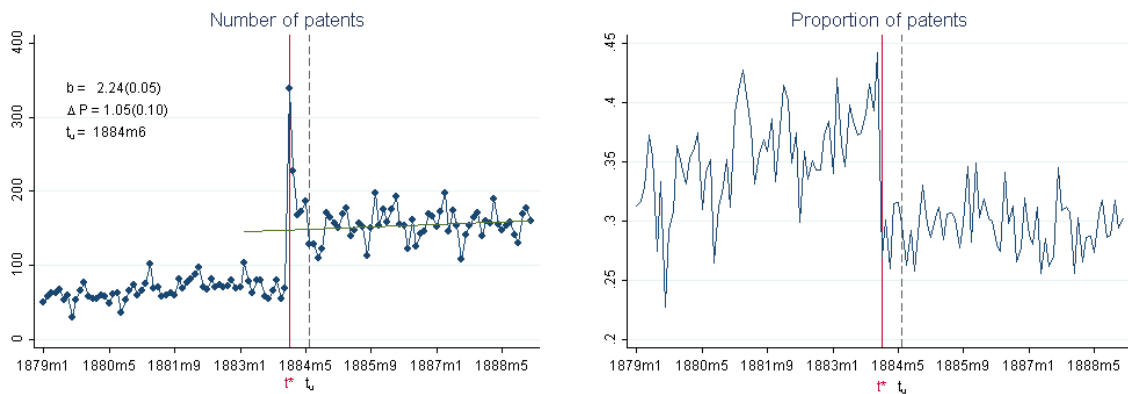
The data includes information on whether a patent was granted only, granted and renewed at four years, or granted and renewed for years up until the full term of 14 years. Figure 1.14 decomposes the aggregate patent number into three quality types according to renewal status. In line with Prediction 1, higher-quality renewed patents exhibit less excess bunching, and excess bunching is smallest for the highest quality patents that are renewed for the full term of 14 years. The graphs in the right column of Figure 1.14 show the proportion of patents by renewal type and the increasing quality of patents just before the fee notch confirms Prediction 1. It is more costly to delay high-quality patents, so that high-quality patents are patented even if the cheaper fee is imminent. The proportion of renewed patents exhibits a pronounced fall at the fee notch to a new lower steady-state level. The precise fall in quality proportions at the fee notch indicates that individuals know about the quality of their patented ideas and optimise the timing of patenting. The average quality of ideas patented reaches a new lower equilibrium level in period t^* .

Figure 1.14 British patents by quality type of patent

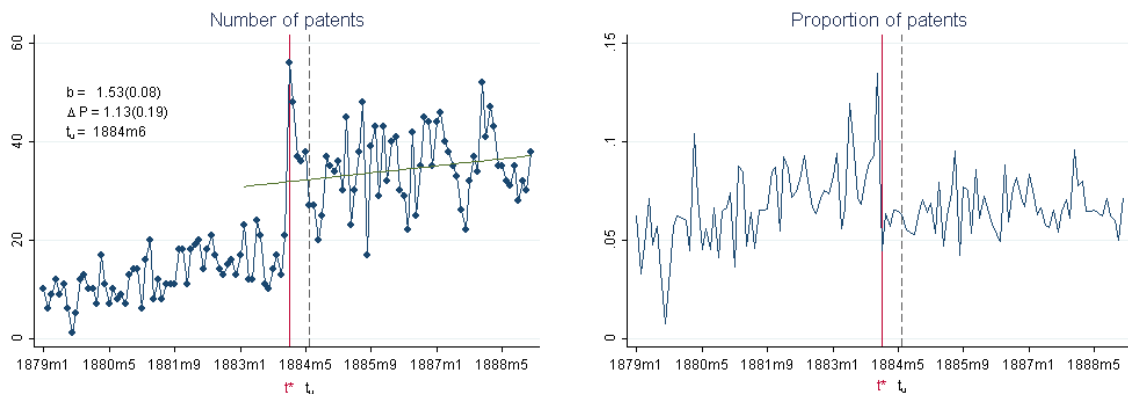
Not renewed



Renewed after four years



Renewed for 14 years



In the longer run, monthly rates of patenting shift upward to a new steady-state, and to analyse this response average monthly percentage changes between 1885 and 1882 are compared. These years are close to the fee reduction but are not affected by bunching, and for these two years the renewal fee regime is the same. The percentage change in average patenting rates in 1882 compared to 1885 is denoted by ΔP and is equal to 1.78. As described in the framework in Section 1.3, this longer-run effect reflects increased effort and investments from inventors who take more draws from the quality distribution of ideas after the fall in the patent fee. At the same time, the quality threshold for patenting an idea falls so that some additional patents are of lower quality. As summarised in Prediction 2, the incentive to exert more effort results in an increased number of renewals after the fee reduction at t^* . This increase in renewed high-quality patents is equal to new innovation if the measures of patent quality capture value. Figure 1.14 shows that the average percentage change in patents which are renewed after four years is 1.05 and the percentage change in patents renewed until full term is 1.13. The longer-run elasticity of innovative activities in response to the fee change can be approximated by the percentage change in high-quality renewed patents P_q over the percentage change in fees,

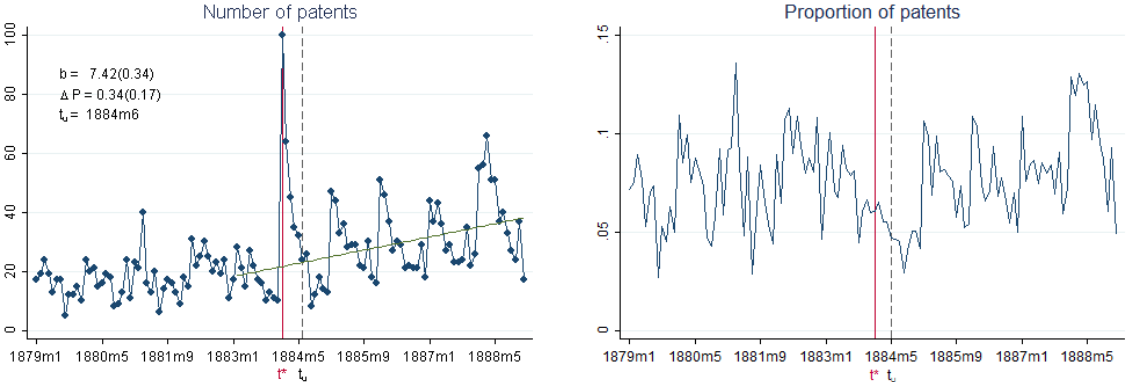
$$\epsilon_{LR} = \frac{\Delta P_q}{\Delta F}. \quad (1.16)$$

These longer-run elasticity estimates are reported in Table 1.3 by patent quality, with the largest responses for patents that were only granted and not renewed, and the smallest responses for patents that were renewed until the maximum possible duration of 14 years.

The qualitative effect of increased innovation also holds when using British patents that received patent protection in the US as an alternative quality measure, as visible in Figure 1.15. While the effect is not as strong as for renewed patents, the longer-run increase in British patents in the US is 0.34. At the moment British US patents are matched by computer, which results in bias toward finding matches at the beginning of the year. In a next step matching will be carried out by hand to avoid this bias, so that the size of bunching is expected to decrease.

According to Prediction 3, the proportion of high-quality patents is lower after the fee reduction if patent quality declines due to the quality threshold effect. This effect on the proportion of high quality patents from t^* onward is visible in the data for renewed patents. Column 3 in Table 1.4 shows that the proportion of patents renewed after four years as well as the proportion of patents renewed until full term and the share of patents with protection in the US decline after the fee change, as described in Prediction 3.

Figure 1.15 British patents that also received protection in the US



Notes: The x-axis plots the application date of patents. Excess bunching over the counterfactual density after the fee reduction at t^* in January 1884 is denoted by b , and ΔP refers to the percentage change in average monthly patent numbers between years 1885 and 1882. Period t_U marks the upper bound for the months affected by bunching. Bootstrapped standard errors are reported in parentheses.

Table 1.4 also lists the share of the patenting increase in 1885 compared to 1882, which is 0.27 for patents renewed after four years. This proportion compared to the initial quality share in 1882 is used to approximate the additional effort exerted after the patent reform.

As an implication of Predictions 2 and 3, it is possible to approximate the share of increased total patenting that is a result of increased effort and investments by accounting for the change in high-quality patents relative to the pre-reform share of high-quality patents. Focusing on the example of renewals, with increased draws from the quality distribution of ideas and in the absence of a negative selection effect, the proportion of renewals would remain constant since the renewal threshold has not changed. Any decline in the proportion of renewals can thus be attributed to the decline in the quality threshold for patents. The relative importance of increased effort in the overall increase in patent numbers can be approximated by comparing the high-quality share of the overall patenting increase to the pre-reform share, which is reported in the last column of Table 1.4. For renewals at four years, the change in effort and investment after the fee reduction accounts for approximately three quarters of the pre-reform share of high-quality patents. The share of patents renewed until 14 years in the patenting increase is slightly larger with around 80 percent of the initial share of renewals in 1882. In comparison, the share of patents in the increase that also received protection in the US only make up 24 percent of the initial quality share in 1882. This difference between the two quality measures could partly be due to market access motives dominating the quality signal of additionally patenting an idea in the US.

Table 1.4 Share of patent quality types out of total patents

	Share in 1882	Share in 1885	Difference 1985 - 1882	Increase share 1882 to 1885	Increase share over 1882 share
Granted only	0.64 (0.00)	0.69 (0.00)	0.05*** (0.00)	0.73 (0.01)	1.14 (0.02)
Renewed after four years	0.36 (0.03)	0.31 (0.02)	-0.05*** (0.00)	0.27 (0.01)	0.74 (0.04)
Renewed for 14 years	0.08 (0.01)	0.07 (0.01)	-0.01*** (0.00)	0.06 (0.01)	0.80 (0.10)
Patented in the US	0.10 (0.02)	0.06 (0.02)	-0.05*** (0.01)	0.02 (0.01)	0.24 (0.10)

Notes: Share of the increase refers to $(P_{q,1885} - P_{q,1882}) / (P_{1885} - P_{1882})$. Standard errors are reported in parentheses and for the difference between 1885 and 1882 shares, significance at the 10-percent level is denoted as *, significance at 5 percent as **, and significance at 1 percent as ***.

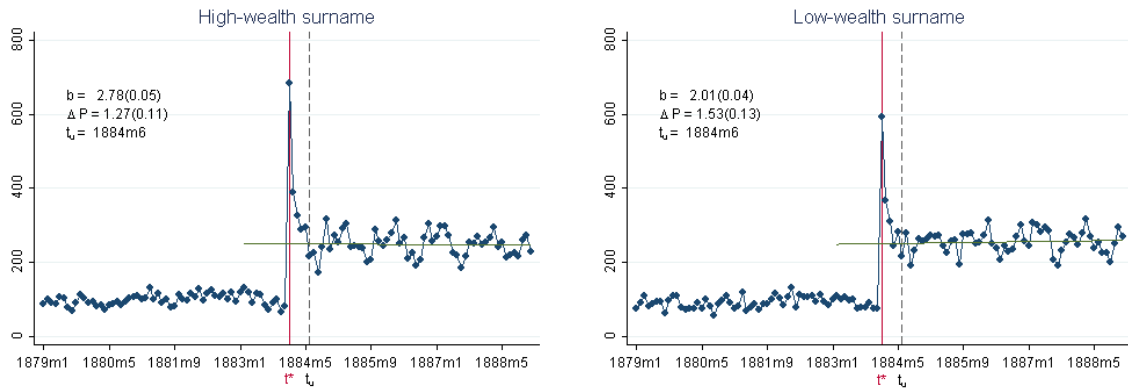
1.5.2 Responses for Inventors with High and Low Wealth

To test for the importance of credit constraints, I generate two proxy measures of wealth to distinguish between high- and low-wealth inventors. First, the overall sample of patentees is decomposed into groups with high and low surname wealth rank, as shown in Figure 1.16. Tables 1.5 and 1.6 provide an overview of the difference in responses. Longer-run elasticities for inventors with lower wealth in response to a negative fee change are higher by 0.33, and this difference is significant at the 10-percent level of significance. As for the overall sample, the proportion of patents renewed after four years falls for both wealth groups. The high-quality share of the overall increase in patenting compared to the pre-reform share is slightly higher for the low-wealth group at 75 percent compared to 70 percent for the high-wealth group.

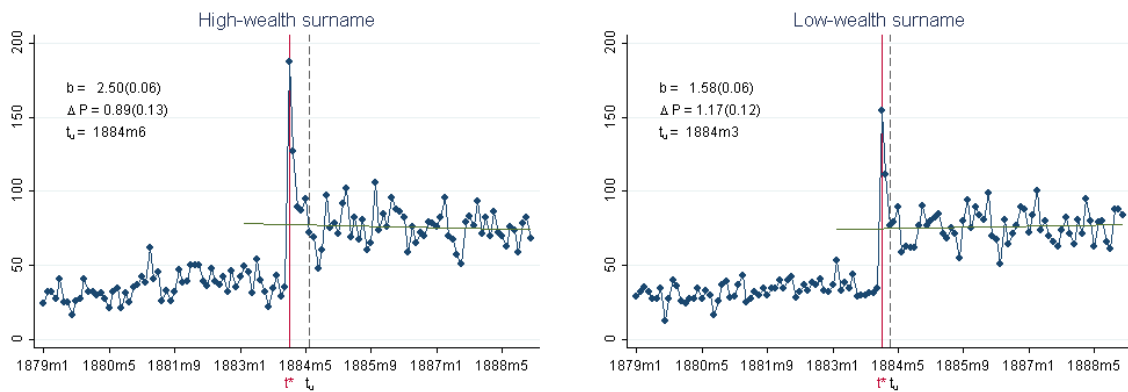
Second, matching patentees in the census enables a decomposition of the sample into inventors that employ servants in their household and those who do not have servants. Figure 1.17 plots the response in patent numbers after January 1884 for these two groups. The response of patentees that do not employ servants is much stronger and significant in terms of total patent numbers as well as for patents renewed after four years. These findings are consistent with Prediction 4, the case when constrained inventors increase effort rapidly from very low levels once credit constraints are relaxed. If constraints continue to bind after t^* , they are likely to prevent patenting and also to interfere with the payment of renewal fees for granted patents, as pointed out by MacLeod et al. (2003). Such an effect would decrease the response of renewed patents to the fee change.

Figure 1.16 Number of British patents by inventor surname rank

All patent durations



Renewed after four years



Renewed for 14 years

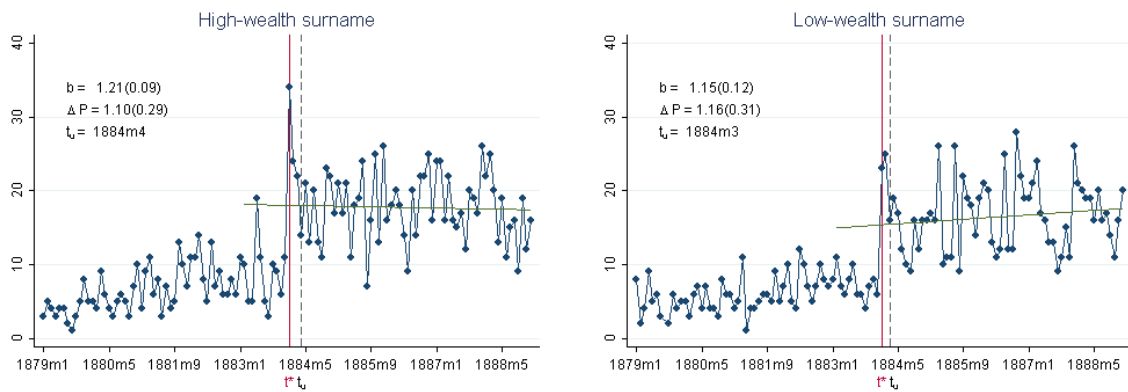


Table 1.5 Patentees by surname wealth rank

	b	e_{SR}	ΔP	ε_{LR}
All patent durations				
High-wealth surname	2.78 (0.04)	-3.31 (0.26)	1.27 (0.11)	-1.51 (0.12)
Low-wealth surname	2.01 (0.04)	-2.39 (0.23)	1.53 (0.13)	-1.82 (0.16)
Difference high - low	0.77*** (0.06)	-0.92*** (0.35)	-0.27* (0.16)	0.32* (0.19)
Renewed after four years				
High-wealth surname	2.50 (0.06)	-2.98 (0.12)	0.89 (0.13)	-1.06 (0.33)
Low-wealth surname	1.58 (0.06)	-1.88 (0.16)	1.17 (0.12)	-1.39 (0.14)
Difference high - low	0.92*** (0.08)	-1.10*** (0.20)	-0.27* (0.17)	0.33* (0.21)
Renewed for 14 years				
High-wealth surname	1.21 (0.09)	-1.44 (0.33)	1.10 (0.29)	-1.30 (0.33)
Low-wealth surname	1.15 (0.12)	-1.37 (0.29)	1.16 (0.31)	-1.38 (0.37)
Difference high - low	0.06 (0.15)	-0.07 (0.44)	-0.07 (0.41)	0.08 (0.50)

Notes: Short-run excess bunching is given by b , e_{SR} denotes the reduced-form elasticity estimated from bunching, $\Delta P = (P_{1885} - P_{1882})/P_{1882}$ is the percentage change in the monthly average number of patents in 1885 compared to 1882, and ε_{LR} gives the longer-run elasticity. Standard errors are reported in parentheses, and significance for parameter differences for patentees with high- and low-wealth surnames at the 10-percent level is denoted as *, significance at 5 percent as **, and significance at 1 percent as ***.

Table 1.6 Share of renewed patents after four years by surname wealth rank

	Share in 1882	Share in 1885	Difference 1985 - 1882	Increase share 1882 to 1885	Increase share over 1882 share
High-wealth surname	0.38 (0.00)	0.32 (0.00)	-0.06*** (0.00)	0.27 (0.02)	0.70 (0.05)
Low-wealth surname	0.35 (0.00)	0.30 (0.00)	-0.05*** (0.00)	0.27 (0.01)	0.75 (0.04)
Difference high - low	0.03*** (0.00)	0.02*** (0.00)	-0.01*** (0.00)	0.00 (0.02)	-0.06 (0.06)

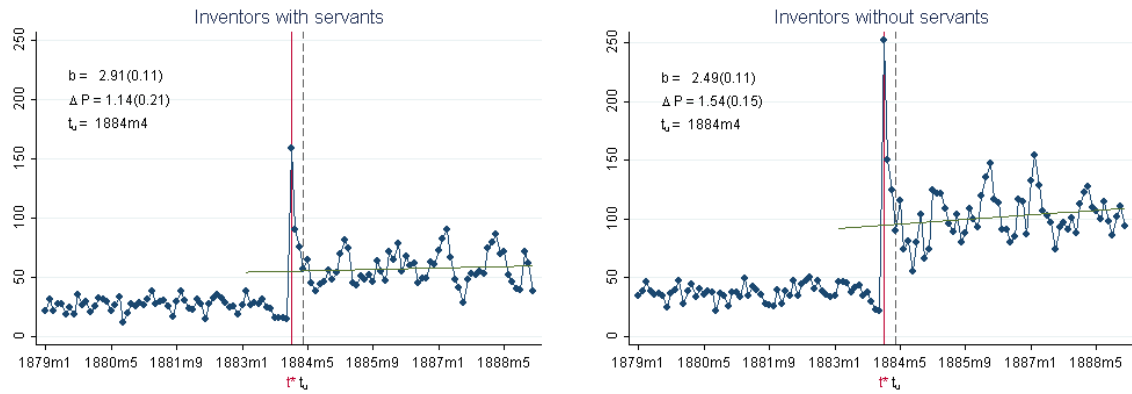
Notes: Share of the increase refers to $(P_{q,1885} - P_{q,1882}) / (P_{1885} - P_{1882})$. Standard errors are reported in parentheses and for 1885 and 1882 shares, significance at the 10-percent level is denoted as *, significance at 5 percent as **, and significance at 1 percent as ***.

Similarly, constrained inventors could on average produce lower-quality inventions even after the constraints are relaxed if human capital or other investments over their life time also suffered due to credit constraints. The presence of these types of constraints would dampen the observed responses by inventors with lower wealth.

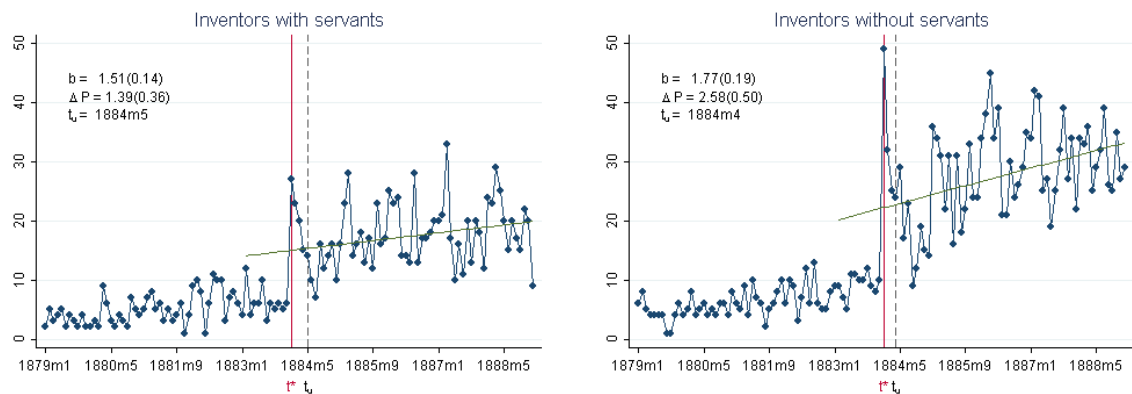
For both groups the percentage increase in renewals exceeds that of renewals in the full patent data sample. Table 1.7 documents correspondingly high elasticities, and the proportion of renewed patents increases slightly for both groups as shown in Table 1.8. The reason for larger increases in renewed patents in the matched compared to the overall sample is that the sample of unique patentee matches is not random. These estimates indicate that patentees with rare names and constant address information in their patent specifications are on average individuals who exert higher levels of effort in response to a patent fee drop. In interpreting the effects by inventor wealth group the focus is therefore placed on the relative differences between the groups.

Figure 1.17 Number of British patents by employment of servants in inventor household

All patent durations



Renewed after four years



Renewed for 14 years

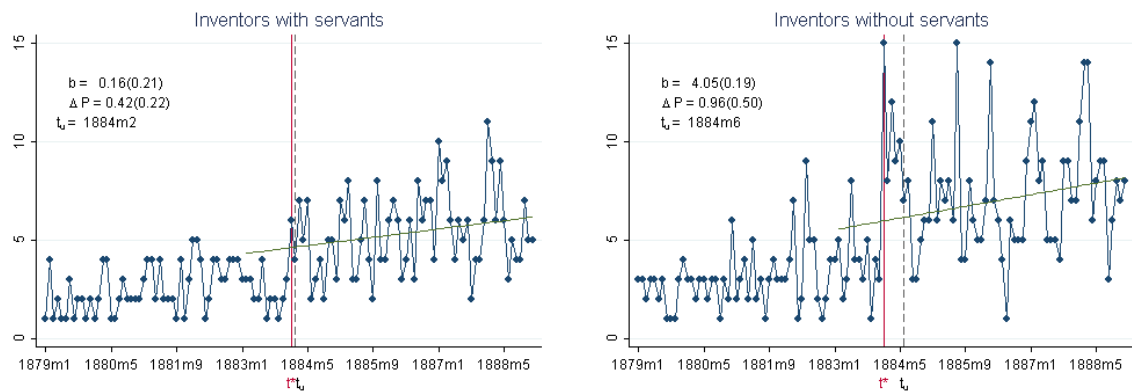


Table 1.7 Patentees matched in the census by employment of servants

	b	e_{SR}	ΔP	ε_{LR}
All patent durations				
With servants	2.91 (0.11)	-3.46 (0.13)	1.14 (0.20)	-1.36 (0.23)
Without servants	2.49 (0.11)	-2.96 (0.13)	1.54 (0.15)	-1.83 (0.18)
Difference with - without	0.42 (0.15)	-0.50 (0.18)	-0.40 (0.26)	0.47 (0.29)
Renewed after four years				
With servants	1.51 (0.14)	-1.80 (0.17)	1.39 (0.35)	-1.66 (0.43)
Without servants	1.77 (0.19)	-2.11 (0.23)	2.58 (0.49)	-3.07 (0.64)
Difference with - without	-0.26 (0.23)	0.31 (0.28)	-1.18** (0.60)	1.41** (0.77)
Renewed for 14 years				
With servants	0.16 (0.21)	-0.19 (0.26)	0.42 (0.22)	-0.50 (0.26)
Without servants	4.05 (0.19)	-4.82 (0.23)	0.96 (0.48)	-1.14 (0.57)
Difference with - without	-3.89*** (0.29)	4.63*** (0.34)	-0.54 (0.53)	0.64 (0.62)

Notes: Short-run excess bunching is given by b , e_{SR} denotes the reduced-form elasticity estimated from bunching, $\Delta P = (P_{1885} - P_{1882})/P_{1882}$ is the percentage change in the monthly average number of patents in 1885 compared to 1882, and ε_{LR} gives the longer-run elasticity. Standard errors are reported in parentheses, and significance for the parameter differences for patentees with and without servants at the 10-percent level is denoted as *, significance at 5 percent as **, and significance at 1 percent as ***.

Table 1.8 Share of renewed patents after four years by employment of servants

	Share in 1882	Share in 1885	Difference 1985 - 1882	Increase share 1882 to 1885	Increase share over 1882 share
With servants	0.28 (0.01)	0.31 (0.00)	0.02*** (0.01)	0.32 (0.04)	1.13 (0.14)
Without servants	0.18 (0.01)	0.26 (0.00)	0.06*** (0.01)	0.31 (0.02)	1.59 (0.13)
Difference with - without	0.10*** (0.01)	0.04*** (0.00)	-0.04*** (0.01)	0.01 (0.05)	-0.46*** (0.19)

Notes: Share of the increase refers to $(P_{q,1885} - P_{q,1882}) / (P_{1885} - P_{1882})$. Standard errors are reported in parentheses and for the difference between 1885 and 1882 shares, significance at the 10-percent level is denoted as *, significance at 5 percent as **, and significance at 1 percent as ***.

1.6 Conclusion

The patent fee reduction legislated by the 1883 Patents, Designs and Trade Marks Act had stark effects on patenting behaviour. This Chapter decomposes the behavioural responses of inventors into an effect as a result of increased effort, and an effect due to the lower quality threshold after the fee reduction. This analysis of innovative behaviour is made possible by the creation of a new detailed dataset on 54,000 British inventors, which includes renewal information for each patent. I present a framework for understanding inventor responses that generates four predictions. These predictions about short-run bunching behaviour, longer-run innovation and the effects of credit constraints are confirmed by the data.

In the short run, inventors delay patenting until the fee is reduced, which gives rise to significant bunching after the cheaper fee comes into effect on January 1 1884. The increase in patent quality and the decline in the number of patents before the fee reduction show that patent renewals are a result of inventor choice and not simply a function of the number of patented draws from the quality distribution of ideas. As predicted by the framework, bunching is less pronounced for high-quality renewed patents because it is more costly to delay high-quality patents. In line with Predictions 2 and 3, innovation increases significantly in the longer run both in terms of increased renewed patents and when measured in terms of British inventions that were also patented in the US. The fee elasticity of patents that are renewed after four years is -1.25. I approximate the negative selection effect due to the fall in the quality threshold with the decline in the proportion of high-quality renewed patents. The share of patents of the overall increase that are a result of higher effort and investment

accounts for three quarters of the pre-reform share of high-quality patents. These findings indicate that efficiency increases as a result of the reduction in the patent application fee. While these quality measures are widely used in the literature to gauge innovative activities, one aim of further research is to confirm the effect of the fee change on the amount of economically useful ideas with data that does not rely on patenting information.

To test for the importance of credit constraints, the patenting responses are compared across inventors that have high and low wealth holdings. I generate a wealth proxy from the ratio of the probate likelihood of an inventor's surname relative to its general frequency in a county. A second wealth measure is created from census information on the number of servants employed in an inventor household. Both measures show a stronger innovation response to the fee reduction from inventor groups with lower wealth. These estimates suggest that in addition to the overall effect efficiency increases as a result of relaxed credit constraints after the fee reduction. The proportion of renewed patents is somewhat lower for inventors with lower wealth, which implies that some differences either in patent quality or in the ability to pay renewal fees persist after the fee reform in 1884.

The large responses to the fall in the fixed cost for patenting highlight the potential effectiveness of innovation policies that reduce the cost of inventing. A decrease in the patenting fee is an incentive with a benefit, which is conditional on effort exerted.

While the findings presented in this Chapter are time- and context-specific, they highlight the large responses in terms of the effort and investment exerted by inventors. Nowadays, patent fees are less likely to impede inventive activities, so that the impact of subsidies and tax incentives for research and development is more relevant for the design of innovation policies. A particularly relevant area for further research are the efficiency effects of dynamic constraints in the formation of human capital.

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- Patent Specifications*, 1879-1888
- Report of the Commissioners of Patents for Inventions*, 1873-1883
- The Patents, Designs, and Trade Marks Act, 1883*, 46 & 47 Vict. c. 57

Chapter 2

Residential Segregation and Ethnicity

2.1 Introduction

In many places, residential segregation along dimensions such as ethnicity or income is a feature of local neighbourhoods. How do neighbourhoods become segregated and how does this evolve through time? The popular press reports on ‘white flight’ from neighbourhoods when minority shares rise, and there is substantial support that individuals care about neighbourhood composition from the ethnographical literature. A difficulty in establishing the reasons for segregation and their dynamic evolution, however, is the endogenous sorting of people with similar characteristics to places. There might, for example, be a link between the spatial provision of jobs or amenities and the demographic mix. In this Chapter, we exploit an increase in the allocation of publicly provided housing in England and Wales to minorities to investigate the causal effect of ethnic composition changes. This quasi-experiment changed the ethnic composition of small local neighbourhoods within larger areas without initially changing the socio-economic make-up. Investigations in the early-1990s highlighted positive discrimination towards native whites in social housing. Changes in legislation in 1996 were therefore targeted at enforcing equality in access to social housing for ethnic minorities. The Housing Act was passed in 1996, with a central aim to make the eligibility criteria for social housing transparent and to abandon policies that allowed for discrimination in the allocation process.

Between 1991 and 2011 the minority share in England and Wales increased from six to 14 percent, and better understanding of segregation dynamics in England and Wales is important. Cities like Leicester, Luton and Slough are now majority ethnic minority cities, and the second and third largest cities - Birmingham and Manchester - will be majority minority cities by the end of the decade. These changes have been accompanied by rising popular concern over immigration and increasing political presence of anti-immigrant parties

and platforms. In the wake of the 2005 London bombings by British islamists, the conjecture was raised that Britain is sleepwalking to US-style racial segregation, with ghettoisation in cities like Bradford or Leicester being comparable to Chicago.¹ An ensuing debate amongst economic geographers questioned whether segregation in Britain has increased (Finney and Simpson, 2009; Peach, 2009), and to our knowledge, neither descriptive analysis nor causal evidence is available on segregation trends for disaggregated geographies in England and Wales over time.

We develop an empirical estimation approach from a residential segregation model, where ethnic composition impacts on private housing choice. Our results show that an exogenous inflow of ethnic minority households into social housing leads to greater residential segregation and a decline in the local economy, as measured by house prices. An increase in the ethnic minority share in local social housing by ten percentage points raises the minority share in private housing by 1.2 percentage points initially, and this effect is more pronounced for privately rented than for privately owned housing. A ten-percentage point increase in minority share in social housing decreases the growth rate of local house prices by 0.6 percent. Our findings are robust to excluding the most segregated neighbourhoods, or neighbourhoods that were particularly affected by immigrant inflows from recent EU accession countries. We further distinguish between neighbourhoods with high and low housing supply elasticity by using data on land cover and use, and show that our results are driven by neighbourhoods whose housing supply is more constrained.

The remainder of the Chapter is structured as follows. Section 2.2 discusses the related literature on ethnic and residential segregation. Section 2.3 presents the residential segregation model from which we derive our empirical specifications. The historical context for our instrumentation strategy is described in Section 2.4. Section 2.5 outlines the data and includes descriptive statistics. Details about the empirical estimation are provided in Section 2.6. Section 2.7 presents our findings, and Section 2.8 concludes.

2.2 Related Literature

A distaste for racial diversity can arise due to racist attitudes or due to concerns about local public goods such as education or crime, when these differ across ethnic groups. According to economic theory, full segregation can be an outcome under a broad range of household preferences over neighbourhood composition. In the seminal models of social interactions by Schelling (1971, 1972) even small differences in preferences for neighbourhood racial

¹These speculations were voiced in a controversial speech by Trevor Phillips, then head of the Commission for Racial Equality, delivered to the Manchester Council for Community Relations on September 22 2005.

composition can give rise to high levels of racial segregation. Sethi and Somanathan (2004) describe that segregated outcomes can be stable with extreme racial income disparities but unstable in an intermediate range, when accounting for the joint determination of household preferences of income and racial composition of their communities.

Segregation is a relevant policy issue as higher ethnic concentration often leads to less integration and worse economic outcomes for minorities. Cutler and Glaeser (1997) show that blacks in more segregated areas in the US have significantly worse outcomes in terms of schooling, employment and single parenthood than blacks living in less segregated neighbourhoods. Areas of low intergenerational mobility in the US are characterised by high residential segregation (Chetty et al., 2014), and segregation increases urban black poverty as well as black-white income disparities (Ananat, 2011). Card and Rothstein (2007) point to large negative effects of segregation on test score gaps between white and black students in US cities, but much of this effect operates through neighbours' income and is not due to race per se. The importance of neighbourhood composition is supported by evidence from Sweden, which indicates that the labour market outcomes of refugees vary significantly with the quality of residential enclaves they are assigned to (Edin et al., 2003). Algan et al. (2016) find a detrimental impact of diversity on the quality of local public spaces, in an analysis of exogenous social housing allocations at a detailed housing block level in France. This effect is either due to vandalism or due to collective action failure to ensure effective property management.

Changes in ethnic composition can also reflect adjustments in the quality of the housing stock or expectations about future house price developments. As a result, the effect of minority inflows on population growth and house prices is theoretically ambiguous. If housing demand from minorities in an area is high, whites can be replaced by minorities one-for-one and house prices increase unless housing supply is fully elastic. On the other hand, with taste-based preferences for ethnic self-segregation native whites leave disproportionately and pay more to live in ethnically homogeneous neighbourhoods. Controlling for quality of the housing stock and holding supply constant, house prices may also decrease if the income composition of the neighbourhood changes. Bayer et al. (2007) argue that the correlation between the share of blacks and lower house prices in the US is entirely due to unobserved neighbourhood quality. In the paper by Boustan (2012) concerns about education are one channel for out movements of whites following schooling desegregation in the US in the 1960s and 1970s, in areas where public good provision is locally financed.

Much of the empirical work on segregation focuses on the US, documenting 'white flight' from neighbourhoods that experience minority inflows (Boustan, 2010; Card et al., 2008; Cutler et al., 1999; or Saiz and Wachter, 2011). Up to 50 percent of the early increase in

segregation in the US from 1900 to 1930 was driven by such sorting behaviour by whites (Shertzer and Walsh, 2016). Boustan (2010) shows that the influx of Southern blacks also triggered white out-migration of northern cities in the US between 1940 and 1970, with each black arrival leading to approximately 2.7 white departures. She finds that a 10-percent increase in black housing share reduces house prices by six percent. Due to the high correlation between income and race, Boustan cannot distinguish between distaste for the race or for the income of Southern arrivals as explanations for the outflow of whites. Saiz and Wachter (2011) focus on immigrants instead of US-born minorities, and show that increasing immigrant density in a neighbourhood leads to native flight and slower growth of house values. Their results indicate that this effect is due to native preferences for living with individuals of the same ethnic group and of higher socio-economic status, rather than reflecting changes in housing quality attributes or crime in the local area. Findings by Card et al. (2008) also indicate that segregation in the US is at least partly driven by preferences of whites over the ethnic composition of neighbourhoods, in an analysis of tipping in the racial composition of census tracts in US cities between 1970 and 2000.

In the absence of experimental data, most previous empirical work on ethnic composition changes addresses the bias arising from endogenous location decisions of ethnic minorities by employing variants of a shift-share instrument (for example, Boustan, 2010; Sá, 2015; Saiz and Wachter, 2011), based on work by Card (2001). This approach relies on the tendency of newly arriving minorities to settle in places where members of the same minority already live and assigns new inflows using the settlement patterns of earlier immigrants. By contrast, we exploit a policy change in social housing allocation in the early 1990s to identify the effects of ethnic composition changes at the neighbourhood level. Compared to an identification strategy based on shift shares, our approach is thus resilient to bias from labour demand or house price shocks that are intertemporally correlated and affect minority composition changes both in an earlier and in the contemporaneous time period.

While immigrants in England and Wales are still significantly less likely to be in social housing than natives once controlling for relevant household characteristics, the immigrant penalty has fallen over time (Battistón et al., 2014). Sá (2015) studies the effect of immigration on local house prices in England and Wales using data from the Labour Force Survey on 170 local authorities for 2003 to 2010. Local authorities are similar to counties in the US, which are often comprised of a city and have an average population of 160,000 in 2011. The level of geographical disaggregation in Sá is thus much coarser than the one we construct in this Chapter. Our data covers 348 local authorities and exploits significantly more geographic detail from variation across small neighbourhoods within local authorities, which allows controlling for local authority fixed effects. Sá instruments for the inflows of

immigrants into a local authority by using the immigrant share in a local authority from the 2001 census. She finds that immigration leads to a fall in house prices because high-income natives leave the neighbourhood when non-natives move in, which leads to fewer housing units being constructed due to a negative income effect. In this Chapter, we use a social housing policy change as a source of quasi-experimental variation in minority in-movements instead of an instrument based on recent immigrant settlement patterns. We furthermore focus on ethnic minorities, which include native minorities, and not only on foreign-born immigrants. Sections 2.3 and 2.4 provide more detail about the theoretical framework and the policy change used for empirical identification.

2.3 Theoretical Framework

2.3.1 A Model of Residential Segregation

We consider a general equilibrium model of neighbourhood composition. An area a , such as a local authority, at time t contains two groups seeking accommodation in the private sector: white group W_{at} , and minorities M_{at} . For simplicity we assume the supplies of these groups are exogenous. For our empirical analysis we do not require this assumption, because we control for area fixed effects as explained in more detail in Section 2.6. The area has a number of neighbourhoods and individuals have to decide on the neighbourhood in which they want to live. The attractiveness of neighbourhood i depends in part of its amenities, which can be race-specific, the price of housing in that neighbourhood P_{iat} and the fraction minority of the neighbourhood, μ_{iat} . We assume that the neighbourhood is partly private and partly public, which we refer to as social housing, and the overall fraction minority is given by:

$$\mu_{iat} = (1 - s_{iat}) \mu_{iat}^p + s_{iat} \mu_{iat}^s \quad (2.1)$$

where s_{iat} is the share of social housing in the neighbourhood, μ_{iat}^p is the minority share in the private sector and μ_{iat}^s is the minority share in the social housing sector. The fraction of minorities who wish to live in neighbourhood i at time t is given by:

$$\alpha_{iat}^m = \frac{\Psi(P_{iat}) \phi_{ia}^m \theta^m(\mu_{iat})}{\sum_j \Psi(P_{jat}) \phi_{ja}^m \theta^m(\mu_{jat})} = \frac{1}{V_{at}^m} \Psi(P_{iat}) \phi_{ia}^m \theta^m(\mu_{iat}) \quad (2.2)$$

where ϕ_{ia}^m is the intrinsic attractiveness of neighbourhood i to minorities, which we assume to be constant over time, j denotes neighbourhoods in the area other than i , $\theta^m(\mu)$ measures how attractiveness is affected by the ethnic mix, and $\Psi(P)$ captures how attractiveness is

affected by the price of housing in the neighbourhood. For convenience we assume $\Psi(P)$ is iso-elastic with elasticity $-\varepsilon_\Psi$.

Similarly, the fraction of white people is given by:

$$\alpha_{iat}^w = \frac{\Psi(P_{iat}) \phi_{ia}^w \theta^w (1 - \mu_{iat})}{\sum_j \Psi(P_{jat}) \phi_{ja}^w \theta^w (1 - \mu_{jat})} = \frac{1}{V_{at}^w} \Psi(P_{iat}) \phi_{ia}^w \theta^w (1 - \mu_{iat}) \quad (2.3)$$

These allocations of whites and minorities across neighbourhoods could be thought of as being derived from an underlying multinomial logit model of neighbourhood choice at the individual level. From these models, we know that $\ln(V_{at}^m)$ and $\ln(V_{at}^w)$ can be interpreted as the expected utility of minorities and whites respectively in area a at time t , which are known as the inclusive value. These demand functions embody some special features. First, we assume the price and amenity components to be separable and that the sensitivity of the demands to house prices is the same for whites and minorities. Second, we write the demand functions as a function of the own-group share, such that we can easily consider the case where both, the white and the ethnic groups have the same preferences for neighbourhood composition, that is $\theta^m(\mu) = \theta^w(1 - \mu)$. When we combine this with equations (2.2) and (2.3) in equilibrium, the following must hold:

$$\frac{\mu_{iat}^p}{1 - \mu_{iat}^p} = \frac{M_{at} V_{at}^w \phi_{ia}^m \theta^m(\mu_{iat})}{W_{at} V_{at}^m \phi_{ia}^w \theta^w(1 - \mu_{iat})} \quad (2.4)$$

Due to the assumptions about the separability of prices and the similar sensitivity to prices for the two groups prices drop and make the specification more tractable. Although our primary interest is in the evolution of neighbourhood ethnic mix we also investigate the impact of composition changes on house prices and on total population. For this analysis we need a model of the housing market. The demand for housing is determined by the number of people that want to live in a neighbourhood (which depends on prices) and by the per capita housing demands, which also depend on prices and might differ by ethnic group. We denote the per capita housing demands by $H_d^m(P_i)$ and $H_d^w(P_i)$, and $H_i^s(P_i)$ refers to the supply of housing in neighbourhood i . Then equilibrium in the housing market requires:

$$\alpha_{iat}^m M_{at} H_d^m(P_{iat}) + \alpha_{iat}^w W_{at} H_d^w(P_{iat}) = H_i^s(P_{iat}) \quad (2.5)$$

To lead to a simple estimable equation we assume that housing demands and supplies take the following form:

$$H_d^m(P_{iat}) = h^m h_{ia}^d P_{iat}^{-\varepsilon_d^h}, \quad H_d^w(P_{iat}) = h_{ia}^d P_{iat}^{-\varepsilon_d^h}, \quad H_i^s(P_i) = h_{ia}^s P_{iat}^{\varepsilon_s^h} \quad (2.6)$$

where demands and supplies are iso-elastic, the price elasticity of housing demand is the same for whites and minorities though the level of demand can differ. We assume the ratio of minority per capita demands to white per capita demands is given by h^m . Using (2.2), (2.3), (2.5) and (2.6) we can, after some re-arrangement, write the equation for log house prices as:

$$\begin{aligned} \left[\varepsilon_d^h + \varepsilon_s^h + \varepsilon_\Psi \right] \ln(P_{iat}) &= \ln \frac{h_{ia}^d}{h_{ia}^s} + \ln(\phi_{ia}^w) + \ln \left(\frac{W_{at}}{V_{at}^w} \right) \\ &+ \ln(\theta^w (1 - \mu_{iat})) + \ln \left(1 + \frac{h^m \mu_{iat}^p}{1 - \mu_{iat}^p} \right) \end{aligned} \quad (2.7)$$

There are two channels by which house prices in a neighbourhood affect demand: through the number of people who want to live in a neighbourhood, and the per capita demand of those who do. If per capita demand is inelastic then this would correspond to the case $\varepsilon_d^h = 0$.

Finally we are interested in the total population in the neighbourhood, N_{iat} , which is given by:

$$N_{iat} = \alpha_{iat}^m M_{at} + \alpha_{iat}^w W_{at} \quad (2.8)$$

Using (2.2) and (2.3) we can, after some re-arrangement, write the equation for population in a neighbourhood as:

$$\ln(N_{iat}) = -\varepsilon_\Psi \ln(P_{iat}) + \ln(\phi_{ia}^w) + \ln \left(\frac{W_{at}}{V_{at}^w} \right) + \ln(\theta^w (1 - \mu_{iat})) - \ln(1 - \mu_{iat}^p) \quad (2.9)$$

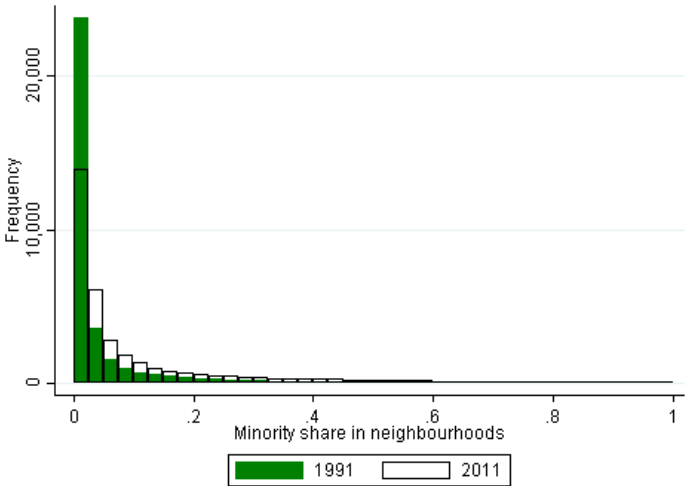
Equations (2.4), (2.7) and (2.9) form the basis for our empirical specifications. Before we derive these, we provide some discussion of the model and the nature of the equilibrium. Since the pioneering work of Schelling (1971, 1972), it is known that multiple equilibria are possible, for example, when both ethnic groups prefer to live with their own group. Some of the equilibria may be unstable, and equilibria can also be corner solutions in which a neighbourhood is completely segregated. Within the structure of preferences we have assumed, completely segregated equilibria are only possible if there is some minimum level of co-ethnics below which one will not live in a neighbourhood under any circumstance, for instance, if $\theta^w (1 - \mu) = 0$ when $\mu \geq \mu^*$.

The possibility of multiple equilibria raises potential problems for interpreting our empirical results, which describe how changes in the minority share in social housing affect the proportion in private housing. We focus on the case of a stable interior equilibrium. Our justification for this assumption is that we do not see the extreme levels of segregation in the UK that characterise the US.² The histogram of minority shares in UK neighbourhoods

²The US was characterised by high levels of segregation also at the time when Schelling was writing: “the demographic map of almost any American metropolitan area suggests that it is easy to find residential areas

in Figure 2.1 for 1991 and 2011 shows that our assumption is not unrealistic, as it does not depict the bimodality suggestive of corner solutions.

Figure 2.1 Number of neighbourhoods by minority share in 1991 and 2011



Although the predictions about the shift in the minority mix in private housing are unambiguous, the predictions for total population and prices are not. As equation (2.7) indicates prices may rise or fall as the minority mix changes, for example, depending on whether whites or minorities are more or less sensitive to ethnic mix. For instance, if minorities do not care about ethnic mix but whites do, whites will leave the areas while minorities will not enter and total population would fall. On the other hand, if minorities care more about ethnic mix population would rise. If the per capita housing demands for whites and minorities differ, there will also be a composition effect. For similar reasons the total population may rise or fall in response to the shock.

All of this discussion has been about a shock to a single neighbourhood, assumed to be sufficiently small that the overall area equilibrium does not change. The changes we consider in the empirical part of the Chapter generally affect many neighbourhoods and cannot be assumed to leave the area equilibrium unchanged. In our empirical implementation it is not necessary to model these general equilibrium effects because we include area fixed effects.

that are all white or nearly so and areas that are all black or nearly so but hard to find localities in which neither whites nor non-whites are more than, say, three-quarters of the total” (Schelling, 1971).

2.3.2 Empirical Specifications

Ethnic Mix

We are interested in the impact of an increase in the minority share in social housing on the minority share in private housing. Differentiating equation (2.4) gives:

$$\frac{d\mu_{iat}^p}{\mu_{iat}^p(1-\mu_{iat}^p)} = d\ln\left(\frac{M_{at}V_{at}^w}{W_{at}V_{at}^m}\right) + \left[\frac{\partial \ln \theta^m(\mu_{iat})}{\partial \mu} + \frac{\partial \ln \theta^w(1-\mu_{iat})}{\partial (1-\mu)}\right] [(1-s_{ia})d\mu_{iat}^p + s_{ia}d\mu_{iat}^s] \quad (2.10)$$

By defining

$$\frac{\partial \ln \theta^m}{\partial \ln\left(\frac{\mu}{1-\mu}\right)} = \varepsilon^m, \quad \frac{\partial \ln \theta^w}{\partial \ln\left(\frac{1-\mu}{\mu}\right)} = \varepsilon^w, \quad (2.11)$$

we can express equation (2.10) as

$$\left[\frac{1}{\mu_{iat}^p(1-\mu_{iat}^p)} - \frac{(1-s_{ia})(\varepsilon^w + \varepsilon^m)}{\mu_{iat}(1-\mu_{iat})}\right] d\mu_{iat}^p = d\ln\left(\frac{M_{at}V_{at}^w}{W_{at}V_{at}^m}\right) + \frac{(\varepsilon^w + \varepsilon^m)}{\mu_{iat}(1-\mu_{iat})} s_{ia} d\mu_{iat}^s. \quad (2.12)$$

If for convenience we evaluate $\mu_i^p = \mu_i^s = \mu_i$ such that the minority share in social and private housing is the same, which is a reasonable approximation, (2.12) can be written as:

$$d\mu_{iat}^p = \frac{\mu_{iat}^p(1-\mu_{iat}^p)}{1-(1-s_{ia})(\varepsilon^w + \varepsilon^m)} d\ln\left(\frac{M_{at}V_{at}^w}{W_{at}V_{at}^m}\right) + \frac{(\varepsilon^w + \varepsilon^m)}{1-(1-s_{ia})(\varepsilon^w + \varepsilon^m)} s_{ia} d\mu_{iat}^s \quad (2.13)$$

Stability of equilibrium requires that $(1-s_{ia})(\varepsilon^m + \varepsilon^w) < 1$, a condition we can check in our estimations. Using (2.13) are able to derive an empirical model for estimation.

The term $d\ln\left(\frac{M_{at}V_{at}^w}{W_{at}V_{at}^m}\right)$ in (2.13) is an area fixed effect and can be treated as such in the estimation. It controls both for general equilibrium effects on the value of being white or minority in an area, and for area-wide changes in the minority mix of the population. Equation (2.13) also suggests that the impact of this fixed effect depends on both s_{ia} and μ_{iat}^p . We take two approaches to dealing with this. In our basic specification, we approximate and assume that s_{ia} and μ_{iat}^p do not vary across neighbourhoods within an area so this first term can be treated as an area fixed effect in estimation. In Section 2.6, however, we also report models where the area fixed effect is interacted with the initial minority share in private

housing. The intuition for this is that we expect the area fixed effect to reflect in part the minority share in the area as a whole and that a change in this share would have a different impact on neighbourhood minority shares according to the pre-existing minority share.

The main variable of interest in equation (2.13) is the last term, the change in the minority share interacted with the initial share of social housing. In the empirical specification we also include the initial share in social housing, that is the main effect, even though the theoretical model suggests it should be zero. With this approximation, we obtain an empirical specification of the form:

$$\Delta\mu_{iat}^p = \beta_a + \beta_1\beta_a\mu_{iat-1}^p + \beta_2s_{iat-1} + \beta_3s_{iat-1}\Delta\mu_{iat}^s \quad (2.14)$$

where we have discretised (2.13) to reflect that our data is in decadal differences.

Prices

We consider the following linearisation of (2.7):

$$\Delta\ln(P_{iat}) = \frac{1}{\varepsilon^h} \left[\Delta\ln\left(\frac{W_{at}}{V_{at}^w}\right) - \left[\frac{\varepsilon^w\Delta\mu_{iat}}{\mu_{iat}(1-\mu_{iat}^p)} \right] + h^m\Delta\mu_{iat}^p \right] \quad (2.15)$$

with $\varepsilon^h = [\varepsilon_d^h + \varepsilon_s^h + \varepsilon_\Psi]$. The equation for (2.14) can then be substituted in to lead to an equation for the price change as a function of the change in minorities in social housing. The nature of the price data is such that it is better to estimate in levels, which we write as:

$$\ln P_{iat} = \gamma_i + \gamma_{at} + \gamma_1s_{ia}\mu_{iat}^s \quad (2.16)$$

where a neighbourhood fixed effect γ_i is included.

Population

First-differencing equation (2.9) leads to:

$$\Delta\ln(N_{iat}) = -\varepsilon_\Psi\Delta\ln(P_{iat}) + \Delta\ln\left(\frac{W_{at}}{V_{at}^w}\right) - \left[\frac{\varepsilon^w\Delta\mu_{iat}}{\mu_{iat}(1-\mu_{iat}^p)} \right] + h^m\Delta\mu_{iat}^p \quad (2.17)$$

Substituting in (2.13) and (2.15) yields an empirical specification of the form:

$$\Delta\ln N_{iat} = \delta_a + \delta_1\delta_a\mu_{iat-1}^p + \delta_2s_{ia}\Delta\mu_{iat}^s \quad (2.18)$$

so that the change in log population is a function of the change in the neighbourhood minority share in social housing, $s_{ia}\Delta\mu_{iat}^s$, controlling for an interaction between the area fixed effect δ_a and the initial minority share in private housing μ_{iat-1}^p .

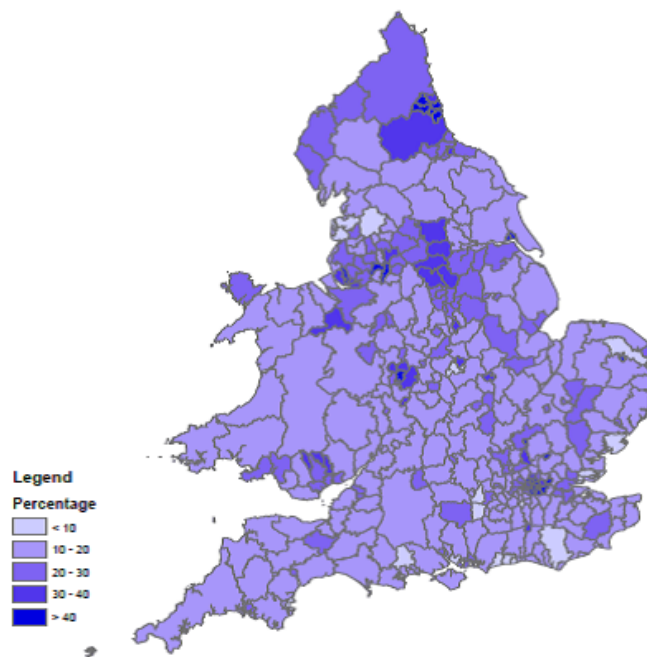
2.4 Increased Minority Access to Social Housing

We use a policy change in the 1990s that increased the minority share in social housing to investigate the causal effect of ethnic neighbourhood composition changes. Using this variation in neighbourhoods within larger areas, we can estimate how an exogenous increase in ethnic minorities in a neighbourhood affects neighbourhood outcomes in the following years. A neighbourhood with a high fraction of social housing that is part of an area with a high fraction of ethnic minorities is more likely to be affected by the policy change.

Publicly-provided housing in the UK, often described as ‘social’ or ‘council’ housing, refers to housing owned by the local authorities and by housing associations. The importance of social housing in the UK increased after World War II, and it then declined in the 1980s partly due to the ‘right-to-buy’ policy initiated by Margaret Thatcher, which gave residents the opportunity to buy their homes. Since the 1990s, the period that we focus on in this Chapter, the share of social housing has remained fairly constant. Social housing is distributed fairly evenly across the UK, and is mostly found in urban areas. As shown in Figure 2.2, most local authorities have a share of over ten percent of social housing and few have more than 40 percent. While those living in social housing pay rent to the local authorities, rent is significantly below market value. On average, rent in social housing is around 40 percent lower than in private housing and, in parts of London, it can be as low as 70 percent below market value. The cheaper rental price for social housing means that there tends to be excess demand for it. Eligibility for social housing depended on socio-economic characteristics and eligible households are typically placed on a waiting list.

Until the 1990s, the decision of who to allocate social housing to was largely at the discretion of local authority or council officers. There was a widely-held belief in the 1980s and the early 1990s that the allocation of housing discriminated against ethnic minorities. Despite the Race Relation Act 1968 outlawing overt discrimination, subjective discrimination exercised by housing officers remained central to council housing allocation processes during the 1970s and 1980s (Commission for Racial Equality, 1984; Henderson and Karn, 1987; Sarre and Skellington, 1989; Simpson, 1981). A government sponsored review found that ethnic minority households often faced difficulties accessing social housing (Harrison and Phillips, 2003).

Figure 2.2 Share of social housing in 1991 by local authority



The Housing Act was passed in 1996 partly in response to this criticism. An important aim of the Act was to make the criteria for social housing eligibility transparent and to abandon policies that allowed for discrimination in the allocation process. The Housing Act required the authorities to maintain a ‘housing register’, which listed all individuals eligible for social housing. The institutional reform was also partly a response to lacking social housing access for minorities that arose because the allocation process favoured individuals with long held historical neighbourhood attachments. Ethnic minorities often waited longer than white applicants for a social housing offer. Moreover, when they did receive a housing offer, minorities were often allocated less desirable properties in the poorest areas (Commission for Racial Equality, 1984; Henderson and Karn, 1987; Phillips, 1986). Various practices such as the ‘date order’ scheme prioritised waiting time and thereby discriminated against incomers, most of whom were ethnic minorities. The Housing Act continued to allow for some preferences for people with a local connection but these were defined as including residents currently living in the area, rather than being restricted to people with a long history of living locally. An ‘allocation scheme’ was introduced, which clearly specified individuals’ circumstances and determined priorities in allocating. Although there was still scope for some discretion by housing officers, allocating housing based on historical local connections that favoured the native white group was forbidden. Overall, as

a result of the Housing Act the allocation process became more transparent and formal, with an explicit focus on eradicating ethnic discrimination in the allocation of social housing.

2.5 Data and Descriptive Statistics

For the estimations we use census data for England and Wales for 1991, 2001 and 2011, house price transactions data for years 1995 to 2011, and land cover data. For years 1991, 2001 and 2011, ethnicity by tenure information is available in the census for geographic units that allow aggregation at the local neighbourhood level for household reference persons for whites, Asians, blacks, and other ethnic minorities. The census data used in this Chapter are for household reference persons, which are treated as approximations to households.

In this Chapter our interest is the spatial disaggregation underpinning aggregate changes. The census data is aggregated at the geographic level of Lower Layer Super Output Areas (LSOAs), which we call neighbourhoods. Neighbourhoods are composed of between 400 to 1,200 households in 2011 and align within local authorities (LAs), which we refer to as areas. Areas are comparable to counties in the US, and have an average population of 160,000 in 2011. In 2011, there were 348 LA areas and 34,753 LSOA neighbourhoods in England and Wales. Geographies are not constant over time and LSOAs only exist from 2001 onward but we ensure that the data consists of consistent geographic units over time. The largest feasible samples are for 34,378 consistent neighbourhoods for 1991-2001 and for 34,058 neighbourhoods for 1991-2011. A more detailed description of the census data and geographies, as well as about the construction of consistent geographical units over time is included in Appendix 2.1.

Table 2.1 Population shares by household ethnicity for census years 1991-2011

	1991	2001	2011
Whites	0.96	0.93	0.89
Minorities	0.04	0.07	0.11

The share of white households in England and Wales decreased from 0.96 in 1991 to 0.89 in 2011 as reported in Table 2.1. Figure 2.3 compares the spatial distribution of minority shares in percentage terms across areas in England and Wales in 1991 and 2011. In 1991 only 15 percent of areas had minority shares above five percent, which increased to almost 40 percent of areas in 2011, with higher minority shares in cities such as London,

Manchester and Birmingham. Similar to trends in the US, where segregation between natives and immigrants continued to increase over the last decades (Cutler et al., 2008; Saiz and Wachter, 2011), neighbourhoods in the UK have become more segregated. Only 909 out of 34,058 neighbourhoods, however, have minority shares above 0.60, as Table 2.2 shows.

Figure 2.3 Local authority areas by minority share in 1991 and 2011

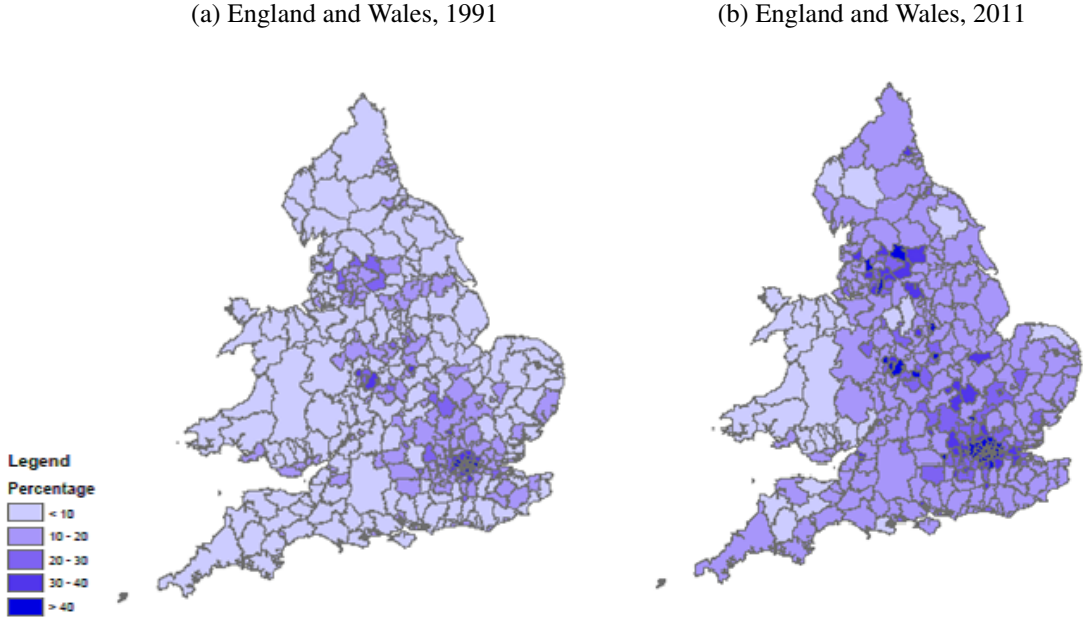


Table 2.2 Number of neighbourhoods by share of minority households

Minority share:	1991	2001	2011
Less than 0.05	27,400	24,637	20,007
0.05-0.20	4,539	5,953	8,432
0.20-0.40	1,616	2,198	3,093
0.40-0.60	374	922	1,617
0.60 and above	129	348	909
Total number	34,058	34,058	34,058

The tenure type of household accommodation changed markedly from 1991 to 2011, as visible in Table 2.3. The share of social housing declined from 0.23 to 0.18 while the share of those privately renting increased. Table 2.4 shows an increase in minorities across all tenure categories. Whites are over-proportionally represented in privately owned housing.

Table 2.3 Share of all housing by tenure type

	1991	2001	2011
Social housing	0.23	0.19	0.18
Privately owned	0.69	0.69	0.64
Privately rented	0.08	0.12	0.18

Note: These shares are calculated for household reference persons using census data for England and Wales. Social housing is the sum of available social housing categories in the census.

Table 2.4 Tenure type by household ethnicity share

		1991	2001	2011
Social housing:	Whites	0.96	0.93	0.87
	Minorities	0.04	0.07	0.13
Privately owned:	Whites	0.95	0.94	0.90
	Minorities	0.05	0.06	0.10
Privately rented:	Whites	0.95	0.92	0.87
	Minorities	0.05	0.08	0.13

To analyse the effect of ethnic composition changes on house prices, we study house prices for England and Wales from the Land Registry. This data is available from 1995 onwards and contains information on the price paid and house type for over 17.2 million house transactions during 1995-2011. An overview of this data is provided in Appendix 2.2. Nominal house prices grew from an average of around £68,700 in 1995 to an average of £232,000 in 2011, with a growth rate of eight percent for around one million house transactions on average per year.

We further construct a proxy measure of housing supply elasticity by local authority to group areas above- and below-median housing elasticity. Housing supply constraints are approximated by using the degree of physical development measured as the share of all developable land. Appendix 2.3 contains further details about this topographic data.

2.6 Empirical Estimation

This Section presents our estimation strategy for studying ethnic segregation dynamics. We first describe the link between the ethnic minority share in social and private housing in neighbourhoods that are grouped within larger areas. As both social and private housing minority shares are endogenously determined we exploit the policy change in social housing allocation after 1996 to estimate the exogenous effects of an inflow of minorities into a neighbourhood. This identification approach is described in more detail in subsection 2.6.2.

2.6.1 The Effect of the Minority Share in Social Housing

To analyse whether an inflow of minorities leads to an outflow of whites, we compile detailed data on ethnic housing shares for small geographic units. Our baseline unit of analysis are neighbourhoods and we control for the characteristics of areas, which are composed of around hundred neighbourhoods on average. Neighbourhoods consist of private and social sector housing, and in the context of our estimation strategy ‘white flight’ implies that an increase in the share of minorities in social housing leads to an increase in the minority share in private housing. To test this hypothesis we estimate the following Ordinary Least Squares (OLS) specification:

$$\mu_{iat}^p = \alpha_1 s_{ia0} + \alpha_2 (\mu_{iat}^s \times s_{ia0}) + \rho_a + (\rho_a \times \mu_{ia0}^p) + \varepsilon_{iat} \quad (2.19)$$

where μ_{it}^p is the proportion of ethnic minorities in private housing in neighbourhood i at time t . The coefficient α_2 captures the impact of the interactive effect of the ethnic minority share in social housing μ_{it}^s in neighbourhood i at time t and the initial share of local social housing s_{ia0} , area fixed effects are denoted by ρ_a and $(\rho_a \times \mu_{ia0}^p)$ controls for the initial minority share in neighbourhood private housing interacted with the area fixed effect.

Intuitively, the area fixed effect measures the overall supply of minorities relative to whites in an area. The impact of this supply on neighbourhoods within areas depends on the share of initial social housing and the overall share of minorities in the neighbourhood. The area fixed effect is interacted with the initial minority share in neighbourhood private housing because we expect the area minority share and other area characteristics to differ in their impact according to the pre-existing neighbourhood minority share. Very segregated areas experience smaller changes in their minority shares.

To distinguish between the effects of the ethnic composition on owned versus rented accommodation, we regress the outcomes minority share in privately owned housing μ_{it}^{po} and minority share in privately rented housing μ_{it}^{pr} respectively on the minority share in

social housing weighted by the initial social housing share in a neighbourhood, controlling for area fixed effects and interactions:

$$\mu_{iat}^{po} = \beta_1 s_{ia0} + \beta_2 (\mu_{iat}^s \times s_{ia0}) + \theta_a + (\theta_a \times \mu_{ia0}^{po}) + u_{iat}, \quad (2.20)$$

and

$$\mu_{iat}^{pr} = \gamma_1 s_{ia0} + \gamma_2 (\mu_{iat}^s \times s_{ia0}) + \lambda_a + (\lambda_a \times \mu_{ia0}^{pr}) + v_{iat}. \quad (2.21)$$

We further test the hypothesis that population growth is also affected by the ethnic composition of a neighbourhood. Population growth $\frac{\Delta N_t}{N_0}$ is defined as the change in neighbourhood population numbers over a ten-year period relative to the initial population. We estimate:

$$\left(\frac{\Delta N_t}{N_0} \right)_{ia} = \delta_1 s_{ia0} + \delta_2 (\mu_{iat}^s \times s_{ia0}) + \eta_a + (\eta_a \times \mu_{ia0}^p) + \omega_{iat} \quad (2.22)$$

Finally, we study the effect of the minority composition in social housing on house prices in the private sector:

$$\ln P_{hiat} = \zeta_1 t + \zeta_2 (\mu_{ia0}^s \times s_{ia0} \times t) + \zeta_3 \mathbf{X}_{hiat} + \phi_{ia} + (\tau_a \times \mu_{ia0}^p \times t) + \xi_{hiat} \quad (2.23)$$

where $\ln P_{hiat}$ is the log house price for house h at time t , which now refers to years. Equation (2.23) includes a yearly time trend, by which the interaction term of initial shares $(\mu^s \times s)_{ia0}$ is multiplied because census variables are only available in decadal intervals. Furthermore, we control for housing type characteristics \mathbf{X}_{hiat} , comprised of dummy variables that take value one when a house is detached, semi-detached, terraced, a flat, new-built, or a leasehold as opposed to a freehold. Since this information is geographically more disaggregated and available for individual houses, we can additionally estimate neighbourhood fixed effects ϕ_{ia} , and include a triple interaction between area fixed effects, initial neighbourhood minority share and the time trend.

2.6.2 Estimation and Identification

The specifications described above are likely to be biased if social housing and private housing minority shares are endogenously determined. For example, minorities may move to neighbourhoods that whites are already leaving, irrespective of the ethnic composition of a neighbourhood. To address this concern changes in the allocation of public housing in the 1990s are used as a quasi-experiment to estimate the causal impact of ethnic neighbourhood composition changes on segregation, population growth and house prices.

We therefore implement two-stage least squares estimations for equations (2.19) to (2.23) with an instrument that captures the combined effect of varying sizes of the initial minority population across areas interacted with the initial importance of social housing in a neighbourhood. The explanatory variable $(\mu_{iat}^s \times s_{ia0})$ is instrumented using $(\mu_{a0} \times s_{ia0})$ in the post-reform period, where μ_{a0} is the initial pre-policy share of ethnic minorities in a local authority area. Intuitively, the policy change that reduced discrimination in social housing allocation disproportionately affects a neighbourhood with a high initial social housing share that is at the same time located in an area with a high ethnic minority share. The first-stage estimation is specified as:

$$(\mu_{iat}^s \times s_{ia0}) = \gamma_1 s_{ia0} + \gamma_2 (\mu_{a0} \times s_{ia0}) + \phi_a + (\phi_a \times \mu_{ia0}^p) + \omega_{iat} \quad (2.24)$$

The instrument is only effective after the housing allocation policy reform in 1996, and the regression controls for area fixed effects and the interaction between the initial neighbourhood minority share in 1991 and area fixed effects.

For the exclusion restriction to hold we have to assume that the instrument $(\mu_{a0} \times s_{ia0})$ only affects second-stage outcome variables through the neighbourhood minority share in social housing weighted by the initial social housing share. This exclusion assumption seems plausible, also because the regressions control for area fixed effects and the private housing neighbourhood minority share interactions, but it cannot be tested formally. As ethnic composition data is only available at the highly disaggregated level of neighbourhoods for census years 1991, 2001 and 2011, our analysis is limited to estimating the quasi-experimental reform effects in years 2001 and 2011. While we cannot trace yearly movements in ethnic composition and population growth, these outcomes are unlikely to adjust fully from one year to the next.

For the outcome house prices yearly values are observed. The yearly instrument used for the second-stage estimation of log house prices is defined as $(\mu_{a0} \times s_{ia0} \times t)$, with t representing years, to account for the yearly availability of the house price data.

2.7 Results

2.7.1 First-Stage Outcome Social Housing Minority Shares

We regress the social housing minority share in a neighbourhood in the post-reform period on the instrument, the initial social housing share in a neighbourhood interacted with the initial area minority share, and controls as specified in equation (2.24). Table 2.5 reports the first-stage results for year 2001 and year 2011, which are the only two periods post-reform

for which census data is available. The interacted instrumental is significant and has a large positive effect for the social housing minority share both in 2001 and in 2011. For both years the instrument is strong, with F-statistics above 400.

Table 2.5 First stage: outcome social housing minority share

	2001 (1)	2011 (2)
1991 share in social housing × 1991 area minority share	1.704*** (0.082)	2.325*** (0.094)
Control variables	YES	YES
Area fixed effects	YES	YES
Number of areas	348	348
Number of neighbourhoods	34,378	34,058

Notes: The Table reports the coefficients for 2001 and 2011 from regressing the social housing minority share times the 1991 share in social housing on the interaction of the 1991 share in social housing times the area minority share. All variables are aggregated at the neighbourhood level, unless areas are specified. Control variables are the 1991 share in social housing and area fixed effects interacted with the 1991 minority share in private housing. Regressions are weighted by average neighbourhood population. Standard errors clustered by area are in parentheses, and levels of significance are * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

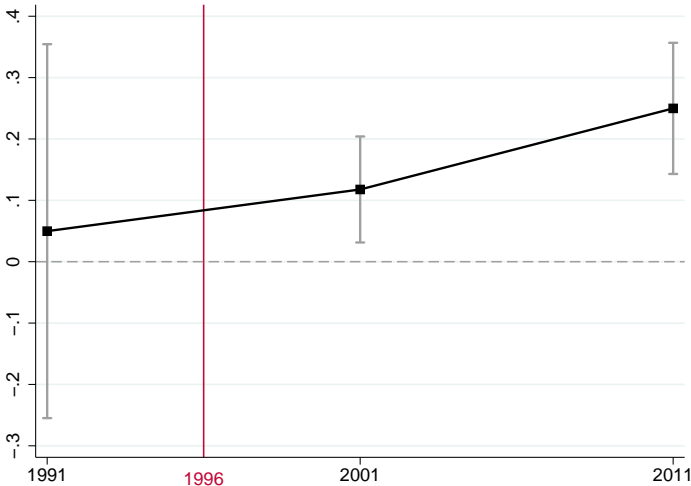
2.7.2 The Impact on the Minority Shares in Private Housing

The instrument-induced effect of minority inflows into social housing on the share of minorities in private housing in 1991, 2001 and 2011 is shown in Figure 2.4. The instrumented coefficient is positive and significant in years 2001 and 2011. For the outcome in year 2001, the impact is equivalent to an increase of the minority share in private housing by 1.2 percentage points when the ethnic minority share in local social housing rises by ten percentage points, as reported in column (2) in Table 2.6. When estimating the cross-sectional regression for 2011, this effect is also significant and slightly bigger with an increase of 1.3 percentage points for a ten-percentage point rise in the ethnic minority share in social housing. The instrumental variable (IV) coefficients are smaller than the OLS values, which indicates that the OLS estimates are upwards biased due to unobserved neighbourhood characteristics.

For the interaction between initial social housing and area minority share to be a valid instrument, it must be uncorrelated with the second-stage outcome variable before 1996, the year when the Housing Act of 1996 was introduced. As expected, the coefficient of the

instrumented variable is insignificant in pre-reform year 1991. The reason for the differing number of neighbourhoods in the estimation samples for years 2001 and 2011 is that we are using 2001 LSOA neighbourhood boundaries for 1991-2001 and time-consistent LSOA boundaries for 1991-2011, as explained in more detail in Appendix 2.1.

Figure 2.4 Effects on the private housing minority share



Notes: Coefficient estimates are for 1991, 2001 and 2011 only and report the instrumented effect of the minority share in social housing on the private housing minority share, exploiting variation across neighbourhoods within larger areas. The effects plotted are cumulative. Control variables are the 1991 share in social housing and area fixed effects interacted with the 1991 minority share in private housing, and regressions are weighted by average neighbourhood population. The grey bars indicate 95-percent confidence intervals, for which standard errors are clustered by area.

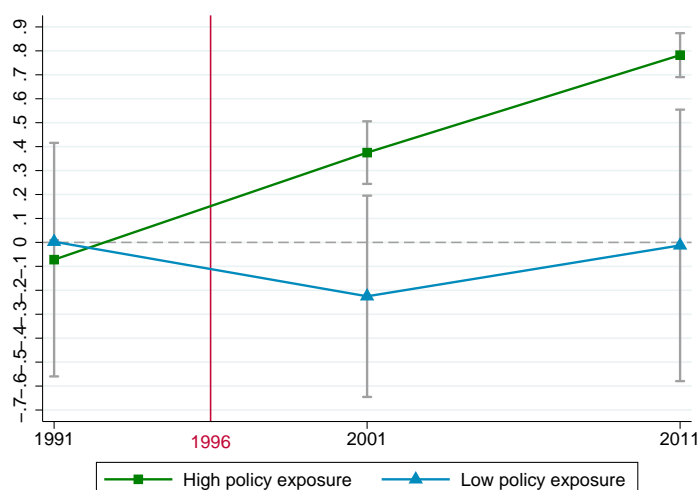
If our instrumenting strategy works, neighbourhoods with higher social housing shares in 1991 that are located in areas with higher initial minority shares should be more affected after the 1996 policy change. To illustrate that the effects are indeed driven by neighbourhoods that are more exposed to the policy change, Figure 2.5 plots the instrumented effects for neighbourhoods that have both a share of social housing and an area share of minorities in 1991 that are higher than average, and 4,331 neighbourhoods are in this high-policy exposure category. Figure 2.5 also shows effects for the 16,825 neighbourhoods with both social housing share and an area minority share below average in 1991, referred to as low-policy exposure neighbourhoods. The neighbourhoods that are more exposed to the policy change experience a more pronounced increase in the private sector minority share in 2001 and in 2011, compared to the overall effect shown in Figure 2.4. By contrast, the effects for the less exposed neighbourhoods are not significantly different from zero.

Table 2.6 Estimates of the effect on the minority share in private housing

	2001		2011	
	OLS (1)	IV (2)	OLS (3)	IV (4)
Social housing minority share × 1991 share in social housing	0.183*** (0.032)	0.118*** (0.044)	0.318*** (0.038)	0.132** (0.055)
Control variables	YES	YES	YES	YES
Area fixed effects	YES	YES	YES	YES
Number of areas	348	348	348	348
Number of neighbourhoods	34,378	34,378	34,058	34,058

Notes: The Table reports OLS and IV estimates of the effect of the social housing minority share weighted by the initial social housing share on the minority share in private housing. Reported variables are aggregated at the neighbourhood level, and regressions are weighted by average neighbourhood population. Control variables are the 1991 share in social housing and area fixed effects interacted with the 1991 minority share in private housing. Standard errors clustered by area are in parentheses, and levels of significance are * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Figure 2.5 Private housing minority share effects by exposure to the 1996 reform



Notes: High-policy exposure refers to neighbourhoods with an above-sample average share of social housing in 1991 as well as an above-average share of minorities in the area in 1991. Neighbourhoods are defined as low-policy exposure if both their 1991 social housing as well as their area minority shares are below average.

The data allows us to decompose minority shares in private housing into minority shares in privately owned and in privately rented housing, and results for these outcomes are reported in Table 2.7 for 2001 and 2011. Comparing the instrumented coefficients for 2001 in columns (1) and (3) shows that the social housing minority share has a larger effect on the minority share in privately rented than in privately owned housing. A 10-percentage point increase in the social housing minority share in a neighbourhood increases the minority share in privately rented housing by 1.5 percentage points but only leads to a 1.0-percentage point rise in the minority share in privately owned housing. This difference indicates faster initial ethnic composition adjustments in the rental sector than in privately owned housing, which is consistent with the fact that minorities predominantly live in privately rented housing.

Table 2.7 IV estimates of minority share effects in privately owned and rented housing

	Privately owned		Privately rented	
	2001 (1)	2011 (2)	2001 (3)	2011 (4)
Social housing minority share × 1991 share in social housing	0.096** (0.044)	0.148** (0.060)	0.150** (0.068)	0.078 (0.066)
Control variables	YES	YES	YES	YES
Area fixed effects	YES	YES	YES	YES
Number of areas	348	348	348	348
Number of neighbourhoods	34,378	34,378	34,058	34,058

Notes: The Table reports OLS and IV estimates of the effect of the social housing minority share weighted by the initial social housing share on the minority share in privately owned and in privately rented housing. Reported variables are aggregated at the neighbourhood level, and regressions are weighted by average neighbourhood population. Control variables are the 1991 share in social housing and area fixed effects interacted with the 1991 minority share in privately owned and in privately rented housing respectively. Standard errors clustered by area are in parentheses, and levels of significance are * p<0.10, ** p<0.05, *** p<0.01.

2.7.3 The Impact on Local Population Growth

Table 2.8 reports second-stage results for the outcome variable neighbourhood population growth for 2001 and 2011. The instrumented coefficient reported in column (2) implies that a 10-percentage point increase in the neighbourhood social housing minority share leads to a rise in population growth of 2.2 percentage points in 2001. The instrumented effect on population growth for a 10-percentage point increase in the social housing minority share

in 2011 is 3.4 percentage points. For estimating the effects on population growth we drop neighbourhoods that grow by over 500 percent. Such high population growth rates are likely due to the imputed boundary definitions for 1991, and affect 99 neighbourhoods between 1991-2001 and one neighbourhood between 2001-2011. We also estimated the regressions reported in Table 2.8 including these outlier neighbourhoods and results do not change.

Table 2.8 Population growth estimates

	2001		2011	
	OLS (1)	IV (2)	OLS (3)	IV (4)
Social housing minority share × 1991 share in social housing	0.324*** (0.078)	0.217** (0.108)	0.799*** (0.136)	0.340*** (0.098)
Control variables	YES	YES	YES	YES
Area fixed effects	YES	YES	YES	YES
Number of areas	348	348	348	348
Number of neighbourhoods	34,378	34,378	34,057	34,057

Notes: The Table reports OLS and IV estimates of the effect of the social housing minority share weighted by the initial social housing share on population growth. The estimation samples exclude outliers with population growth above 500 percent, which affects 99 neighbourhoods between 1991-2001 and one neighbourhood between 2001-2011. Reported variables are aggregated at the neighbourhood level, and regressions are weighted by average neighbourhood population. Control variables are 1991 share in social housing and area fixed effects interacted with the 1991 minority share in private housing. Standard errors clustered by area are in parentheses, and levels of significance are * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

2.7.4 The Impact on Local House Prices

For estimating the effects on outcome variable log house price for individual house price transactions, we adjust the regressions as described in equation (2.23). Using the detailed yearly house price transaction data at the individual house level, this estimation exploits variation within a neighbourhood by accounting for neighbourhood fixed effects and controls for house type. Table 2.9 shows the house price results, and a 10-percentage point increase in the minority share in social housing decreases the yearly growth rate of local house prices by 0.6 percent. This suggests that the negative effect on house prices from an increase in the minority share dominates the positive pressures from rising population.

Table 2.9 Estimates of yearly log house prices 1995-2011

	1991 social housing minority share \times 1991 share in social housing \times trend	Yearly log house price	
	First stage (1)	OLS (2)	IV (3)
1991 social housing minority share \times 1991 share in social housing \times trend		-0.042*** (0.008)	-0.059*** (0.009)
1991 share in social housing \times 1991 area minority share \times trend	0.744*** (0.017)		
Control variables	YES	YES	YES
Neighbourhood fixed effects	YES	YES	YES
Number of neighbourhoods	34,058	34,058	34,058
Number of houses	17.2 m.	17.2 m.	17.2 m.

Notes: Except for house prices and house type variables all variables are aggregated at the neighbourhood level, unless areas are specified. Regressions are weighted by average neighbourhood population. Regressions control for whether a house is detached, semi-detached, terraced, new-built or a leasehold, a time trend and area fixed effects interacted with 1991 neighbourhood minority share in private housing and a time trend. Million is abbreviated as m., and standard errors are in parentheses, with levels of significance * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

2.7.5 Robustness Checks

Neighbourhoods with High Initial Minority Shares

To ensure that results are not driven exclusively by a few observations with very high initial minority shares, we exclude the five percent of neighbourhoods with the highest minority shares in 1991. Results for these slightly smaller estimation samples are reported in columns (2) and (4) in Table 2.10. For both 2001 and 2011 the results remain significant and the effects of the social housing minority share on the minority share in private housing remain approximately of similar magnitude. The coefficient for population growth increases for both periods, which might indicate that neighbourhoods with high initial minority shares are more constrained in terms of additionally possible increases in population. In line with this interpretation, house prices decline more in response to an increase in the social housing minority share in the neighbourhoods with lower initial minority shares.

Table 2.10 Robustness checks

	Full sample	Excluding 5% of 1991 neighbourhoods with the highest minority share	Full sample	Excluding 5% of 1991 neighbourhoods with the highest minority share	Excluding neighbourhoods in 2011 with above 10% A12 minorities
IV coefficients for outcome:	2001 (1)	2001 (2)	2011 (3)	2011 (4)	2011 (5)
Table 2.6: Minority share in private housing	0.118*** (0.044)	0.157*** (0.048)	0.132** (0.055)	0.153*** (0.054)	0.142** (0.058)
Table 2.7: Minority share in privately owned housing	0.096** (0.044)	0.106** (0.045)	0.148** (0.060)	0.154*** (0.053)	0.163** (0.064)
Table 2.7: Minority share in privately rented housing	0.150** (0.068)	0.351*** (0.065)	0.078 (0.066)	0.193*** (0.057)	0.083 (0.072)
Table 2.8: Population growth	0.217** (0.108)	0.359* (0.197)	0.340*** (0.098)	0.549*** (0.176)	0.341*** (0.104)
Table 2.9: Log house price (for 1995-2011)			-0.059*** (0.009)	-0.070*** (0.013)	-0.065*** (0.010)
Number of areas	348	348	348	348	348
Number of neighbourhoods	34,378	32,660	34,058	32,356	33,344
Number of houses (in Table 2.9)			17.2 m.	16.6 m.	16.8 m.

Notes: The estimation sample in columns (2) and (4) excludes the 5 percent of neighbourhoods with the highest minority share in 1991. The estimation sample in column (5) only includes neighbourhoods with less than 10 percent of the population in 2011 from the twelve EU 2001-2011 accession countries. Regression controls, fixed effects, clustering of standard errors and weights are implemented as described in the respective Tables. Outliers with population growth above 500 percent are dropped for Table 2.8 estimates. Million is abbreviated as m., and standard errors are in parentheses, with levels of significance * p<0.10, ** p<0.05, *** p<0.01.

Immigration from Recent EU Accession Countries

For the results presented so far we do not distinguish between ethnic minority groups, such as immigrants that arrived in the UK from EU accession countries after 2004 and other minorities. As a robustness check we therefore exclude neighbourhoods that have a ten percent or higher share of immigrants from A12 accession countries in the 2011 census, which is the case for 714 out of 34,058 neighbourhoods. With A12 countries we refer to the Czech Republic, Estonia, Hungary, Latvia, Lithuania, Poland, Slovakia, Slovenia, Cyprus and Malta that joined the European Union in 2004, as well as Bulgaria and Romania that

joined in 2007. Column (5) in Table 2.10 compares results when these neighbourhoods are omitted from the regression sample with the results from Tables 2.6 to 2.9 for outcomes in year 2011.

The results from this smaller estimation sample suggest that the effects found for 1991-2011 are not driven by neighbourhoods with large influx of immigrants from EU accession countries. The effects on neighbourhood change in private housing as well as in privately owned housing minority shares are significant and increase slightly, while the coefficient on neighbourhood change in privately rented housing minority share is insignificant. The coefficients on population growth and on housing prices are slightly smaller than for the full sample.

Housing Supply

To understand the effects of differences in housing supply stocks for our results, we approximate housing supply elasticities for areas in England and Wales. We follow Hilber and Vermeulen (2016) and use land cover data to group areas into a below-median constrained and into an above-median elasticity group. High elasticity areas are defined as areas with a share below the median of developable land that is developed or land that cannot be developed. Appendix 2.3 describes this constraint measure in more detail..

Table 2.11 presents coefficients on the instrumented dependent variable for the five second-stage outcome variables for high- and low-elasticity areas compared to the full sample of areas for 2001 and 2011. The effect on the minority share in private housing closely overlaps with the coefficient low housing stock elasticity areas for both years. Similarly, the impact on log house price is significant and of nearly the same magnitude than the average effect for 1995-2011. The coefficients for the subsample of high elasticity areas are insignificant. Overall, these results indicate that the estimates for private housing minority share and house prices are more affected by areas with lower housing supply elasticity.

2.8 Conclusions

This Chapter uses a policy change in the allocation of public housing in the 1990s in the UK to estimate the impact of an increase in ethnic minority numbers in a neighbourhood on the ethnic composition in private housing, on population growth and on local house prices. This approach exploits variation in the ethnic composition in social housing due to

Table 2.11 Results for areas with high and low housing supply elasticities

	All areas	High-elast. areas	Low-elast. areas	All areas	High-elast. areas	Low-elast. areas
IV coefficients for outcome:	2001 (1)	2001 (2)	2001 (3)	2011 (4)	2011 (5)	2011 (6)
Table 2.6: Minority share in private housing	0.118*** (0.044)	-0.003 (0.265)	0.117* (0.046)	0.132** (0.055)	0.248 (0.227)	0.115 (0.059)
Table 2.7: Minority share in privately owned housing	0.096** (0.044)	-0.007 (0.267)	0.102* (0.046)	0.148** (0.060)	0.285 (0.227)	0.135* (0.066)
Table 2.7: Minority share in privately rented housing	0.150** (0.068)	0.405 (0.335)	0.139* (0.070)	0.078 (0.066)	0.379 (0.235)	0.067 (0.071)
Table 2.8: Population growth	0.217** (0.108)	-0.142 (0.726)	0.165 (0.112)	0.340*** (0.098)	0.034 (0.421)	0.286** (0.103)
Table 2.9: Log house price (for 1995-2011)				-0.059*** (0.009)	0.089 (0.061)	-0.052*** (0.009)
Number of areas	348	174	174	348	174	174
Number of neighbourhoods	34,378	16,948	17,430	34,058	13,689	20,369
Number of houses (in Table 2.9)				17.2 m.	7.3 m.	9.9 m.

Notes: High-elasticity areas are areas with a share below the median of developable land that is developed or land that cannot be developed, and low-elasticity areas have shares above the median. Regression controls, fixed effects, clustering of standard errors and weights are implemented as described in the respective Tables. Outliers with population growth above 500 percent are dropped for Table 2.8 estimates. Million is abbreviated as m., and standard errors are in parentheses, with levels of significance * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

this policy change in a neighbourhood, which does not initially change the socio-economic characteristics of a neighbourhood otherwise.

For the empirical analysis we build a new dataset with detailed geographic information from census data, so that we can exploit variation at the local level of LSOA neighbourhoods within local authority areas. We find evidence that is consistent with some ‘white flight’ from neighbourhoods and significant negative effects on local house prices.

It is likely that the increased residential segregation affects the local labour market and local public goods, such as education and crime. Schooling allocation, for instance, is largely based on distance in England and Wales, and residential segregation is likely to give rise to segregation in schools. An important next step would be to study these implications of ethnic composition changes in further research.

Appendix 2.1: Census Data

The estimations use census data for England and Wales for years 1991, 2001 and 2011, which is aggregated at the geographic level of Lower Layer Super Output Areas (LSOAs) that align within Local Authority Districts (LAs).³ In this Chapter we refer to LSOAs as neighbourhoods and LAs as areas. The Office of National Statistics minimum and maximum population thresholds for a LSOA are 1,000 and 3,000 inhabitants, with minimum and maximum thresholds for the number of households being 400 and 1,200 in year 2011. Figure A2.1 shows LSOA neighbourhoods within LA boundaries in London.

Figure A2.1 LSOA neighbourhoods within local authority area boundaries in London



LSOAs only exist since 2001 and data at the LSOA level for 1991 in this Chapter is created from 113,465 Enumeration Districts (EDs) as explained in more detail below. The UK census is undertaken every ten years, with the most recent census carried out in March 2011. The census data used was downloaded from the websites <http://casweb.mimas.ac.uk> and www.nomisweb.co.uk.

³We adopt the definition of LA areas from the Office of National Statistics, which covers London boroughs, metropolitan districts, unitary authorities and non-metropolitan districts in England, and unitary authorities in Wales. There are 32 London boroughs, the City of London, 36 metropolitan district councils, 22 unitary authorities in Wales, 56 unitary authorities in England, and 27 English shire counties split into 201 non-metropolitan districts. All but non-metropolitan districts are served by single-tier (unitary) administrations. Non-metropolitan districts are subdivisions of non-metropolitan counties in a two-tier arrangement.

Ethnicity by Tenure of Household Reference Persons

The census data estimations in this Chapter are for household reference persons, which are treated as approximations to households. In the census a household reference person is defined based on age and economic activity, and is the oldest full-time worker in most households.

Ethnicity by tenure information is provided at the smallest geographical disaggregation in the census for 1991, 2001 and 2011 for household reference persons for whites, Asians, blacks, and other ethnic minorities, from which we can generate area level variables. More detailed ethnicities are available for individual-level data for the smallest geographies but not for cross-tabulations with tenure status, which is of key interest for the analysis in this Chapter. Data for the 1991 census variable housing tenure by ethnic group are generated from 113,465 Enumeration Districts (EDs) using data from Casweb Table SAS49 and were converted into LSOAs by means of GeoConvert, accessed at <http://casweb.mimas.ac.uk> and <http://geoconvert.mimas.ac.uk> respectively. The geography conversion with GeoConvert is explained in more detail in the subsection on census geographies below. Data for 2001 LSOAs are sourced from Nomisweb Table CAST04 and for 2011 LSOAs from Nomisweb Table LC4201EW, accessed at www.nomisweb.co.uk.

While the category ‘mixed’ is available as a separate ethnicity category for household reference persons for 2001 and 2011, it is summed with the category ‘other’ for 2001 and 2011 to enable comparisons between ethnicity categories across census years 1991-2011.

For 1991, social housing is defined as the sum of the available categories social housing provided by the local authority and social housing in housing associations, and for 2001 social housing is the sum of the available census categories ‘rented from council’ and ‘other social rented’.

Ethnicity by tenure in 2001 is only available for ethnicity subcategories, which are summed to make ethnicity categories comparable to 1991 and 2011. For example, ‘Asian’ in 2001 is defined as the sum of the available categories ‘Indian’, ‘Pakistani’, ‘Bangladeshi’ and ‘other Asian’.

In the census raw data, total persons and total ethnicity counts do not always add up to the sums of tenure type subcategories, which particularly affects 1991 EDs. These discrepancies seem to be due to the fact that there is no tenure category ‘no response’ or ‘other’, so that non-responses or missing information regarding tenure type were probably not reported. Assuming that the non-entries are random across housing tenure categories, we therefore adjust the variable ‘share in social housing’ as the share of all persons in social housing over the sum of tenure subcategories, and the variable ‘difference share of non-whites in private housing’ is defined accordingly.

In addition to ethnicity by tenure, religion is first recorded in the 2001 census and is available in cross-tabulations with tenure type for household reference persons aggregated by LSOAs in 2001 and 2011.

Individual Level Data

Census data contains detailed disaggregations of ethnicity, but ethnicity information at disaggregated geographic levels is not available by tenure status. One possibility for additional analyses is to calculate ethnicity shares by tenure types for England and Wales from the Labour Force Survey. For example, Table A2.1 provides shares of each ethnicity in social housing by the ethnicity disaggregation available for individual-level census data for 1991-2011, calculated from the Labour Force Survey 1991 and the Quarterly Labour Force Surveys for 2001 and 2011 (April-June) respectively.

Table A2.1 Shares of ethnic groups in social housing 1991-2011

Year	All	White	Indian	Pakistani	Bangla- deshi	Chinese	Other Asian	Black Caribbean	Black African	Other black	Other
1991	0.24	0.23	0.08	0.11	0.34	0.21	0.22	0.42	0.47	0.55	0.34
2001	0.19	0.19	0.09	0.17	0.51	0.19	0.22	0.41	0.57	0.52	0.20
2011	0.16	0.15	0.06	0.14	0.40	0.07	0.18	0.41	0.49	0.46	0.16

Census data is also available for country of birth of individuals for 1991 EDs, and for LSOAs in 2001 and 2011, but not for cross-tabulations with tenure types.

Consistent Census Geographies over Time

The analysis in the Chapter focuses on Lower Layer Super Output Areas, a geography that only exists from 2001 onward. For 1991, a total of 34,378 LSOAs were thus created from 113,465 Enumeration Districts for the ethnicity by tenure variable by means of the geography-conversion service GeoConvert, to reflect 2001 LSOA boundaries. GeoConvert is an online geography matching and conversion tool using the National Statistics Postcode Directories in a web interface to allow converting data from one geography to another, and was accessed at <http://geoconvert.mimas.ac.uk>. GeoConvert works by dissecting zones of a source geography into postcodes and uses these to reconstitute zones of a target geography, by approximating the population in the postcode with the number of delivery points attached to each postcode.

LSOAs created following the 2001 census continue to exist unless a significant population change occurred between 2001 and 2011 and household minimum and maximum thresholds

were breached. Simplistically, where populations have become too big, the LSOAs have been split into two or more areas; where populations have become too small, the LSOAs have been merged with an adjacent one.

In terms of LSOAs affected by such boundary changes, 1.1 percent of 2001 LSOAs that have been split into two or more 2011 LSOAs, 0.4 percent of 2001 LOAS that have been merged with one or more other 2001 LOAS, and 0.4 percent of LSOAs that had complex changes which cannot easily be corrected. We therefore apply a boundary standardisation procedure that corrects for LSOA splits in 2011 by adding the 2011 split parts to recreate 2001 boundaries for these LSOAs, and for 2001 LSOAs that were merged by adding the 2001 parts. The resulting data file only comprises summed LSOA codes that are thus corrected for merges and splits, and LSOAs affected by complex corrections are not included. The same strategy is applied to make 1991 LSOAs comparable, which have been converted from 1991 EDs. As a result, 34,058 LSOAs are generated that are comparable across 1991-2011. Table A2.2 provides a summary of these source geographies and conversions by year.

Table A2.2 Creation of comparable geographic units across 1991-2011

Year	Initial units	Coherent units 1991-2011
1991	34,378 LSOAs (generated from 113,465 EDs using Geoconvert)	34,058 LSOAs
2001	34,378 LSOAs	
2011	34,753 LSOAs	

Appendix 2.2: House Price Data

Yearly house prices for England and Wales are available from the Land Registry from 1995 on, and were downloaded at <http://data.gov.uk/dataset/land-registry-monthly-price-paid-data>. The resulting data file contains information on over 17.2 million house price transactions during 1995-2011, and an overview of transaction numbers and average prices by year is provided in Table A2.3. LSOA codes were added to the house transactions data by means of aggregating postcodes, and LSOAs for 2001 and 2011 were consequently made compatible by accounting for merges and splits as described above, so that house price transaction data is available for 34,058 LSOAs for 1995-2011.

The Land Registry data distinguishes between ‘detached’, ‘semi-detached’, ‘terraced’ and ‘flat’ housing types. Additional information details whether the housing is newly built, and whether it is a leasehold or a freehold.

Table A2.3 Land Registry house price transaction data 1995-2011

Year	N transactions	House price
1995	762,084	68,701
1996	925,823	72,325
1997	1,056,197	79,134
1998	1,021,973	85,670
1999	1,170,591	96,080
2000	1,107,712	107,322
2001	1,223,451	118,711
2002	1,329,086	137,800
2003	1,219,889	155,550
2004	1,223,969	178,419
2005	1,046,224	189,053
2006	1,307,900	203,141
2007	1,254,411	219,010
2008	639,070	216,506
2009	615,014	212,862
2010	653,620	235,567
2011	651,461	232,010
Average	1,012,263	153,404

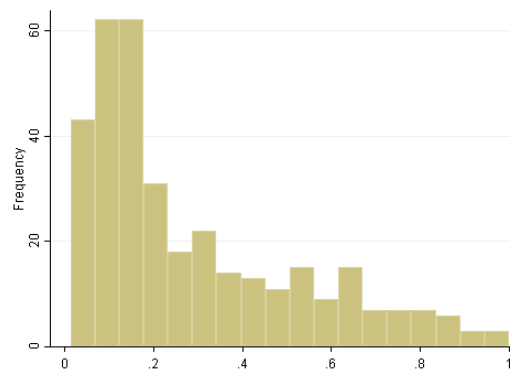
Appendix 2.3: Data on Land Cover

An approximation to the elasticity of housing supply is constructed based on physical constraints using land cover data for England and Wales. We use this data to define local authority areas above and below the median housing elasticity measures. Figure A2.2 plots a histogram of the measure we use, the share of developed land in 1990, which varies between 0.01 and 1 with a mean of 0.29 and a median of 0.19.

The share developed land is derived from the 1990 Land Cover Map of Great Britain, obtained from the Centre for Ecology and Hydrology. This land cover map was first developed in 1990 as part of the long-running series of UK Countryside Surveys and provides data derived from satellite images that allocates land to 25 cover types on a 25 times 25 metre grid. In order to get an operational measure different land use classes were categorised into developed land, non-developable land, and developable yet undeveloped land as done by Hilber and Mayer (2009), Hilber (2010) or Hilber and Robert-Nicoud (2013). From the available classes, the share developed land is defined as the share of total land in an area that is either developed or non-developable.

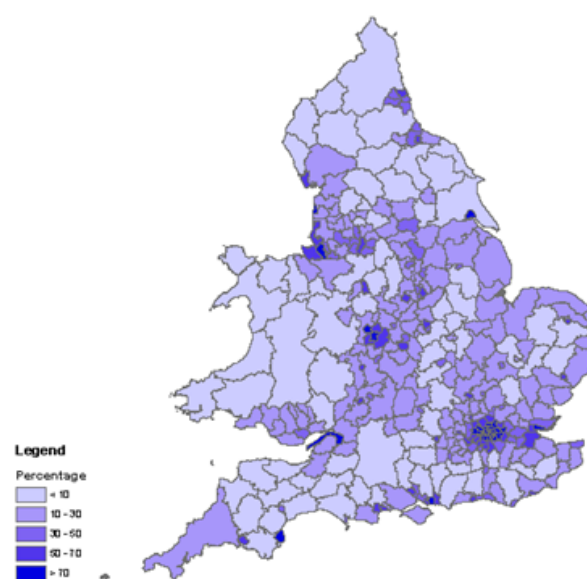
Specifically, the following land uses were classified as ‘developed’: ‘suburban/rural developed’ and ‘urban development’. Classified as ‘non-developable’ are: ‘sea/estuary’,

Figure A2.2 Histogram of areas by share of developed land in 1990



'inland water', 'costal bare ground', 'saltmarsh', 'ruderal weed' and 'felled forest'. Classified as 'developable' are: 'grass heath', 'mown/grazed turf', 'meadow/verge/semi-natural swards', 'bracken', 'dense shrub heath', 'scrub/orchard', 'deciduous woodland', 'coniferous/evergreen woodland', 'tilled land', 'inland bare ground' and 'open shrub heath'. Finally, classified as 'semi-developable' are: 'rough/marsh grass', 'moorland grass', 'open shrub moor', 'dense shrub moor', 'upland bog' and 'lowland bog'. About one percent of all land cover in 1990 was unclassified, which are discarded for the computations. Figure A2.3 illustrates the variation in the physical constraints measure across areas in England and Wales.

Figure A2.3 Share of developed or non-developable land by area in 1990



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Chapter 3

Labour Market Reforms: An Evaluation of the Hartz Policies in Germany

3.1 Introduction

Evaluating the impacts of labour market policy changes is not straightforward. Often reforms that aim to increase employment have important effects on wages by changing incentives, the search behaviour and the sorting of workers and firms. This Chapter proposes a new method for analysing policies with pronounced differential impacts by worker and firm type. We apply this approach to evaluate the effects of a comprehensive recent labour market reform package in Germany, the Hartz reforms. The objective of these reforms was to reduce unemployment, by implementing four reform laws in 2003, 2004 and 2005. To assess the effects of these reforms a structural framework is developed that is empirically tractable. The timing of reform announcement and policies is used for estimating the labour market parameters, using matched data on 430,000 workers employed in 340,000 firms. As a result, we do not rely on the convergence of the economy to its steady-state for identification and statistical inference is simplified. These features make our approach suitable for evaluating complex labour market policy changes in settings where detailed microeconomic data are available.

The German labour market reforms in the early 2000s are often referred to as exemplary policies for reducing unemployment. After lacklustre economic growth in the 1990s and early 2000s, Germany outperformed many other industrialised countries from 2006 on and during the Great Recession. Unemployment fell from 12.3 percent in 1998 to 8.7 percent in 2008, and Germany attracted international attention for its transformation from the ‘sick man of Europe to economic superstar’ (Dustmann et al., 2014). It remains unclear, however, to what extent the Hartz reforms altered the performance of the German labour market, and how

they affected unemployment and wages. In particular the decrease in unemployment is often attributed to the Hartz reforms. Other less prominent explanations for the strengthening of the German economy include pre-reform wage moderation and a favourable export environment.

Our work is the first to estimate the impact of the Hartz package on labour market structures by using detailed worker-firm data. The Hartz policies are difficult to evaluate because they were anticipated, implemented universally across Germany, and general equilibrium reform effects are slow to materialise. Consequently within-country variation in reform treatment cannot be used for reduced-form analyses such as differences-in-differences or regression discontinuity. Cross-country variation is also not suitable due to stark differences in macroeconomic trends between Germany and other OECD countries in the early 2000s. Furthermore, structural evaluations of the Hartz reform cannot easily be implemented due to the extensive scope of the reforms and a lack of clear evaluation metrics. In this Chapter we do not model reform changes explicitly, but assume that policy is reflected in structural labour market parameters that change with the implementation of new reforms. In our model reforms affect wages and employment through search frictions and heterogeneity in worker-, firm- and match-specific productivity. Wages are the result of a worker-firm bargaining game, and they vary with the employment status of the worker. Policy changes in our setting are fully anticipated and parameters evolve according to a deterministic process.

We find that the Hartz reforms resulted in a small expansion of employment of 0.8 percentage points. This employment effect is smaller than the expansions often attributed to the reforms. Our evaluation shows that this employment increase comes at the cost of a five-percent reduction in mean wages, with the lowest earners suffering the largest losses. There are large differences in the contributions of each reform wave to the overall effect. The first wave, composed of the Hartz I and II policies, would lead to a reduction in employment and wages if implemented in isolation. By contrast the Hartz III wave that aimed at improving matching efficiency by itself would be expansionary in both employment and wages. Hartz IV, with an emphasis on labour supply measures, increased employment but reduced wages. Overall, we find that the reforms lead to a structural shift in the sources of wage variation. As a consequence of the first reform wave, the importance of the match-specific wage component increases relative to the firm-specific component. In addition, wage variation due to sorting falls after the reform as a consequence of diminished worker outside options, which is primarily driven by the last reform that cut unemployment benefits. Longer employment spells result in greater frictional wage dispersion, which arises in our context when a worker bids up wages using new job offers.

Our approach builds on the literature of labour market equilibrium models, and derives from the sequential auction model in Postel-Vinay and Robin (2002). In our framework

wage determination is tractable out of steady-state as in Postel-Vinay and Turon (2010) and Lise and Robin (2017). We extend the framework in Lise and Robin (2017) by including a match-specific component, a wage setting mechanism that can replicate the empirical wage distribution, and shocks that affect the parameter space rather than labour productivity. Equilibrium labour models with search frictions have frequently been implemented to evaluate specific policies explicitly, for example, by Bentolila et al. (2012), Bradley et al. (2016) and Shephard (2016). Typically, policies are evaluated by estimating the model pre-reform and directly imposing the reform into the context of the model. This methodology, however, cannot easily be expanded for investigating labour market reforms with extensive scope or when policies lack a clear evaluation metric. Murtin and Robin (2016) develop a more indirect approach to reform evaluation that is comparable to ours, by assuming that specific labour market policies govern the parameters of a structural model. The mapping between policy and parameters in their paper is identified from cross-country differences, and their analysis focuses on employment and its volatility only.

We model wage bargaining with on-the-job search. One reason for including on-the-job search is its quantitative importance. The overwhelming majority of job flows are not from unemployment to employment but from one job to another. Secondly, on-the-job search is an important determinant of the equilibrium wage distribution by governing a worker's outside option and creating a job ladder over time. In addition, we account for significant amounts of heterogeneity to capture the distributional impacts of the different policies. Workers vary in observable and unobservable components, firms differ in productivity and each match has a unique additional source of heterogeneity. This match-specific heterogeneity is important as the reforms changed the type of jobs and contracts that can be offered.

This Chapter contributes to existing studies of the Hartz reform policies. Previous analyses of the Hartz reforms focus on a specific subset of the reform elements, while our approach differs by accounting for the employment and wage effects of all four reforms. The existing analyses fall into two categories: calibrated or estimated macroeconomic models that explicitly model certain aspects of the reforms, and reduced form approaches that exploit discontinuities arising from a specific reform or a structural break in the time series.

The papers that calibrate the effects of specific Hartz reforms in macroeconomic models show declines of unemployment that vary in size and mixed evidence on wages. Launov and Wälde (2013) assess the impact of the Hartz IV benefit reductions, and Launov and Wälde (2016) additionally account for Hartz III effects calibrated as a shift in matching efficiency. They find a negligible effect of the benefit cuts on unemployment, with a stronger relative impact of increased matching efficiency. In Launov and Wälde (2013) wages increase in

response to lower benefits because of lower endogenous taxation and increased market tightness. The calibration of Hartz IV in Krause and Uhlig (2012) points to a 2.8-percentage point reduction in unemployment, at the cost of depressing overall wages and a 12.5-percent wage cut for the low-skilled. In Krebs and Scheffel (2013) the reforms reduce unemployment even more substantially, with Hartz I-III and Hartz IV accounting for around half of the unemployment reduction each. Felbermayr et al. (2016) show that Hartz III and IV decreased unemployment slightly but had little effect on wages.

Price (2016) evaluates the Hartz IV reduction in long-term benefits in a more reduced-form way, with similar findings to our estimates of the Hartz IV effect. Re-entry wages in Price (2016) fall by around 2 percent in response to the benefit reduction and unemployment decreases by over 1 percentage point. Another strand of papers model the Hartz reforms collectively as a shock to matching efficiency and test for reform effects using empirical matching functions. Focusing only on the first two waves Fahr and Sunde (2009) find a modest expansion of total employment. Klinger and Rothe (2012) report a positive impact of the four Hartz reforms on matching efficiency, and Hertweck and Sigris (2013) document a large positive employment effect of the reforms. These studies do not account for wage effects.

This Chapter is organised as follows. Section 3.2 provides an overview of the Hartz reforms, summarises the evolution of employment and wages over the reform periods and motivates our conceptual approach. Section 3.3 describes the model. The estimation protocol is presented in Section 3.4. Section 3.5 discusses the estimation results and simulates the model to uncover the reform impacts on wages and employment. Section 3.6 concludes.

3.2 The Hartz Reforms

The Hartz reforms consist of four labour market reform laws that were implemented in Germany between 2003 and 2005. The main objective of the reforms was to reduce unemployment. To reach this objective the reforms included extensive changes for workers and firms, such as increased working hour flexibility, improved job matching and more stringent work incentives for the unemployed.

The Hartz laws were based on suggestions by the Commission for Modern Services in the Labour Market, also called the Hartz Commission. After years of rising unemployment, labour market policy was a central issue in the German elections in 1998 and 2002. When unemployment remained high the Hartz Commission was appointed on February 22 2002 in response to a scandal, which revealed that the Federal Employment Agency had significantly embellished the numbers of successfully placed job seekers. The Hartz Commission was

composed of 15 experts from industry, politics and academia, and named after the chairman of the Commission, Peter Hartz, who was CEO of Volkswagen at the time. The Commission published its suggestions for labour market policy changes in August 2002. These suggestions led to the Hartz reform package, which was implemented from January 1 2003 onward. Table 3.1 gives an overview of the timing and content of the Hartz I-IV laws, and Appendix 3.1 provides more details on the reform contents. Broadly summarised, the first wave aimed at raising labour demand, the objective of the second wave was to improve market efficiency, and the final wave was targeted at increasing labour supply.

Table 3.1 The Hartz Reforms

Announcement: February 22 2002

- The Hartz Commission is appointed to suggest labour market reforms.

Labour demand: Hartz I & II laws, taking effect on January 1 2003

- Hiring of temporary workers is made easier.
- Continued training is subsidised with vouchers.
- Tax exemptions are given for low hour jobs, called mini- and midi-jobs.
- Subsidies for startups by the unemployed are introduced.

Market efficiency: Hartz III law, taking effect on January 1 2004

- The Federal Employment Agency is restructured to improve service delivery and job placement of the unemployed.

Labour supply: Hartz IV law, taking effect on January 1 2005

- The long-term unemployed receive less support, now in the form of a flat-rate payment.
 - Unemployment benefit receipt is made more contingent on asset-based means testing.
 - Sanctions are introduced for the refusal of job offers.
-

The Hartz I and II reforms came into effect on January 1 2003. Hartz I, the first of the four ‘Laws for Modern Services in the Labour Market’, facilitated temporary employment and introduced new training subsidies. Hartz II further regulated marginal employment, introduced mini- and midi-jobs, and sponsored business startups by the unemployed. Mini-jobs provide tax exemption for worker contributions to social security for monthly incomes up to 400 Euros, and midi-jobs allow tax deductions for incomes up to 800 Euros a month. The third reform law, Hartz III, was implemented from January 1 2004 on, and restructured the Federal Employment Agency with the objective of making it a modern client-oriented service provider. Hartz IV came into effect on January 1 2005, and was one of the most extensive and controversial labour market reforms that was ever implemented in Germany. It

significantly changed the structure and generosity of unemployment benefits, by combining unemployment assistance for the longer-term unemployed with social assistance into a flat-rate payment, and introduced sanctions to promote more active job search. The effects of Hartz IV for payments received by the unemployed were ambiguous. For example, households with low incomes in employment and single parents profited from the reform while those with higher employment incomes experienced a reduction of benefits (Koch and Walwei, 2005). A separate law in January 2005 specified reductions of unemployment benefit durations, which we do not analyse in this Chapter. These reductions in benefit duration were applied to unemployment spells starting from February 2006 on, with the first duration cuts in effect only in 2007.

3.2.1 The Reform Effects

To examine the impact of the Hartz reform laws we use data on 430,000 males working in 340,000 firms from the Sample of Integrated Labour Market Biographies (SIAB) between 2001 to 2005. The data are stratified into three skill groups. Workers with an intermediate school leaving certificate or below are defined as unskilled, workers with a vocational qualification such as an apprenticeship and with an upper secondary school certificate are combined in a medium-skill group, and university graduates are classified as high-skill workers.

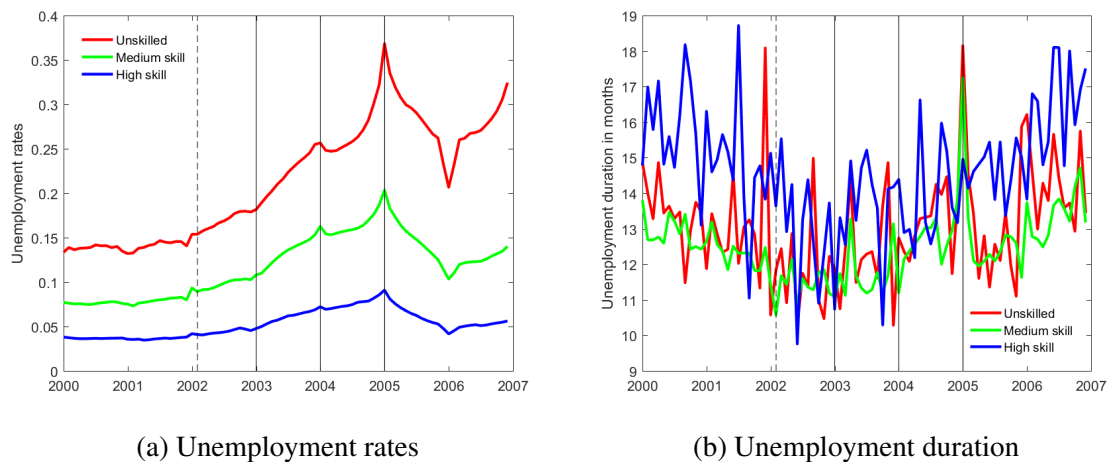
Employment

Figure 3.1 plots unemployment rates and unemployment durations for new hires by skill group between 2000 and 2006. The dates of the announcement and implementations of the Hartz reforms are denoted by vertical dashed and solid lines respectively. All monthly series have been seasonally adjusted using the X-12-Arima program.¹

As shown in panel (a) of Figure 3.1, unemployment increases during the implementation of the reforms between 2003 and 2005 and falls after the Hartz IV law comes into force in 2005. The increase in unemployment is already visible from the initial announcement of reforms after the appointment of the Hartz Commission in February 2002. With the implementation of the fourth Hartz law, unemployment rose to a historical high with over 5.2 million workers unemployed. The spike in unemployment in January 2005 is largely due to a change in measuring unemployment (Bundesagentur für Arbeit, 2005). The combination of unemployment and social assistance payments under Hartz IV meant that many previous

¹X-12-Arima is a software package developed by the US Census Bureau for seasonally adjusting time series data.

Figure 3.1 Unemployment rates and duration 2000-2006

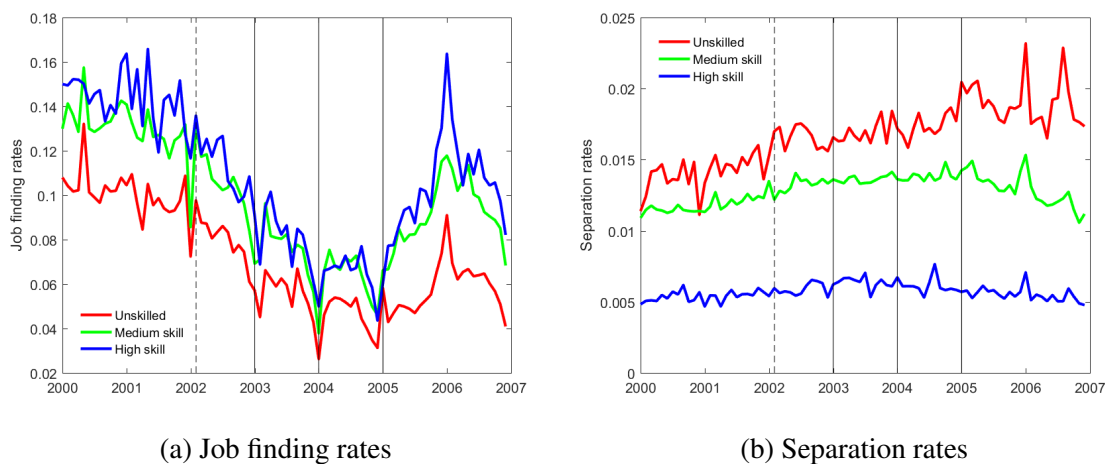


Notes: Unemployment rates are constructed from Benefit Recipient History data that is a part of the SIAB dataset. Unemployment duration refers to months of unemployment for workers who exit unemployment. The monthly series are for male workers, use SIAB data and are seasonally adjusted.

recipients of social assistance now also registered as unemployed. Unskilled workers account for 80 percent of the overall increase between January and March 2005. The duration of unemployment exhibits more volatility than the unemployment rates. Duration is reported for new hires who exit unemployment and is defined as the time for which a worker was unemployed since his last employment spell, as recorded in the Benefit Recipient History data source. By contrast to the unemployment rate, the duration series displays a u-shaped pattern in Figure 3.1. In times of high (low) unemployment, new hires have on average spent less (more) time in unemployment. Changes in the worker composition of the pool of unemployed are one potential explanation for this pattern. Our model accommodates such composition changes by accounting for worker heterogeneity.

Panel (a) in Figure 3.2 shows the outflows from unemployment and panel (b) the inflows into unemployment. The series indicate that the increased unemployment over the implementation period is primarily driven by a fall in the job finding rate, and the post-reform fall in unemployment is associated with a higher job finding rate. Separation rates increase slightly for the unskilled over the reform periods. Unskilled workers have the highest separation rates and these remain higher post-2005 compared to the pre-reform period.

Figure 3.2 Transition rates 2000-2006



Notes: Job finding rates are the monthly shares of unemployed workers who find a job. Separation rates capture the monthly share of employed workers who exit into unemployment. The monthly series are for male workers, use SIAB data and are seasonally adjusted.

Wages

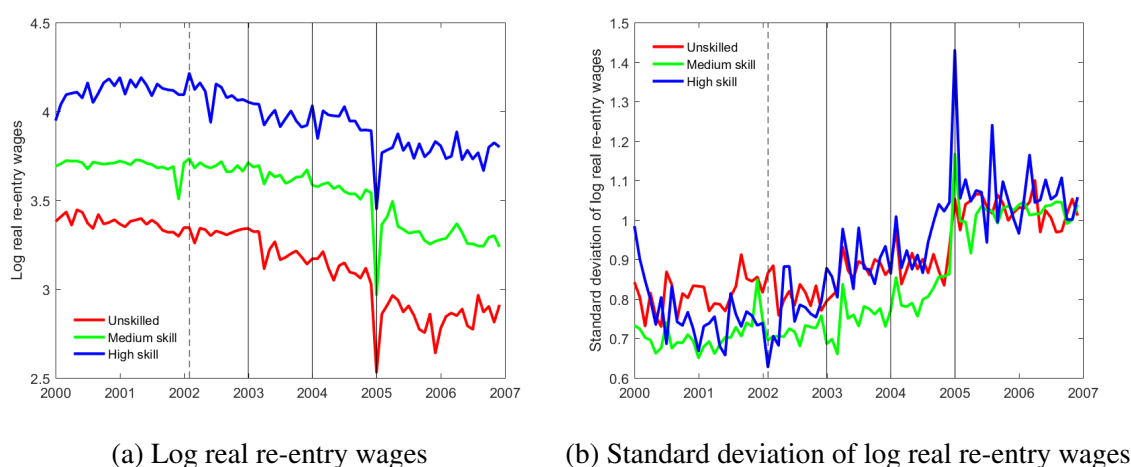
The monthly mean and standard deviation of log real daily wages for workers hired from unemployment are reported in Figure 3.3. Log real daily wages for new hires show a pronounced decline for all skill groups and a corresponding increase in the standard deviation of wages. Wages are measured in Euros, which are deflated using the Consumer Price Index published by the German Federal Statistical Office.

Before announcing the appointment of the Hartz Commission on February 22 2002, both series appear relatively stable. A large change in wages coincides with the introduction of the Hartz reforms. Over the reform periods mean log wages fall across all three skill strata, with the unskilled and lowest paid bearing the bulk of the decrease. Raw wages for low-skilled new hires fall by over 50 percent over this period, and the dispersion of wages increases within each skill strata. In our framework wages are set endogenously, so that our model can uncover the drivers of this structural change.

3.2.2 Conceptual Approach

This Chapter develops a framework for assessing the marked decrease in wages that occurred contemporaneously with the Hartz reforms. Due to the comprehensive impact of the Hartz reforms standard reduced-form or structural approaches are not suitable for analysing the effects on wages and employment. In our model the structural parameters respond to labour

Figure 3.3 Log real re-entry wages 2000-2006



Notes: Log real re-entry wages refer to the log of daily wages in Euros for new hires, which are deflated by the Consumer Price Index. The monthly series are for male workers, use SIAB data and are seasonally adjusted.

market interventions. The exact timing of reforms in the model is stochastic, and instead of modelling each reform element explicitly we treat a reform wave as a shock to the parameter space. In our structural setting we include important sources of wage dispersion, and account for variability in wages due to observable and unobservable worker differences, firm productivity, a match-specific component, search frictions, and sorting across all these dimensions.

A reduced-form evaluation compares outcomes before and after a specific policy is implemented, which is not feasible in the context of the Hartz reforms. It is likely that firms and workers anticipated the Hartz policy changes before the implementation of the reform policies and adjusted their behaviour before the first Hartz reform and until Hartz IV took effect. A reduced-form assessment may also fall short because of the persistence of the endogenous variables, employment and wages. An alternative approach would impose full structure on the data generating process and specify each policy explicitly in a structural model. The Hartz reforms, however, lack clear evaluation metrics and were so wide-ranging that modelling all different reform features is unrealistic.

Furthermore, we assess the impacts of the Hartz reform waves in isolation. To mitigate the effects of contemporaneous macroeconomic developments we restrict our estimation to a relatively short time horizon and subtract a trend component in the moments used for identification. As a result, our findings can be interpreted as the impact of the Hartz reforms net of other macroeconomic trends.

3.3 The Model

3.3.1 The Environment

Time is continuous and denoted by t , where $t \in \mathbb{R}_+$. Parameters subscripted by t vary over time, and θ_t denotes the vector of parameters at time t . The structural parameters of the model evolve according to a jump process that occurs at the instance of the introduction of each labour market reform wave. Changes to θ_t are fully anticipated by the agents, but in order to keep the problem stationary, the exact instance at which the policy is implemented is not known. Instead, risk neutral agents know the instantaneous probability that a policy will be implemented. The Poisson rate η_t is calibrated to match the frequency of the Hartz reforms. Assuming that agents do not know the exact implementation dates makes the setting tractable. Instead of an infinite number of states, at any point in time the Poisson process ensures only five possible states between the announcement and implementations of individual policy, as described in Section 3.2.

The labour market consists of a continuum of infinitely lived workers of mass one, who are indexed by their level of productivity $x \in (\underline{x}, \bar{x})$. Workers can either be employed or unemployed, and the measure of workers of productivity x is given by $\ell(x)$. When a worker is unemployed he receives a flow utility value $b_t(x)$. A continuum of firms exist that are indexed by their productivity $y \in (\underline{y}, \bar{y})$. When a worker is hired by a firm, the amount produced depends on the productivities of the worker and the firm as well as on a match-specific draw, $z \in (\underline{z}, \bar{z})$. The match-specific component z is drawn from a known distribution with density $\gamma(z)$, which is independent of worker and firm productivities. The decision whether to form a match is made after the realisation of z . A worker and firm of productivity x and y with a match-specific productivity draw z produce an amount $f_t(x, y, z)$, where $f_t : (\underline{x}, \bar{x}) \times (\underline{y}, \bar{y}) \times (\underline{z}, \bar{z}) \rightarrow \mathbb{R}_+$. Our initial assumption for the functional form of $f_t(x, y, z)$ is that as $z \rightarrow \bar{z}$, $f_t(x, y, z) \rightarrow \infty$.

The economy is characterised by search frictions and workers cannot observe the full menu of jobs. Instead job offers arrive randomly to a worker at time t with an exogenous Poisson arrival rate $\lambda_{0,t}$ if the worker is unemployed and $\lambda_{1,t}$ if the worker is employed. The sampling density of firms is fixed over time and given by $\nu(y)$. Jobs are destroyed at an exogenous rate δ_t , after which the worker becomes unemployed.

3.3.2 Wage Determination

Wages are fully flexible and can be re-negotiated either after an alternative job offer arrives or when the state of the world changes through policy shocks. It is unlikely that our estimation

results rely on the assumption of flexible wages.² In our baseline setting, an employment contract can be thought of as a fixed threat point in a Nash bargaining game, and employment can be terminated at will or destroyed exogenously. In either case the worker becomes unemployed.

For an unemployed worker, wages are determined as in Cahuc et al. (2006) and Dey and Flinn (2005), where a firm hires a worker from unemployment and the worker and the firm split the surplus. The worker receives a fraction β of the generated surplus and the firm receives the rest. When a worker is employed, however, wages are determined as in Postel-Vinay and Robin (2002), where on the job search triggers Bertrand competition between a worker's current employer and the poaching firm. If the unemployed worker's bargaining power β were equal to zero, then wages are determined as in Postel-Vinay and Robin (2002). This combination of wage setting mechanisms allows us to retain much of the tractability of the setting in Postel-Vinay and Robin (2002) while allowing more flexibility over wage formation.³

For a given wage w , the surplus is shared between the worker and the firm. $W_t(\cdot)$ denotes the value function of an employed worker, $U_t(\cdot)$ is the value function of an unemployed worker, $\Pi_t(\cdot)$ is the value function of a firm that hires a worker, and $S_t(x, y, z)$ is the total surplus generated by a match.

$$W_t(w, x, y, z) - U_t(x) + \Pi_t(w, x, y, z) = S_t(x, y, z) \quad (3.1)$$

It is assumed that the outside option of the firm is zero. The wage provides an unemployed individual with an additional value equal to $\beta S_t(x, y, z)$. The wage of a worker's first job after leaving unemployment is a function of his productivity, the firm's productivity and the match-specific draw, and denoted by $\phi_{0,t}(x, y, z)$. If a positive surplus is generated then it is in the interest of the worker and the firm to form a match. Thus the values of y and z that result in matches for the worker are a function of his own productivity x and given by $\mathcal{M}_{0,t}(x) \equiv \{y, z | S_t(x, y, z) \geq 0\}$. The wage solves the following equality:

$$W_t(\phi_{0,t}(x, y, z), x, y, z) - U_t(x) = \beta S_t(x, y, z). \quad (3.2)$$

²We draw this conclusion after describing the consequences of a model with less flexible wages, which is available in a supplementary document online at www.sites.google.com/site/kuegleralice/research.

³As in Cahuc et al. (2006) and Dey and Flinn (2005), the relationship between entry wages and firm type is ambiguous. Workers are willing to accept lower wages today knowing that they will be compensated with higher wages tomorrow, which is the only mechanism at play in Postel-Vinay and Robin (2002). Since workers take a fraction β of the surplus, however, the wage is higher when the surplus is larger. The magnitude of β mostly determines which effect dominates.

3.3.3 Wage Mobility

When a firm meets an employed worker, the poaching firm draws a match-specific productivity that is observable to all parties. The incumbent and the poaching firm then engage in Bertrand competition to hire or retain the worker. For a worker of productivity x employed in a firm of productivity y with match-specific productivity z , three possible things can happen.

Move jobs: The worker moves if the surplus generated from the poaching firm is greater than the current surplus. The set of poaching firm and match-specific productivities y', z' is given by $\mathcal{M}_{1,t}(x, y, z) \equiv \{y', z' | S_t(x, y', z') \geq S_t(x, y, z)\}$. Due to asymmetries in the wage bargaining process between employed and unemployed workers the determination of the new wage remains ambiguous. We therefore partition $\mathcal{M}_{1,t}(x, y, z)$ into $\mathcal{M}_{10,t}(x, y, z)$ and $\mathcal{M}_{11,t}(x, y, z)$, where, $\mathcal{M}_{1,t}(x, y, z) = \{\mathcal{M}_{10,t}(x, y, z) \cup \mathcal{M}_{11,t}(x, y, z)\}$. The more familiar case is when new offers (y', z') are in the set $\mathcal{M}_{11,t}(x, y, z)$ and the set is defined as $\mathcal{M}_{11,t}(x, y, z) \equiv \{y', z' | S_t(x, y', z') \geq S_t(x, y, z) \geq \beta S_t(x, y', z')\}$. In this instance the worker moves to the new firm and uses his current employment as his outside option in Bertrand competition. The new wage of the worker is given by equation (3.3) and he is able to extract all the surplus from his former match.

$$W_t(\phi_{1,t}(x, y', z', y, z), x, y', z') - U_t(x) = S_t(x, y, z) \quad (3.3)$$

If the difference in surplus generated between the poaching firm and the incumbent firm, however, is sufficiently large, when $(y', z') \in \mathcal{M}_{10,t}(x, y, z)$ and $\mathcal{M}_{10,t}(x, y, z) \equiv \{y', z' | \beta S_t(x, y', z') > S_t(x, y, z)\}$, then the worker gets a larger share of the surplus if he uses unemployment as his outside option. After meeting a higher surplus match, the worker instantaneously quits his current job and bargains with the poaching firm as an unemployed agent. The worker's new wage is defined in equation (3.2).

Stay in the same job with a wage increase: The worker receives a within-firm promotion if the surplus generated by a new offer is high enough to trigger Bertrand competition with the incumbent firm but not higher than the surplus of the current match. Bertrand competition is triggered if the surplus of a new match is greater than the worker surplus in the current match. Formally, the set of y', z' is defined as $\mathcal{M}_{2,t}(w, x, y, z) \equiv \{y', z' | S_t(x, y, z) > S_t(x, y', z') > W_t(w, x, y, z) - U_t(x)\}$. The worker's new wage solves the equality:

$$W_t(\phi_{1,t}(x, y, z, y', z'), x, y, z) - U_t(x) = S_t(x, y', z').$$

No change: If a worker receives an offer that generates less surplus than he is already taking from his current match, then the incumbent firm does not need to offer a higher wage to retain the worker. The set of y', z' is defined as $(y', z') \setminus \{\mathcal{M}_{1,t}(x, y, z) \cup \mathcal{M}_{2,t}(w, x, y, z)\}$.

3.3.4 Wage Re-negotiation

There are two types of shocks. Either a shock takes the form of an announcement of future changes to the parameter set, in which case agents re-optimize, or it is a direct shock to the parameter set. Wages are flexible and wages are re-negotiated after shocks take place. Wages are re-negotiated assuming the worker has the same firm-match outside option (y', z') . The worker can only use this outside option as a bargaining tool with his current employer, and we do not consider the possibility of changing employers. This re-negotiation mechanism ensures tractability. An alternative approach with greater wage rigidity leads to identical wage distributions in steady-state with slightly different wage dynamics.⁴ Unlike the mechanism presented here, however, wage equations are computationally more expensive as they require solving a fixed point.

After a shock, a match either dissolves and the worker returns to unemployment, or wages are re-negotiated.

The match separates: The match dissolves if the participation (positive surplus) constraint no longer holds. The set of time-varying parameters $\theta_{t'}$ immediately after a shock, for which a (y, z) match with a worker of productivity x is endogenously destroyed, is given by $\mathcal{N}_{0,t'}(x, y, z) \equiv \{\theta_{t'} | S_{t'}(x, y, z) < 0\}$.

If a worker's outside option is unemployment, the outcome of the wage re-negotiation is trivial. Before the shock a worker of type x in a match (y, z) earned a wage $\phi_{0,t}(x, y, z)$. After a shock, as long as the match is not separated, $\theta_{t'} \notin \mathcal{N}_{0,t'}(x, y, z)$, the worker's new wage is given by $\phi_{0,t'}(x, y, z)$. These wages are determined as the solution to the equality given by equation (3.2).

If the same worker in the same match with an outside offer (y', z') and currently earning $w := \phi_{1,t}(x, y, z, y', z')$, however, is hit by a shock, his new wage is re-negotiated in one of three ways. In each case we denote the new wage as w' , which can be a function of a worker's type (x) , his job type (y, z) and his best outside option (y', z') .

⁴A further description of this alternative approach is available in a supplementary document online at www.sites.google.com/site/kuegleralice/research.

Use the same outside offer: The worker's new wage is re-negotiated using the same firm-match threat point if $\theta_{t'}$ is such that

$$\mathcal{N}_{1,t'}(x, y, z, y', z') \equiv \{\theta_{t'} | S_{t'}(x, y, z) \geq S_{t'}(x, y', z') \geq \beta_{t'} S_{t'}(x, y, z) \geq 0\}.$$

In this scenario the match remains incentive compatible. The worker uses the same threat point when bargaining with his incumbent firm, and the new wage is given by

$$w' = \phi_{1,t'}(x, y, z, y', z').$$

Use unemployment as outside offer:

$$\mathcal{N}_{2,t'}(x, y, z, y', z') \equiv \{\theta_{t'} | \beta S_{t'}(x, y, z) > S_{t'}(x, y', z') \geq 0\}$$

Given the above, a worker gains a greater share of the surplus using unemployment as a threat point as opposed to his previous best outside option. In the re-negotiation procedure he bargains with unemployment as his outside option and his new wage is given by

$$w' = \phi_{0,t'}(x, y, z).$$

The worker takes all the surplus:

$$\mathcal{N}_{3,t'}(x, y, z, y', z') \equiv \{\theta_{t'} | S_{t'}(x, y', z') > S_{t'}(x, y, z) \geq 0\}$$

Finally, it could be that after realisation of the new parameter set the outside option of the worker generates a larger surplus than continued employment with his current firm. In our setting, a worker cannot move to previous job offers, as in such a case a change in policy would increase job mobility by construction. In this case we assume the worker has all the bargaining power and is able to extract the entire surplus. His new wage is given by

$$w' = \phi_{1,t'}(x, y, z, y, z).$$

3.3.5 The Surplus

This class of models has the advantage that only the expression that defines the surplus needs to be solved. By contrast, solving for the worker and firm individual value functions would involve five (rather than three) continuous variables. The surplus function is given by equation (3.4) and is formally derived in Appendix 3.2. The + superscript denotes

$A^+ := \max\{A, 0\}$.

$$(r + \delta_t + \eta_t)S_t(x, y, z) = f_t(x, y, z) - b_t(x) - \beta\lambda_{0,t} \int \int S_t(x, y', z')^+ v(y')\gamma(z')dy'dz' \\ + \lambda_{1,t} \int \int [\beta S_t(x, y', z') - S_t(x, y, z)]^+ v(y')\gamma(z')dy'dz' + \eta_t S_{t'}(x, y, z)^+ \quad (3.4)$$

Equation (3.4) describes the surplus generated by a match and is the fundamental equation of the model. It dictates the decisions of agents about who to match with and determines the resulting wages from consummating the match. The surplus consists of the net gain in flow utility, output minus home production, and three option values. The first integral term is the option premium in unemployment, the value of future employment to the unemployed. We refer to the second integral term as the quit premium, which is the additional surplus generated by being able to use unemployment as a worker's outside option. Since this expression is non-negative, it increases the total number of feasible matches. The final term represents the agent's expectations about the time-varying parameters after a shock. If future parameters, $\theta_{t'}$ generate more (less) surplus than the current parameters this adds (reduces) value to the current surplus and further encourages (deters) realising a match today.

We solve equation (3.4) numerically. Since the surplus at t depends on the surplus at t' , it is solved by backward induction.⁵ Furthermore, one does not need to form expectations about the value of the future surplus because the policy implications are anticipated. This makes the solution far simpler in computational terms and also means we do not have to make distributional assumptions about agents' beliefs. An additional computational burden arises due to the quit premium. Unlike the option value of unemployment, the set $\mathcal{M}_{10,t}(x, y, z)$ over which we integrate is a function of y and z . Under the majority of parametrisations that we have experimented with, however, this constitutes a relatively small share of total surplus and it thus proves computationally more efficient not to update this term at every iteration.

Lemma 1 As $z \rightarrow \bar{z}$, $S_t(x, y, z) \rightarrow \infty$.

Lemma 1 is proved in Appendix 3.3.

Proposition 1 The set,

$$\mathcal{M}_t^{xy} \equiv \left\{ x, y \mid \int_{\underline{z}}^{\bar{z}} \mathbf{1}\{S_t(x, y, z) \geq 0\} \gamma(z) dz > 0 \right\}$$

is equal to the universe of (x, y) , that is $\mathcal{M}_t^{xy} : (\underline{x}, \bar{x}) \times (\underline{y}, \bar{y})$.

⁵Solving by backward induction relies upon the final state being absorbing. After Hartz IV it is assumed that agents anticipate no further reforms, and $\eta_t = 0$ at a time t that is sufficiently large, as described in Section 3.3.7.

Proposition 1 is proved in Appendix 3.3. The set of all feasible worker-firm matches at time t is given by \mathcal{M}_t^{xy} . The fact that this set covers the universe of (x, y) suggests that all worker-firm pairs are feasible. No worker-firm match observed empirically can be used to falsify the model.

Lemma 2 *For any x, y, y' and z' , there is a z such that $S_t(x, y, z) > S_t(x, y', z')$.*

Lemma 2 is proved in Appendix 3.3.

Proposition 2 *The set*

$$\mathcal{M}_{1,t}^{y-}(x, y, z) \equiv \{y', z' | S_t(x, y', z') \geq S_t(x, y, z) \cap y > y'\}$$

is non-empty for all (x, y, z) .

Proposition 2 follows directly from Lemma 2. In equilibrium any employed agent may voluntarily move to a less productive firm. We use the type of job mobility defined in Proposition 2 as an identification argument for the variation in the match-specific component z .

3.3.6 Wage Equations

The wage a worker receives depends on whether he has any outside options in employment. The outside option affects the current wage either because the worker moved from one employer to another or because he received sufficiently good job offers while with his current employer. Equation (3.5) represents the wage of a worker of type x in a firm of type y and a match-specific draw of z with no outside options. This case arises for all workers who join a firm from unemployment.

$$\begin{aligned} \phi_{0,t}(x, y, z) = & f_t(x, y, z) - (1 - \beta)(r + \delta_t + \eta_t)S_t(x, y, z) \\ & - (1 - \beta)\lambda_{1,t}S_t(x, y, z) \int \int_{y', z' \in \mathcal{M}_{1,t}(x, y, z)} v(y')\gamma(z') dy' dz' \\ & - \lambda_{1,t} \int \int_{y', z' \in \mathcal{M}_{2,t}(x, y, z)} [S_t(x, y', z') - \beta S_t(x, y, z)] v(y')\gamma(z') dy' dz' \\ & + \eta_t(1 - \beta)1\{\theta_{t'} \notin \mathcal{N}_{0,t'}(x, y, z)\}S_{t'}(x, y', z') \end{aligned} \quad (3.5)$$

Equation (3.5) is derived by solving the equality given by equation (3.2). This derivation and the formal definitions of the integral supports are provided in Appendix 3.4.

A worker of type x in a firm of type y' with match-specific draw z' who previously received an offer from a firm of type y with match-specific draw z receives a wage given by equation (3.6). This wage is derived by solving the equality given by equation (3.3). The derivation and the definition of all sets are given in Appendix 3.5.

$$\begin{aligned}
\phi_{1,t}(x, y, z, y', z') &= f_t(x, y', z') \\
&- \lambda_{1,t} \int \int_{y'', z'' \in \mathcal{M}_{1,t}(x, y, z)} [S_t(x, y, z) - S_t(x, y', z')] v(y'') \gamma(z'') dy'' dz'' \\
&- \lambda_{1,t} \int \int_{y'', z'' \in \mathcal{M}_{2,t}(x, y, z)} [S(x, y'', z'') - S(x, y', z')] v(y'') \gamma(z'') dy'' dz'' \\
&+ \eta_t 1\{\theta_{t'} \in \mathcal{N}_{2,t'}(x, y, z, y', z')\} [S_{t'}(x, y', z') - \beta S_{t'}(x, y, z)] \\
&+ \eta_t 1\{\theta_{t'} \in \mathcal{N}_{3,t'}(x, y, z, y', z')\} [S_{t'}(x, y', z') - S_{t'}(x, y, z)] \quad (3.6)
\end{aligned}$$

Proposition 3 *The set*

$$\mathcal{M}_{1,t}^{w-}(w, x, y, z) \equiv \{y', z' | S_t(x, y', z') \geq S_t(x, y, z) \cap \phi_{1,t}(x, y', z', y, z) < w\}$$

is non-empty for some (t, w, x, y, z) .

Bertrand competition between employers for employed workers retains the attractive feature of Postel-Vinay and Robin (2002) that some employment transitions are associated with a wage cut. The worker accepts a wage cut because he is sufficiently compensated by the increase in the option value of future job offers. The proof for this mechanism is provided in Appendix 3.6. Since Proposition 2 is for all (x, y, z) the set $\mathcal{M}_{1,t}^{w-}(w, x, y, z)$ defined above can be partitioned further, by conditioning on an increase or decrease in firm productivity. In this way, the model is able to generate any combination of increase or decrease in wage or firm productivity.

3.3.7 Labour Dynamics

Rather than modelling the specifics of each reform package, we implement the Hartz policy waves as a series of shocks to the structural parameters of the model. The impact of each reform package on the parameter space is fully anticipated. At time t agents believe policies arrive at a Poisson arrival rate η_t . This model feature is somewhat unrealistic because agents are likely to know the exact date of the reform in the immediate lead up to a policy implementation. Since in our setup agents are risk neutral, however, uncertainty over the exact timing of the policy is not important. Furthermore, before the formation of the Hartz Commission on February 22 2002 and after the implementation of Hartz IV on January 1

2005, agents believe the parameter space is stable indefinitely. In these two stable periods, the probability that the parameter space changes is zero, $\eta_t = 0$. Therefore, from equation (3.4) the value of the surplus in a match (x, y, z) at time t is equal to the value of the surplus in the same match for any $t' > t$.

The two stable periods can be solved for independently of the evolution of the structural parameter set before or after the reforms. There are three periods when agents anticipate further changes to the parameter set, which we refer to as the unstable periods. These unstable periods take place after the announcement but before implementation of Hartz I and II, after Hartz I and II but before Hartz III, and after Hartz III but before Hartz IV. In the unstable periods, the surplus generated of a match today depends on how the structural parameters evolve in the future. These structural parameters are solved for sequentially by backward induction.

In the first stable period before the reforms were anticipated the distribution of unobservables (x, y, z) among matched agents or the distribution of worker type (x) among the unemployed are unclear. The initial allocation of worker, firm and match types is consequential for the effects of the reforms. For simplicity we therefore assume that the economy is in steady-state before the reform is announced in February 2002, which seems reasonable because the last recession in Germany occurred almost a decade earlier in 1993.

Initial Steady-State

For ease of exposition we consider a steady-state in this subsection, which implies that the measures of unemployed and employed workers of every productivity combination are stable. For unemployed workers, the flow out of unemployment of workers of any productivity x is equal to the inflow, which is expressed in the equation below. The measure of unemployed agents of productivity x is denoted by $u(x)$ and $e(x, y, z)$ is the measure of employed agents of productivity x in a firm of productivity y with match-specific productivity z .

$$u(x) \left[\lambda_0 \int \int_{y', z' \in \mathcal{M}_0(x)} v(y') \gamma(z') dy' dz' \right] = \delta \int \int e(x, y', z') dy' dz'$$

The total measure of workers of productivity x in the economy at large is $\ell(x)$, so that the right-hand side of equation simplifies to $\delta [\ell(x) - u(x)]$. Rearranging, the measure of unemployed agents of productivity x is

$$u(x) = \frac{\delta \ell(x)}{\delta + \lambda_0 \int \int_{y', z' \in \mathcal{M}_0(x)} v(y') \gamma(z') dy' dz'}. \quad (3.7)$$

Similarly, the flow out of the measure $e(x, y, z)$ is equalised with the inflow, as captured in equation (3.8). We express this equation in terms of surplus conditions rather than feasible matching sets.

$$\begin{aligned} u(x)\lambda_0\{\mathcal{S}(x, y, z) \geq 0\}v(y)\gamma(z) + \lambda_1v(y)\gamma(z) \int \int \{\mathcal{S}(x, y, z) \geq \mathcal{S}(x, y', z')\}e(x, y', z')dy'dz' \\ = \delta e(x, y, z) + \lambda_1e(x, y, z) \int \int \{\mathcal{S}(x, y', z') \geq \mathcal{S}(x, y, z)\}v(y')\gamma(z')dy'dz' \end{aligned} \quad (3.8)$$

We implement an iterative solution algorithm for solving this integral equation.

Labour Adjustment

A series of shocks to the parameter space are realised, corresponding to the initial announcement of the reforms and the subsequent reform implementations. At the incidence of the i^{th} shock, at t equal to t_i , an instantaneous adjustment in labour assignment takes place. All matches that generate negative surplus after the new realisation of the parameter space are separated. Time t_i^- denotes the time immediately before t_i . Formally, t_i^- is given by $t_i^- = \lim_{\varepsilon \rightarrow 0^-} (t_i + \varepsilon)$. Equation (3.9) shows the immediate readjustment of the measure of unemployment.

$$u_{t_i}(x) = u_{t_i^-}(x) + \int \int_{y', z' \notin \mathcal{M}_{0, t_i}(x)} e_{t_i^-}(x, y', z') dy' dz' \quad (3.9)$$

The first term represents the unemployed from the previous period and the second term are the employed agents who no longer generate a positive surplus after the new realisation of the parameter space in t_i . The pre-shock measure of employed individuals in period t_i of productivity x in firm y with match-specific component z is conditional on positive surplus still being generated, and expressed in equation (3.10).

$$e_{t_i}(x, y, z) = \{\mathcal{S}_{t_i}(x, y, z) \geq 0\}e_{t_i^-}(x, y, z) \quad (3.10)$$

After the shock is realised, the labour market continues to adjust. Equation (3.11) is a differential equation in t that defines the evolution of the measure of unemployed workers. The first term is the inflow into unemployment from the exogenous separation of employed workers and the second term represents the outflow, the flow rate at which the unemployed find work.

$$\dot{u}_t(x) = \delta_t (\ell(x) - u_t(x)) - \lambda_{0, t} u_t(x) \int \int_{y', z' \in \mathcal{M}_{0, t}(x)} v(y') \gamma(z') dy dz \quad (3.11)$$

This equation can be solved for $u_t(x)$ and the solution is given below. Intermediate steps are presented in Appendix 3.7. The contemporaneous steady-state unemployment measure $u_{ss,t}(x)$ is obtained by the analogous solution to equation (3.7) at time t and $u_{t_i}(x)$ is the measure of agents in unemployment at the time of the last shock, the solution to equation (3.9).

$$u_t(x) = u_{ss,t}(x) \left(1 - \exp \left[\left(\delta_t + \lambda_{0,t} \int \int_{y',z' \in \mathcal{M}_{0,t}(x)} v(y') \gamma(z') dy' dz' \right) (t_i - t) \right] \right) + u_{t_i}(x) \exp \left[\left(\delta_t + \lambda_{0,t} \int \int_{y',z' \in \mathcal{M}_{0,t}(x)} v(y') \gamma(z') dy' dz' \right) (t_i - t) \right] \quad (3.12)$$

The dynamics for the measure of workers x in (y, z) match at time t is given by equation (3.13), which consists of the inflow from unemployment, the inflow from lower surplus employment, the outflow to unemployment, and the outflow to higher surplus employment respectively.

$$\begin{aligned} \dot{e}_t(x, y, z) = & u_t(x) \lambda_{0,t} \{S_t(x, y, z) \geq 0\} v(y) \gamma(z) \\ & + \lambda_{1,t} v(y) \gamma(z) \int \int \{S_t(x, y, z) \geq S_t(x, y', z')\} e_t(x, y', z') dy' dz' \\ & - \delta_t e_t(x, y, z) - \lambda_{1,t} e_t(x, y, z) \int \int \{S_t(x, y', z') \geq S_t(x, y, z)\} v(y') \gamma(z') dy' dz' \end{aligned} \quad (3.13)$$

This equation is more complex due to the term describing inflow from lower surplus employment, which introduces non-linearities that do not exist in the differential equation for unemployment. We solve equation (3.13) numerically, as to our knowledge it cannot be solved analytically.

3.3.8 Solution of the Model

The solution to the surplus of a match, the wages of a given match, and the distribution of matches in the economy define the solution of the model. The surplus of a match defined by equation (3.4) establishes the sets of feasible matches and job switches, $\mathcal{M}_{0,t}(x)$ and $\mathcal{M}_{1,t}(x, y, z)$. From the surplus equation, the wage paid in a given match can be solved explicitly, which is given by $\phi_{0,t}(x, y, z)$ and $\phi_{1,t}(x, y, z, y', z')$ depending on types and outside offers. Finally, the flow equations from the previous subsection define the distribution of different matches at time t : $u_t(x)$, $e_t(x, y, z)$, and $e_t(x, y, z, y', z')$.

3.4 Data and Estimation

This Section describes our construction of macroeconomic time series for the German labour market, and how we parametrise and estimate the model. The model is simulated so it matches the data series from January 2001, over 13 months before the formation of the Hartz Committee, until the end of 2006, 12 months after the one-year period defined by the last Hartz reform. For estimating we split the data into a pre-reform period from January 2001 to January 2002, an announcement period from February to December 2002, the implementation of Hartz I and II from January to December 2003, the implementation of Hartz III from January to December 2004, the implementation of Hartz IV from January to December 2005, and a post-reform period from January to December 2006.

Instead of just the permanent worker type x , we now further distinguish skill by observable worker skill characteristics. Assuming a segmented labour market we stratify the sample and estimate the model by skill group, indexed by k . Our data includes information on eight skill levels that we use to allocate workers into three skill groups. Workers with an intermediate school leaving certificate or below are defined as low-skilled, workers with a vocational qualification such as an apprenticeship and with an upper secondary school certificate (*Abitur*) are combined into a medium-skill group, and university graduates are classified as high-skill. For observations with missing skill information, we impute the skill group by following the IP1 procedure in Fitzenberger et al. (2006), which for a given worker interpolates skill information when it is missing.

The model presented in the previous Section is fully parametrised and we estimate the structural parameters. Our assumptions about the data generating process make an analytically tractable likelihood function feasible. Our approach to maximise a likelihood function is novel, and makes inference significantly more straightforward than more typical estimations by the method of moments or indirect inference.

3.4.1 The Data

To examine the impact of the Hartz reforms we use the Sample of Integrated Labour Market Biographies (SIAB), a German worker-firm dataset. The SIAB is a 2-percent random sample drawn from administrative data and links information on workers from German administrative data with firm information from the Establishment History Panel. We restrict the estimation sample to male full- and part-time workers between the age of 20 and 60, who are not in vocational training. This choice of age group means most individuals in the sample have finished their education and are working. Individual daily employment spell data are available from administrative data for employees covered by social security. Around 80

percent of the German labour force are covered by compulsory social security contributions, which exclude the self-employed, public sector workers and military employees. The SIAB also includes workers that are registered as unemployed but does not provide information on out-of-the-labour-force status. As a result, unemployment in this Chapter refers to registered unemployment benefit recipients but not, for example, to job seekers who do not receive unemployment benefit.⁶ Data access to the SIAB is provided via on-site use at the Research Data Centre of the German Federal Employment Agency at the Institute for Employment Research (IAB) and subsequently by means of remote data access.

The mean of daily real wages for employed workers in our sample is 74.12 Euros and 45.74 Euros for newly hired workers re-entering employment. Unemployed workers receive an average daily benefit payment of 24.47 Euros. Low-skill workers with an average wage of 48.73 Euros account for 10 percent of observations, 76 percent of workers are medium-skill with an average wage of 66.61 Euros and 14 percent are high-skill workers earning an average wage of 105.11 Euros. The sizes of the three skill groups are relatively constant, with some decline in the number of low- and medium-skill workers and a small increase of high-skill workers. The number of workers and the proportion of top-coded wages by skill group are reported in Table 3.2.

Table 3.2 Number of workers and share of top-coded wages by skill group

Year	Number of workers			Share top-coded			Share re-entry top-coded		
	S1	S2	S3	S1	S2	S3	S1	S2	S3
2001	36,715	267,482	46,209	0.005	0.054	0.384	0.004	0.048	0.328
2002	35,825	264,221	46,740	0.005	0.053	0.387	0.004	0.048	0.329
2003	35,303	264,665	46,991	0.002	0.033	0.299	0.002	0.030	0.257
2004	35,014	262,941	47,200	0.002	0.034	0.304	0.002	0.030	0.263
2005	36,491	263,518	47,623	0.002	0.033	0.303	0.002	0.030	0.263

Notes: S1, S2 and S3 refer to low-skill, medium-skill and high-skill workers respectively.

Wages reported in German social security data are subject to top-coding so that wages above a threshold are censored at the threshold value, which is defined for each year and separately for West and East Germany. We apply these social security wage thresholds to top-code the simulated data by the same amounts. This means we can treat the simulated data in the same way as the real data and do not have to interpolate top-coded values as in Card et al. (2013). Of employed workers' wages 8.2 percent are subject to top-coding. Top-coding

⁶The differences between alternative measures and data sources for unemployment in Germany are discussed in more detail in Hertweck and Sigrist (2013) and Rothe and Wälde (2017).

is more pertinent for high-skill workers, of whose wages 33.5 percent are top-coded. Wages of newly hired workers tend to be lower and only 6.7 percent are affected by top-coding.

We construct and match monthly moments by skill group for employment status transition rates, unemployment duration, the mean and standard deviation of the log of real re-entry daily wage, and correlations between log real re-entry wage and unemployment duration, and unemployment duration and firm rank by skill group. Monthly averages for each of these nine moments are shown for the estimation period from 2001 to 2005 in Appendix 3.8.

In the estimation we match four rates of transitions between employment states. First, the job finding rate is defined as the monthly share of unemployed workers who find and accept a job. Moving from unemployment to a job is not the only route for workers to exit from unemployment. Rothe and Wälde (2017) document that during the large reduction of the unemployment rate following the Hartz reforms, 28 percent of those exiting unemployment retired and 13 percent participated in labour market policy programs. Analysing these types of exits in response to the Hartz reforms is beyond the scope of this Chapter. Second, the separation rate captures the monthly share of employed workers who exit into unemployment. We further match two moments that capture on-the-job moves to better and worse firms. Job-to-job promotions are defined as moves of employed workers to a new job with a higher ranked firm. The promotion rate is calculated as the monthly share of promotions out of all employed workers. Job-to-job demotions are moves of employed workers to a new job with a lower ranked firm. Firms are ranked based on their average 75th-percentile real wage for full-time employees during the period January 2001 to December 2005. We use the 75th-percentile average firm wage as a proxy for firm productivity, which Doniger (2015) finds to be a good predictor of firm value added in German worker-firm data. The job-to-job demotion rate is calculated as the monthly share of demotions out of all employed workers.

Unemployment duration is defined as the number of months a worker has spent in unemployment since his last employment spell, as recorded in the IAB Benefit Recipient History data. Attention is restricted to newly hired workers from unemployment instead of accounting for the entire distribution of wages. This focus on re-entry wages is motivated by a number of factors. First, computing the entire distribution of wages is far more computationally expensive as a wage depends on five state variables (x, y, z, y', z') rather than just three (x, y, z) for re-entry wages. In addition, in order to compute the entire distribution one needs to keep track of all employment measures over time, rather than just the unemployed. Furthermore, the model has better empirical grounding as fewer re-entry wages are top-coded. Wages are reported as log real daily wages in Euros, and are deflated using the yearly Consumer Price Index from the German Federal Statistical Office. In the

case of overlapping or multiple spell observations for an individual, we use the spell with the highest recorded wage.

As the monthly moment series exhibit marked seasonality for the month of January, we seasonally adjust all series to ensure that policy reforms are not mistaken with seasonal variation present in the data. For the seasonal adjustment we use the X-12-Arima program, which is a software developed by the US Census Bureau for seasonally adjusting time series data, by accounting for seasonal variation from January 1981 to December 2009. The inclusion of marginally employed workers in the SIAB data from 1999 onward causes a break in the wage series, which we level out by multiplying the pre-break series with the ratio of the 12-months post- to pre-break averages for the purpose of seasonal adjustment. To avoid negative values for seasonally adjusted transition rates, we take the log of transition moments, seasonally adjust, take the exponent of the seasonally adjusted series, and adjust so that the overall means sum to the means of the raw transition rates.

We choose not to include value added data which could feasibly be constructed by generating a measure of business volume net of inputs for workers linked to the German Establishment Panel in the Linked Employer-Employee Data, a companion dataset. Since we stratify our sample by worker skill, value added per worker would be difficult to calculate. We do not need value added information to identify the rent share parameter β , as β is largely identified by the correlation between unemployment duration and wages among re-entrants.

3.4.2 Parametrisation

For the estimation timing is important. Time is measured in months and superscript $\tau \in \{1, 2, 3, 4\}$ denotes the period to which the parameter applies. Pre-reform values are denoted by $\tau = 1$, $\tau = 2$ are the parameter values after the first wave comprising the Hartz I and II laws, $\tau = 3$ after Hartz III has taken effect, and $\tau = 4$ after Hartz IV is implemented. The absence of a τ superscript indicates a time-invariant parameter.

We make a number of parametric assumptions. The discount rate r is calibrated to be equivalent to a five-percent annual rate. The productivity levels x , y and z are bounded between 0 and 1, and are drawn from uniform distributions. Assuming uniformity of type is without loss of generality, and x , y and z are interpreted as ranks in their respective distributions. All variations in productivity occur through a production function of the form:

$$f_k^\tau(x, y, z) = \exp\left(f_{0,k}^\tau\right) \cdot \exp\left(f_{1,k}\Phi^{-1}(x)\right) \cdot \exp\left(f_{2,k}^\tau\Phi^{-1}(y) + f_{3,k}^\tau\Phi^{-1}(z)\right) - \exp\left(f_{4,k}\right) \cdot \left|\exp\left(f_{1,k}\Phi^{-1}(x)\right) - \exp\left(f_{2,k}^\tau\Phi^{-1}(y) + f_{3,k}^\tau\Phi^{-1}(z)\right)\right|. \quad (3.14)$$

Scale parameter $f_{0,k}^\tau$ reflects the level of production, $f_{1,k}$, $f_{2,k}^\tau$ and $f_{3,k}^\tau$ determine the variability in x , y and z , and $\Phi^{-1}(\cdot)$ denotes the inverse of a standard normal distribution. Endogenous adjustments of firm and job types in the economy are captured by changes to f_2 and f_3 respectively. The relative sizes of $f_{0,k}^\tau$ and $f_{4,k}$ capture the relative importance of hierarchical and circle sorting, as pioneered by Shimer and Smith (2000) and Marimon and Zilibotti (1999) respectively in models with labour market frictions. For example, a large $f_{0,k}^\tau$ and a small $f_{4,k}$ imply that firms place more weight on employing the *best* worker rather than on getting the *right* worker for a particular job. The relative size of these parameters is likely to dictate the level of assortative matching in the economy.

Job offer arrival rates for the unemployed, $\lambda_{0,k}^\tau$, are assumed to be time-varying. In order to reduce the dimensionality of the estimation, offer arrival rates for employed individuals are defined as κ_k , a constant factor of the job offer arrival rate in unemployment. The relative efficiency of search in employment relative to unemployment for skill group k is thus denoted as κ_k , and $\lambda_{1,k}^\tau \equiv \kappa_k \lambda_{0,k}^\tau$. The exogenous job destruction rates are given by δ_k^τ , and earnings during unemployment are independent of worker type x , so that home production is denoted as $b_k^\tau(x) = b_{0,k}^\tau$.

The content of the specific Hartz reforms determines our choice of time-varying and constant parameters, and Table 3.3 provides an overview of parameter changes in our estimation after policy shocks. The Hartz reforms affect the rates at which employed and unemployed workers receive job offers, and reforms affect the two job arrival rates proportionally as κ is fixed. Exogenous job arrival and destruction rates are allowed to vary after the announcement and after every reform, which implies that we estimate four of each rate. We assume that the variability of firm and match type, and the scale parameter are only affected by the first wave of Hartz reforms, which primarily focused on labour demand factors. Finally, unemployment benefits are only influenced by the final wave of reforms, which changed the duration and generosity of unemployment insurance payments.

3.4.3 Identification

Our choice of moments to estimate is motivated with the identification of the model parameters in mind. While parameters are co-dependent to some degree, each parameter is particularly relevant for certain series. Specifically, these parameters are the job finding rate λ_0 , the job-to-job rate λ_1 , the separation rate δ , the level of work production f_0 , the variabilities in worker type f_1 , in firm type f_2 and in match type f_3 , the complementarity of production f_4 , home production b_0 , and the worker's bargaining power β .

Table 3.3 Parameter changes after policy interventions

	Hartz I/II: Labour demand	Hartz III: Market efficiency	Hartz IV: Labour supply
Job transitions:			
Job finding λ_0	✓	✓	✓
Relative search κ	x	x	x
Job loss δ	✓	✓	✓
Production:			
Level f_0	✓	x	x
Worker variation f_1	x	x	x
Firm variation f_2	✓	x	x
Match variation f_3	✓	x	x
Complementarity f_4	x	x	x
Outside options:			
Bargaining β	x	x	x
Home production b	x	x	✓

The transition rates are primarily governed by the job offer arrival rates and the exogenous separation rate δ . In addition to other factors, the level effects of home and work production are significant drivers for the mean and variance of wages. The value of home production b_0 affects the level of wages by determining the threat point in the wage bargaining. The scale parameter of production f_0 has a similar effect and also drives the level of total output variation. The variability in worker type f_1 is pinned down by the mean unemployment duration of workers hired from unemployment, and if f_1 equals zero all workers are homogeneous. In our model, unemployment duration provides a good proxy for worker type, with unemployed workers having a lower value of x on average. Unemployment duration takes the form of an exponential distribution with a distribution parameter equal to the job finding rate. The only way to deviate from this distribution of worker types in our model is through different job finding rates across type.⁷ The relative importance of firm or match type, the difference between f_2 and f_3 , is determined by the proportion of job-to-job transitions to less productive firms. As described by Proposition 2, workers move to worse firms because they are sufficiently compensated by a larger match-specific component. These movements define the difference between f_2 and f_3 . The complementarity of production f_4 reflects the degree of sorting in the labour market. In our setting, the correlation between firm type and unemployment duration for new hires is a proxy for the degree of assortative matching in the labour market. Finally, if the bargaining power of the unemployed worker β equals zero, wages are determined as in Postel-Vinay and Robin (2002). As home production is

⁷A similar argument for identifying the variation in worker type is made in Bagger and Lentz (2014).

orthogonal to worker type, wages of workers hired from unemployment are decreasing in worker type. Workers of higher type are compensated with a larger option value of future employment. Since unemployment duration is a proxy for worker type our model requires a positive β to generate negative correlation between the duration of unemployment and the wage. Simulating the model shows that this correlation becomes more negative when we increase the value of β .

3.4.4 The Data Generating Process

The true data for skill group k , X_k^0 , are a T by N matrix of the macroeconomic time series described in subsection 3.4.1, where T is the length of the time series and N the number of moments targeted. We use moments for 60 months from January 2001 until December 2005, and assume that the true data X_k^0 is the sum of the model prediction $X^M(\theta_k)$, a deterministic trend X_k^T and an irregular cyclical component X_k^C :

$$X_k^0 = X^M(\theta_k) + X_k^T + X_k^C. \quad (3.15)$$

In our setting the trend and cyclical components represent the German economy independent of the reforms. In expectation the cyclical component is of mean zero and at the introduction of the first wave of reforms, we set the trend equal to zero. Given this normalisation the effects of the Hartz reforms can be uncovered from changes in $X^M(\theta_k)$ after subtracting other changes that would have happened in the absence of the reforms. The model and trend components are deterministic but the cyclical component is random. The cyclical component X_k^C allows us to write down an analytical likelihood function, as for any $X^M(\theta_k)$ and X_k^T there exists an X_k^C to rationalise the true data X_k^0 .

The trend and cyclical components are fitted from January 1993 until February 2002. This period corresponds to the first inclusion of a representative East German sample in the data up to the formation of the Hartz Committee. The trend of each moment is assumed to be linear. Results for non-linear trends with higher order polynomials are qualitatively similar. We assume the cyclical component can be represented by the vector autoregressive process in equation (3.16):

$$\mathbf{x}_{t,k}^c = \mathbf{A}_k \mathbf{x}_{t-1,k}^c + \varepsilon_{t,k} \quad \text{where, } \varepsilon_{t,k} \sim N(0, \boldsymbol{\Sigma}_k) \quad (3.16)$$

where \mathbf{A}_k is an $N \times N$ matrix of autoregressive coefficients for skill stratum k and $\boldsymbol{\Sigma}_k$ is an $N \times N$ symmetric variance-covariance matrix. These two objects are estimated by maximum likelihood.

All moments and their forecasts over the policy horizon are presented in Appendix 3.9. These forecast pictures serve two purposes. Firstly, they demonstrate the precision with which each moment is computed. The wider the confidence bands in Figures A3.3, A3.4 and A3.5 the less precision the moment is predicted with and therefore the less weight the estimator puts on attempting to fit a moment. Secondly, these forecasts give insight into the effects the Hartz reforms on the German labour market. Inspection of the figures suggest a marked change in the wage distribution compared with changes in the rate of employment. Across all skill groups the flow into employment falls below trend after the Hartz Committee is formed, and catches up by 2005. The flow out of employment remains broadly on trend for the low-skilled and falls slightly below for the higher skill groups. Back-of-the-envelope calculations suggest a slight increase in employment, and by the end of the forecast time horizon none of these flows are significantly different from trend levels. The distribution of wages of workers newly hired from unemployment exhibit large changes. The mean across all skill groups falls well below trend while the standard deviation exceeds the trend, in particular for more skilled workers. These wage trends suggest an important link between the Hartz reforms and wages, which has received little attention in previous studies.

3.4.5 The Likelihood Function

The likelihood function describes the likelihood of observing the innovative shocks required to rationalise the observed data. For a given \mathbf{A}_k and $\mathbf{\Sigma}_k$ the vector of innovative shocks at time t is defined as a function of the vector of structural parameters θ_k and an initial condition $\varepsilon_{1,k}(\theta_k)$. We assume that $\varepsilon_{1,k}(\theta_k)$ is equal to the initial deviation from trend, which keeps the likelihood expression simple and comparable to a method of moments estimator. We have considered an alternative initial condition but the resulting differences in the value of the likelihood function are insignificant.⁸ All subsequent innovations are uncovered as follows, where lower case ε and x represent the vectors of all moments at time t .

$$\varepsilon_{t,k}(\theta_k) = \mathbf{x}_{t,k}^0 - \mathbf{x}_t^M(\theta_k) - \mathbf{x}_{t,k}^T - \mathbf{A} \left[\mathbf{x}_{t-1,k}^0 - \mathbf{x}_{t-1}^M(\theta_k) - \mathbf{x}_{t-1,k}^T \right]$$

Since $\varepsilon_{t,k}(\theta_k)$ is distributed following a multivariate normal distribution with mean zero and variance-covariance matrix $\mathbf{\Sigma}_k$, we can write the likelihood function as follows.

⁸This alternative initial condition is described in more detail in a supplementary document available online at www.sites.google.com/site/kuegleralice/research.

$$\begin{aligned}
L(\boldsymbol{\varepsilon}_{1,k}(\boldsymbol{\theta}_k), \dots, \boldsymbol{\varepsilon}_{t,k}(\boldsymbol{\theta}_k)) &= \prod_{t=1}^T g(\boldsymbol{\varepsilon}_{t,k}(\boldsymbol{\theta}_k) | \boldsymbol{\Sigma}_k; \boldsymbol{\varepsilon}_{t-1,k}(\boldsymbol{\theta}_k)) \\
&= (2\pi)^{-\frac{NT}{2}} \cdot |\boldsymbol{\Sigma}_k|^{-\frac{T}{2}} \cdot \exp \left\{ -\frac{1}{2} \sum_{t=1}^T \boldsymbol{\varepsilon}_{t,k}(\boldsymbol{\theta}_k)' \boldsymbol{\Sigma}_k^{-1} \boldsymbol{\varepsilon}_{t,k}(\boldsymbol{\theta}_k) \right\},
\end{aligned}$$

where T is the length of the time series, N is the number of series, $g(\cdot)$ is the probability density of a multivariate normal distribution, and $|\cdot|$ represents the determinant. Instead of maximising the likelihood, we minimise the log-likelihood function given by equation (3.17).

$$\begin{aligned}
l(\boldsymbol{\varepsilon}_{1,k}(\boldsymbol{\theta}_k), \dots, \boldsymbol{\varepsilon}_{t,k}(\boldsymbol{\theta}_k)) &\equiv -2 \log L(\boldsymbol{\varepsilon}_{t,k}(\boldsymbol{\theta}_k)) \\
&= NT \log(2\pi) + T \log |\boldsymbol{\Sigma}_k| + \sum_{t=1}^T \boldsymbol{\varepsilon}_{t,k}(\boldsymbol{\theta}_k)' \boldsymbol{\Sigma}_k^{-1} \boldsymbol{\varepsilon}_{t,k}(\boldsymbol{\theta}_k) \quad (3.17)
\end{aligned}$$

As only the final term depends on $\boldsymbol{\theta}_k$, minimising the function is equivalent to minimising the final term of the expression, which is the term we refer to in the remainder of the Chapter.

We estimate a vector of exogenous parameters, which is $\boldsymbol{\theta}_k \in \Theta \in \mathbb{R}^{14}$ for a skill group k , and is defined as:

$$\boldsymbol{\theta}_k = (\vec{\lambda}_{0,k}^4, \boldsymbol{\kappa}, \vec{b}_{0,k}^2, \vec{f}_{0,k}^2, f_{1,k}, \vec{f}_{2,k}^2, f_{4,k}, \beta_k).$$

The vector arrows and superscripts denote that the respective parameters are either two or four dimensional objects that vary over time.

To improve the fit of the moments and to increase the functionality of the estimation procedure, we make two refinements. First, the likelihood function is highly nonlinear, which is partly due to the endogenous job destruction process. Endogenous job destructions occur at the announcement or implementation of policy reform. The mass of matches that are no longer feasible depends on the history of all other variables and can be large, so that they are only rationalised by improbably large draws of $\boldsymbol{\varepsilon}$. To smooth the likelihood function and to decrease the dimensionality of the problem, we fix the values of δ_k^τ to match the job-to-unemployment flow in post-shock periods.⁹

Second, the relative size of the variation in firm type f_2 and match type f_3 can be separately identified through the ratio of job-to-job mobility associated with movements up or down the firm ladder, as described in Proposition 2. Similarly, simulations of the

⁹This is model-consistent as in periods after the shock all job loss is exogenous. The theoretical counterpart of the mean job-to-unemployment transition rate for period τ amongst stratum k is $1 - \exp(-\delta_k^\tau)$. δ_k^τ is fixed accordingly for all k and τ prior to estimation.

model suggest that in order to match the second moments of wages we need to alter the total variability of x , y and z . As the relative contributions of worker, firm and match effects cannot be identified, we set the sum of the match and firm type variabilities equal to unity, $f_{2,k}^\tau + f_{3,k}^\tau := 1$ for all skill groups k in time period τ , and estimate f_1 without constraints. Since the match and firm contributions enter symmetrically into the production function their relative size describes their relative importance in output.

3.5 Results

This section presents the parameter estimates and the fit of the targeted dynamics of the model. We then simulate the model at steady-state before and after the reforms and evaluate the aggregate impact of the policies, the relative importance of the successive waves, and the distributional effect on wages.

3.5.1 Parameter Estimates

The parameter estimates of the model are reported in Table 3.4, with asymptotic standard errors in the parentheses below the point estimates. For completeness, Table 3.4 includes estimates of the job destruction parameters, which are calibrated. To ensure that the estimates represent global minima of the log-likelihood function (3.17) we initiate our estimation with parallel runs of a Metropolis-Hastings type algorithm, which is not as susceptible to stopping at local minima as a standard hill climbing algorithm. The numbered superscripts correspond to time separated by policy implementation.¹⁰

The monthly job offer arrival rates are larger than in most previous studies, which is due to the frequency with which job offers are rejected. Back-of-the-envelope calculations suggest for every offer accepted by an unemployed worker between two to four and a half offers are rejected on average, depending on the period and the skill group.¹¹ The number of rejected jobs increases with skill. Notably, the first wave of the reform reduces the number of job offers for all skill groups. All subsequent reforms increase the amount of job offers workers receive, with the exception of the final wave for the medium-skilled. Aggregating all reforms, workers receive less frequent job offers after the full implementation of the Hartz policies than before the reforms. The effect on the rate of exogenous job destruction is more ambiguous. The reforms leave the low-skilled in slightly less secure jobs and the

¹⁰Specifically, the numbers denote (1) before the first wave, (2) after the first but before the second wave, (3) after the second but before the third wave, and (4) after the third and final wave.

¹¹The average number of rejected offers is calculated as the number of offers in a month, $1 - \exp(-\lambda_{0,k}^\tau)$, divided by the job finding rates pictured in Figure A3.2 in Appendix 3.8.

Table 3.4 Parameter estimates

Low-skill				Medium-skill				High-skill			
$\lambda_0^{(1)}$	$\lambda_0^{(2)}$	$\lambda_0^{(3)}$	$\lambda_0^{(4)}$	$\lambda_0^{(1)}$	$\lambda_0^{(2)}$	$\lambda_0^{(3)}$	$\lambda_0^{(4)}$	$\lambda_0^{(1)}$	$\lambda_0^{(2)}$	$\lambda_0^{(3)}$	$\lambda_0^{(4)}$
0.327 (0.0003)	0.266 (0.0003)	0.272 (0.0003)	0.291 (0.0003)	0.434 (0.0003)	0.399 (0.0002)	0.447 (0.0003)	0.417 (0.0003)	0.612 (0.0008)	0.459 (0.0006)	0.474 (0.0007)	0.491 (0.0007)
$\delta^{(1)}$	$\delta^{(2)}$	$\delta^{(3)}$	$\delta^{(4)}$	$\delta^{(1)}$	$\delta^{(2)}$	$\delta^{(3)}$	$\delta^{(4)}$	$\delta^{(1)}$	$\delta^{(2)}$	$\delta^{(3)}$	$\delta^{(4)}$
0.0157	0.0157	0.0154	0.0164	0.0127	0.0130	0.0127	0.0120	0.0057	0.0063	0.0060	0.0054
$f_0^{(1)}$	$f_0^{(2)}$	f_4		$f_0^{(1)}$	$f_0^{(2)}$	f_4		$f_0^{(1)}$	$f_0^{(2)}$	f_4	
3.78 (0.004)	3.61 (0.004)	1.20 (0.001)		4.11 (0.003)	4.05 (0.002)	0.707 (0.0004)		5.04 (0.007)	4.74 (0.007)	1.24 (0.001)	
f_1	$f_2^{(1)}$	$f_2^{(2)}$		f_1	$f_2^{(1)}$	$f_2^{(2)}$		f_1	$f_2^{(1)}$	$f_2^{(2)}$	
0.545 (0.0005)	0.310 (0.0003)	0.283 (0.0003)		0.607 (0.0004)	0.405 (0.002)	0.392 (0.002)		0.769 (0.001)	0.500 (0.0007)	0.524 (0.0007)	
β	$b_0^{(1)}$	$b_0^{(4)}$	κ	β	$b_0^{(1)}$	$b_0^{(4)}$	κ	β	$b_0^{(1)}$	$b_0^{(4)}$	κ
0.287 (0.0003)	5.92 (0.006)	1.09 (0.001)	0.209 (0.0002)	0.255 (0.0002)	14.00 (0.008)	6.71 (0.004)	0.199 (0.0001)	0.242 (0.0003)	13.07 (0.02)	8.65 (0.01)	0.203 (0.0003)
Log-likelihood = 726				Log-likelihood = 1061				Log-likelihood = 758			
Pseudo $R^2 = 0.67$				Pseudo $R^2 = 0.43$				Pseudo $R^2 = 0.52$			

Notes: All parameter estimates are reported to three significant figures. Asymptotic standard errors are presented in the parenthesis and reported to one significant figure. The log-likelihood value represents the last term of equation (3.17). The pseudo R^2 is given by $1 - \log(L(\hat{\theta})) / \log(L_0)$, where $\log(L(\hat{\theta}_k))$ is the full log-likelihood and $\log(L_0)$ is the log-likelihood with just the trend component.

medium- and high-skilled in somewhat more secure ones. The relative search intensity of the employed is approximately one fifth for all three groups, which implies that an unemployed agent receives five times as many job offers than if he were employed, irrespective of skill.

We assume that the production function changes after the implementation of Hartz I/II, with results that are broadly consistent across all three skill strata. As a consequence of encouraging temporary work contracts, hiring subsidies and creating mini- and midi-jobs, the average productivity of a match is reduced. This effect is largest for the high-skilled, for whom average worker output falls by around 30 percent.¹² In addition to reducing the match productivity, the relative importance of inputs in the production process also changes. Before the reform, for medium- and low-skilled workers the match-specific component is more consequential for total production than the firm they work for. For the high-skilled the

¹²In this instance, by average we refer to the median, and imputing median values $x = 0.5$, $y = 0.5$ and $z = 0.5$ into the production function in equation (3.14) yields $f_k^r(0.5, 0.5, 0.5) = \exp(f_{0,k}^r)$. The mean production of a match is more complicated and depends on the distribution of worker, firm and matched types. The mean production of a match, however, falls by considerably less.

match-specific and the firm component are of equal importance and $f_2^{(1)} = 0.5$. After the reform, for the medium- and low-skilled the match component becomes more important. For the high-skilled the opposite holds, for whom the firm component is now a more critical contributor to total production. Our interpretation is that for the two lower-skilled strata Hartz I and II provide more sources for variation of individual jobs within firms, and as a result a match-specific job type is more consequential than the type of firm that hires. For the high-skilled the effect moves in the opposite direction, but the type of mini- and midi-jobs created by the reforms are less likely to be performed by workers with university degrees.

For all three skill groups, an unemployed worker extracts approximately a quarter of the surplus from the firm. While this value is somewhat smaller than is often estimated in the literature, this bargaining power is compensated by later negotiations, when the worker can extract more rents from the firm after a period of employment. Finally, the value of home production is measured in real daily Euros. Hartz IV considerably reduced the generosity of unemployment benefit for some groups. The data show that mean daily real benefit received by the unemployed decreased from an average of 24.52 Euros between 2001-2004 to 21.73 Euros between 2005-2008. If we attribute this fall to Hartz IV the overall reduction is only 2.79 Euros per day, far less than the reduction predicted by the parameter estimates for all strata. One interpretation of the large predicted reduction is that in addition to decreasing the pecuniary generosity Hartz IV also generated a larger stigma associated with unemployment, and our estimates of $b_{0,k}^\tau$ also account for non-pecuniary factors.

3.5.2 The Fit

Estimating by maximum likelihood means that assessing the relative fit of the model to the data is more difficult than it would be in a moment matching exercise. As the value of the likelihood is not informative, we compute a pseudo R^2 for each skill group based on McFadden's R^2 for binary choice models. These are reported in Table 3.4. By comparing the likelihood of our full model to just fitting the trend component, we get a clear ordering of model fit by skill group.

In structural models a key question is whether the data generating process is correctly specified. To assess our model's specification of the data generating process we compare the joint distribution of realised shocks that rationalise the data with the sampling distribution that the shocks are drawn from. When these two distributions broadly match, it is likely that the model generates the dynamics we observe empirically. The plots of these distributions indicate that the innovative shocks are credibly drawn from their specified distributions.¹³ In

¹³Plots of these comparisons are presented in a supplementary document online at www.sites.google.com/site/kuegleralice/research, where the diagonal of the figures shows the marginal

order to fit the data the model does not rely on unusual draws from the shock distributions. There is no apparent consistent pattern across skill groups of moments that the model has difficulty in replicating. The low-skilled appear to fit the data best with the realised shocks and the sampling distributions largely coinciding. The correlation between firm rank and unemployment duration exhibits the least fit for the medium-skilled, as the realised shocks appear drawn with a lower mean than the sampling density suggests. Finally, the high-skilled appear to fit the data least well, requiring lower draws than the sampling density for the standard deviation of log wages among re-entrants and higher draws for the two measures of job-to-job mobility.

Although the estimation procedure is not directly targeting the best fit of the macroeconomic time series we construct, it is important that the the simulations match their empirical counterparts closely. If we assume that the cyclical component is not persistent, then our likelihood function becomes identical to a method of moments estimator with $T \times N$ independent moments. The simulated series are displayed in Figures A3.6, A3.7 and A3.8 in Appendix 3.10. The solid black line represents the data and the blue line represents the simulation. The shaded blue area is the 95-percent confidence interval obtained by repeated redrawing of the series of shocks. In addition to the moments included in the estimation, we also present the job separation series, which were omitted from the estimation. The Figures in Appendix 3.10 display good fit, in particular for moments that involve wage data.

3.5.3 Simulations

The persistence of employment and wages makes inference about the long-run impact of the Hartz reforms difficult. Using our structural framework we can determine the long-run effect on employment by computing the steady-state wage distribution, evaluated at the parameter estimates pre- and post-reform. To compute the steady-state wage distribution we impose a stricter condition than used for estimation, which is derived in Appendix 3.11. Previously, for t in a steady-state we assumed that the measure $e_t(x, y, z)$ was fixed. Since wages can potentially depend on the best outside offer a worker receives while in employment, the stricter steady-state condition holds that for t in steady-state $e_t(x, y, z, y', z')$ is fixed, where (y', z') is the best firm-match outside offer pair a worker receives.

distributions of the shocks to each series and the off-diagonal represents pairwise joint distributions. Realised shocks are plotted in red and random draws from the sampling distribution are in blue. The ellipses represent 95-percent confidence intervals, and contain 95 percent of all draws.

Aggregate Outcomes

To investigate the long-run impact of the three reform waves jointly, we compare employment and wages in two steady-states, one for the initial values of the structural parameters and the other one for the structural parameter values after the final reform wave implementation. Table 3.5 presents the impact directly attributable to the Hartz reforms before and after the policies are implemented. The final column is weighted according to the relative sizes of the three skill groups given in Table 3.2.

Table 3.5 Combined impact of the Hartz reforms

	Pre/post reform			
	Low-skill	Medium-skill	High-skill	Aggregate
Unemployment rate	15.6%/15.6%	12.5%/11.5%	7.1%/7.1%	12.1%/11.3%
Daily wage (Euros)	70.20/57.45	95.47/91.71	131.98/125.67	97.51/92.65

One main result is that the Hartz reforms expanded employment by around 0.8 percentage points, so that the post-reform unemployment rate decreased to 11.3 percent. Comparing pre- and post-reform wages shows that this employment expansion came at the cost of a 5- percent reduction in wages, from a mean daily wage of 97.51 Euros to 92.65 Euros. Inspection of the first three columns of Table 3.5 highlights the distributional impact of the policy, with the low-skilled bearing the brunt of the wage costs. Wages for workers without formal qualifications fell by almost one fifth without an associated increase in employment. The overall reduction in unemployment is of similar magnitude to that in Fahr and Sunde (2009), who suggest the reforms were associated with a 5- to 10-percent increase in the job finding probability. Hertweck and Sigrist (2013), however, find an effect three times this size. The pronounced effect of the reforms on wages highlights the trade-off labour market policymakers face between reducing unemployment and negatively affecting wages.

Individual Hartz Reforms

We can further examine the impact of each reform separately, as well as by pairs of reform waves. The effects of the first wave and the first and second waves jointly can be uncovered without any further parametric assumptions. Since we estimate the vector of structural parameters pre- and post-reform in both instances, it is straightforward to simulate the steady-state economy imposing these changes. Assessing the other waves in isolation requires parametrising the evolution of the structural parameters. We assume that policies

affect the structural parameters in a proportional way, where π is a vector capturing the proportional impact of a specific wave or of a pair of waves. Under this assumption we can construct a vector of structural parameters as if a latter reform wave was implemented in the initial economy, and $\theta^{\text{post-reform}} = \pi \times \theta^{\text{pre-reform}}$.

Table 3.6 Combined impact of the reforms on employment and wages

Employment percentage point change				Wage percentage change			
	Hartz I/II	Hartz III	Hartz IV		Hartz I/II	Hartz III	Hartz IV
Hartz I/II	0.6% ↓	-	-	Hartz I/II	5.9% ↓	-	-
Hartz III	0.3% ↓	0.4% ↑	-	Hartz III	3.7% ↓	2.3% ↑	-
Hartz IV	0.9% ↑	1.2% ↑	0.8% ↑	Hartz IV	4.9% ↓	1.0% ↑	2.0% ↓
Combined impact: 0.8% ↑				Combined impact: 5.0% ↓			

Table 3.6 shows the aggregate effects on employment and wages of individual reforms. The diagonal elements depict a reform wave in isolation, and the off-diagonal elements represent the implementation of pairs of reforms. If policymakers were only concerned with employment and wage levels, it would be preferable not to implement the first wave of reforms. Implementing Hartz III and IV only, would increase employment by a third more than the overall value, with wages increasing by one percent rather than falling by five percent. Hartz III, the second reform wave that restructured the Federal Employment Agency, is unambiguously successful, and implementing Hartz III in isolation has a positive impact on both employment and wages. These results follow from our parameter estimates. The second wave increases the job finding rate and reduces the job destruction rate for all skills, thereby leading to an increase in employment. Through the job ladder mechanism and re-negotiations, the second wave also raises wages. By contrast, we expect that the first wave reduces both employment and wages as Hartz I/II has a negative effect on the job finding and separations rates, coupled with a reduction in the scale parameters of production. Hartz IV, the final and most controversial reform wave increases the job offer rate and decreases the separation rate, with some variation according to worker skill type. Hartz IV also considerably reduces the flow benefit received in unemployment, thereby providing further expansion to employment as workers accept a greater proportion of their job offers. At the same time, Hartz IV depresses wages by reducing a worker's outside option in wage negotiations. As shown in Table 3.6, this outside option effect dominates any wage gains associated with longer job tenure. If one were to implement only Hartz IV, this would lead

to a 0.8-percentage point increase in employment associated with a 2.0-percent fall in mean wages. These numbers are similar to those estimated in Price (2016), who finds a decrease in wages of 1.9 percent with a slightly larger expansion of steady-state employment. Our analysis quantifies the trade-off between a high-wage and low-employment economy, and a low-wage and high-employment alternative. Policies that implement more stringent rules with respect to unemployment benefits need to evaluate this trade-off explicitly.

Wage Decomposition

The simulation results highlight the marked reduction in wages in response to the Hartz reforms. We further investigate this change in the wage distribution in a decomposition of wage variation pre- and post-reform, by extending the wage decomposition exercises in Postel-Vinay and Robin (2002) and Bagger and Lentz (2014). First, we simulate the model in two steady-states. The initial steady-state takes place before the announcement of the Hartz reforms and the second steady-state is realised after the implementation of all four reforms. We simulate the model for the same number of individuals as in the data. For each simulated individual i we compute his employment status, his wage, his permanent productivity type, his firm's type, his match productivity, the type of firm and the match quality who provide the best counteroffer if applicable, and finally the skill strata he belongs to. Using ordinary least squares the log of wages for individual i are projected on to a constant $\hat{\rho}_0$, a worker component \tilde{x}_i , a firm component \tilde{y}_i , a match component \tilde{z}_i , and a frictional component \tilde{f}_i . Further details of the wage projection are provided in Appendix 3.12.

$$\widehat{\log w_i} = \hat{\rho}_0 + \tilde{x}_i + \tilde{y}_i + \tilde{z}_i + \tilde{f}_i$$

Using Eve's Law we can separate the total variance into within and between firm components. In line with the previous literature we decompose the total variance by firm type.

$$\text{Var}(\widehat{\log w_i}) = \underbrace{\text{Var}(\text{E}[\tilde{x}_i + \tilde{y}_i + \tilde{z}_i + \tilde{f}_i | \tilde{y}_i])}_{\text{between firm}} + \underbrace{\text{E}(\text{Var}[\tilde{x}_i + \tilde{y}_i + \tilde{z}_i + \tilde{f}_i | \tilde{y}_i])}_{\text{within firm}}$$

Expanding and rearranging, we decompose the relevant sizes of firm, worker, match, frictional and sorting effects. We agglomerate all sorting effects into a single measure, because the relative size of each sorting component varies greatly according to the object we initially difference between. The worker, match and frictional components of total variance are the expected variation of each of these factors conditional on firm type. The firm component includes the expected level of outside offers within a firm, and according to

our structural model these vary systematically across firms.

$$\begin{aligned}
\text{Var}(\widehat{\log w_i}) = & \underbrace{\text{Var}(\tilde{y}_i) + \text{Var}(E[\tilde{f}_i|\tilde{y}_i]) + 2\text{Cov}(\tilde{y}_i, E[\tilde{f}_i|\tilde{y}_i])}_{\text{firm effect}} \\
& + \underbrace{E[\text{Var}(\tilde{x}_i|\tilde{y}_i)]}_{\text{worker effect}} + \underbrace{E[\text{Var}(\tilde{z}_i|\tilde{y}_i)]}_{\text{match effect}} + \underbrace{E[\text{Var}(\tilde{f}_i|\tilde{y}_i)]}_{\text{friction effect}} \\
& + \underbrace{\text{Var}(E[\tilde{x}_i|\tilde{y}_i]) + 2\text{Cov}(E[\tilde{x}_i|\tilde{y}_i], \tilde{y}_i) + 2\text{Cov}(E[\tilde{x}_i|\tilde{y}_i], E[\tilde{f}_i|\tilde{y}_i]) + 2E[\text{Cov}(\tilde{x}_i, \tilde{f}_i|\tilde{y}_i)]}_{\text{worker-firm sorting effect}} \\
& + \underbrace{\text{Var}(E[\tilde{z}_i|\tilde{y}_i]) + 2\text{Cov}(\tilde{y}_i, E[\tilde{z}_i|\tilde{y}_i]) + 2\text{Cov}(E[\tilde{z}_i|\tilde{y}_i], E[\tilde{f}_i|\tilde{y}_i]) + 2E[\text{Cov}(\tilde{z}_i, \tilde{f}_i|\tilde{y}_i)]}_{\text{firm-match sorting effect}} \\
& + \underbrace{2\text{Cov}(E[\tilde{x}_i|\tilde{y}_i], E[\tilde{z}_i|\tilde{y}_i]) + 2E[\text{Cov}(\tilde{x}_i, \tilde{z}_i|\tilde{y}_i)]}_{\text{worker-match sorting effect}}
\end{aligned}$$

Table 3.7 presents the proportion of wage variation that is explained by each of the five effects pre- and post-reform.

Table 3.7 Wage decomposition

	% of $\text{Var}(\widehat{\log w_i})$	
	Pre-reform	Post-reform
Worker effect	80.4%	80.7%
Firm effect	3.8%	3.8%
Match effect	2.8%	3.0%
Frictional effect	4.8%	5.4%
Sorting effect	8.2%	7.1%

First, the large explanatory power of the worker effect is notable. Approximately 80 percent of wage variation are due to differences in worker ability, which is greater than the proportion typically found in wage decomposition exercises. In a similar decomposition Card et al. (2013) show that worker effects (observed and unobserved) explain 78 percent of the non-residual German wage variation from 1985 to 1991 and 57 percent from 2002 to 2009. We may be overestimating the importance of the worker effect as a result of our wage projection that assigns all differences in observable worker skill to worker differences. By construction this does not allow firm or match types to differ systematically across strata, and the direction of changes of the pre- and post-reform effects are therefore more important than their magnitudes.

The decomposition shows that the four Hartz reforms structurally changed the sources of wage variation. The importance of match relative to firm effects shifts slightly. As a consequence of Hartz I/II more emphasis is put on the match rather than the skill component for the low- and medium-skilled. The wage decomposition in Table 3.7 shows how this change in production translates into workers' wages. A larger and subtle consequence is the shift in importance from sorting to frictional wage dispersion. The increase in the frictional effect is a consequence of longer job tenures, as separation rates fall for all but the lowest skilled and there is a greater volume of acceptable offers. This means more workers have received offers in a given employment spell that are either good enough to put upward pressure on their current wage, or so good that they move to new firms, using their old employer as an outside option in wage bargaining. The decreased contribution of sorting to wage variation is likely due to workers becoming less picky about firm and match types because of lower outside options in unemployment, driven primarily by the final Hartz reform wave. As a result, workers are willing to accept less productive jobs and the overall sorting pattern is closer to a random assignment.

3.6 Conclusion

This Chapter develops an approach for evaluating comprehensive labour market reforms. We construct and estimate a model of the labour market with search frictions, heterogeneity and complementarities in production. These labour market features are critical for understanding the impact of labour market policy changes in many contexts, where detailed worker-firm data are available. We implement this framework by evaluating the Hartz labour market reforms in Germany in the early 2000s. Similarly, one could adapt our approach to analyse structural labour market reforms in other contexts, such as those introduced by the Spanish government in 2012.

In our setting, the Hartz labour market reform laws are treated as shocks to the structural parameters, which are fully anticipated by forward looking agents. To assess the effects of the German Hartz reforms the model is estimated by maximum likelihood estimation with matched worker-firm data. Identification is achieved by exploiting the off steady-state dynamics of the model. The results of our evaluation show that the Hartz reforms reduced unemployment but to a smaller extent than suggested by previous studies. We also find that this reduction in unemployment was associated with a significant reduction in real wages, with particularly large reductions for the low-skilled. Our results further indicate that the reforms could have been more beneficial for employment and wage growth by not adopting the first reform wave, the labour demand policies which included the introduction

of mini- and midi-jobs. Lastly, we document a shift in the drivers behind wage variation as a direct consequence of the German labour market reforms. In the post-reform labour market, frictional wage dispersion and match-specific variation become more important, while the effects of sorting and variation in firm type decreased.

Our Chapter shows that a comprehensive approach to evaluating labour market policy changes provides insights that are not easily obtained in reduced-form assessments of particular reform aspects, or with calibrated macro models. The evaluation approach we propose makes use of detailed administrative data on workers and firms, which have recently become available for an increasing number of countries. Detailed data thus enable a careful assessment of the trade-off between employment and wage growth that is inherent in many labour market policy choices.

Appendix 3.1: Hartz Policies

The Hartz I and II laws came into effect on January 1 2003. Hartz I facilitated temporary employment, and introduced new training subsidies. The reform simplified and extended case-based exemptions from relatively restrictive employment regulations (Jacobi and Kluve, 2007). Vouchers for career development training of the unemployed were introduced by the Federal Employment Agency to support measures with a maximum duration of three months. The reform also created personnel service agencies, which serve as temporary work agencies to complement the existing local employment agencies in finding job placements for unemployed workers. Hartz II provided further regulation of marginal employment by introducing so-called mini- and midi-jobs, and sponsored business startups by the unemployed. Mini-jobs allow tax exemption of worker contributions to social security and lifted the threshold for such marginal tax-exempt employment from a monthly income of 325 to 400 Euros. Midi-jobs incur reduced social security contributions on a sliding scale for earnings up to 800 Euros per month. The definition of marginal employment was also extended to employees working more than 15 hours per week. Hartz II further introduced startup subsidies for the unemployed under the name Ich-AG (i.e. Me-Company), which resulted in 270,000 such startups receiving subsidies from the Federal Employment Agency until the end of 2004. Further details about the reform elements and the number of workers affected are provided in Ebbinghaus and Eichhorst (2006).

The third reform law, Hartz III, was implemented from January 1 2004 on, and re-structured the Federal Employment Agency. The placement and job search support the employment administration and the management of its 90,000 employees was reorganised, so that the employment agency would become a modern client-oriented service provider. Weise (2011) discusses the reorganisation of the Federal Employment Agency in greater detail.

Hartz IV came into effect on January 1 2005 and significantly changed the structure and generosity of unemployment benefits, with an aim to increase incentives to work. Hartz IV combined parts of unemployment assistance with social assistance payments and introduced sanctions to promote more active job search. In practice, the effect of the benefit changes is determined by worker circumstances with post-reform receipts depending, for example, on the income of the partner and the number of children. Additional allowances may be available for accommodation and heating. Before Hartz IV, three types of unemployment benefits existed: unemployment insurance payments for the short-term unemployed, unemployment assistance, and social assistance for the long-term unemployed. Hartz IV combined unemployment assistance and social assistance, now administered by the Federal Employment Agency. This change decreased payments for many who previously received

unemployment assistance. Before the reform, unemployment assistance could last for 52 months and social assistance payments were unlimited. Post-reform benefit receipts were limited to two years. If acceptable job offers were declined, unemployed workers could incur sanctions in the form of reduced benefits. Benefit payments became more contingent on means testing, and the definition of acceptable job offers was widened. After Hartz IV, unemployed workers were also required to take low-paid jobs including mini-jobs and jobs that did not correspond to the level of a worker's training or his previous job.

Appendix 3.2: Value Functions

The present discounted value of an unemployed worker of productivity x is equal to $b_t(x)$, the flow utility of unemployment, the option value of employment and the associated change if a policy is implemented:

$$rU_t(x) = b_t(x) + \lambda_{0,t} \int \int_{y',z' \in \mathcal{M}_{0,t}(x)} [W_t(\phi_{0,t}(x, y', z'), x, y', z') - U_t(x)] v(y') \gamma(z') dy' dz' + \eta_t [U_{t'}(x) - U_t(x)]$$

Using the identity given by equation (3.2), the above simplifies to:

$$rU_t(x) = b_t(x) + \beta \lambda_{0,t} \int \int_{y',z' \in \mathcal{M}_{0,t}(x)} S_t(x, y', z') v(y') \gamma(z') dy' dz' + \eta_t [U_{t'}(x) - U_t(x)]$$

The value function for an employed worker of productivity x in a firm of productivity y with a match specific draw z earning a wage w at time t , is more cumbersome:

$$\begin{aligned} rW_t(w, x, y, z) = & w + \delta_t [U_t(x) - W_t(w, x, y, z)] \\ & + \lambda_{1,t} \int \int_{y',z' \in \mathcal{M}_{10,t}(x,y,z)} [W_t(\phi_{0,t}(x, y', z'), x, y', z') - W_t(w, x, y, z)] v(y') \gamma(z') dy' dz' \\ & + \lambda_{1,t} \int \int_{y',z' \in \mathcal{M}_{11,t}(x,y,z)} [W_t(\phi_{1,t}(x, y', z', y, z), x, y', z') - W_t(w, x, y, z)] v(y') \gamma(z') dy' dz' \\ & + \lambda_{1,t} \int \int_{y',z' \in \mathcal{M}_{2,t}(w,x,y,z)} [W_t(\phi_{1,t}(x, y, z, y', z'), x, y, z) - W_t(w, x, y, z)] v(y') \gamma(z') dy' dz' \\ & + \eta_t \left[1 \{ \theta_{t'} \in \mathcal{N}_{0,t'}(x, y, z) \} U_{t'}(x) + 1 \{ \theta_{t'} \in \mathcal{N}_{1,t'}(w, x, y, z) \} W_{t'}(w, x, y, z) \right. \\ & + 1 \{ \theta_{t'} \in \mathcal{N}_{2,t'}(w, x, y, z) \} W_{t'}(\phi_0(x, y, z), x, y, z) \\ & \left. + 1 \{ \theta_{t'} \in \mathcal{N}_{3,t'}(w, x, y, z) \} W_t(\phi_{1,t}(x, y, z, y, z), x, y, z) - W_t(w, x, y, z) \right] \end{aligned}$$

The four option values in the above expression are unemployment risk, finding a much better job and using unemployment as a threat point, finding a better job and using the current employer as a threat point, and promotion within one's current employer. Unemployment occurs if a match is exogenously dissolved, which happens at the Poisson rate δ_t . After a worker meets a new firm, depending on the draw of y' and z' , the worker may move if the pair falls in the set $\mathcal{M}_{1,t}(x,y,z)$. If the new job is sufficiently better than the current one $(y',z') \in \mathcal{M}_{10,t}(x,y,z)$ then unemployment is used as a threat point. If the draw is a small improvement, and $(y',z') \in \mathcal{M}_{11,t}(x,y,z)$, then the worker uses his current employer as a threat point in Bertrand competition. Finally, a worker gets a within-firm promotion if his new offer $(y',z') \in \mathcal{M}_{2,t}(w,x,y,z)$. All these sets are formally defined in Section 3.3.3.

In addition to the option value of employment there is a possibility that labour market reforms change the employment value. These reforms occur at a Poisson rate η_t and their implications depend on the way in which matched agents re-negotiate their employment contract. The exact re-negotiation mechanism of our benchmark model is outlined in Section 3.3.4. To demonstrate that other wage re-negotiation mechanisms can be accommodated we write the new re-negotiated wage in time t' as $n_{t'}(w,x,y,z)$. We impose three regularity conditions on $n_{t'}(w,x,y,z)$ that re-negotiation adheres to.

Neither party wants to dissolve the match: The firm's value function is greater than or equal to zero, its outside option.

$$\Pi_{t'}(n_{t'}(w,x,y,z),x,y,z) \geq 0$$

Similarly for a worker, the value of the match must at least match the value obtained in unemployment.

$$W_{t'}(n_{t'}(w,x,y,z),x,y,z) \geq U_{t'}(x)$$

Transferable utility: The wage does not affect the size of the surplus.

$$W_{t'}(n_{t'}(w,x,y,z),x,y,z) - U_{t'}(x) + \Pi_{t'}(n_{t'}(w,x,y,z),x,y,z) = S_t(x,y,z)$$

If one subtracts the value of unemployment from the value of employment as defined previously and applies the identity given by equation (3.3), then the surplus generated for a worker earning a wage w of productivity x in a firm of productivity y with match-specific productivity z at time t is derived as the following expression. The worker surplus is defined as the value of employment net of the worker's outside option, unemployment.

$$\begin{aligned}
(r + \delta_t + \eta_t)[W_t(w, x, y, z) - U_t(x)] &= w - b_t(x) \\
&+ \lambda_{1,t} \int \int_{y', z' \in \mathcal{M}_{10,t}(x, y, z)} [\beta S_t(x, y', z') + U_t(x) - W_t(w, x, y, z)] v(y') \gamma(z') dy' dz' \\
&+ \lambda_{1,t} \int \int_{y', z' \in \mathcal{M}_{11,t}(x, y, z)} [S_t(x, y, z) + U_t(x) - W_t(w, x, y, z)] v(y') \gamma(z') dy' dz' \\
&+ \lambda_{1,t} \int \int_{y', z' \in \mathcal{M}_{2,t}(w, x, y, z)} [S_t(x, y', z') + U_t(x) - W_t(w, x, y, z)] v(y') \gamma(z') dy' dz' \\
&- \beta \lambda_{0,t} \int \int_{y', z' \in \mathcal{M}_{0,t}(x)} S_t(x, y', z') v(y') \gamma(z') dy' dz' \\
&+ \eta_t \mathbf{1}\{\theta_{t'} \notin \mathcal{N}_{0,t'}(x, y, z)\} [W_{t'}(n_{t'}(w, x, y, z), x, y, z) - U_{t'}(x)]
\end{aligned}$$

Turning to the firm, the value for a firm of productivity y , hiring a worker of productivity x at a wage rate w with a match-specific productivity of z at time t is given by the function $\Pi_t(w, x, y, z)$.

$$\begin{aligned}
r\Pi_t(w, x, y, z) &= f_t(x, y, z) - w + \delta_t[0 - \Pi_t(w, x, y, z)] \\
&+ \lambda_{1,t} \int \int_{y', z' \in \mathcal{M}_{1,t}(x, y, z)} [0 - \Pi_t(w, x, y, z)] v(y') \gamma(z') dy' dz' \\
&+ \lambda_{1,t} \int \int_{y', z' \in \mathcal{M}_{2,t}(w, x, y, z)} [\Pi_t(\phi_{1,t}(x, y, z, y', z'), x, y, z) - \Pi_t(w, x, y, z)] v(y') \gamma(z') dy' dz' \\
&+ \eta_t \mathbf{1}\{\theta_{t'} \in \mathcal{N}_{0,t'}(x, y, z)\} [0 - \Pi_t(w, x, y, z)] \\
&+ \eta_t \mathbf{1}\{\theta_{t'} \notin \mathcal{N}_{0,t'}(x, y, z)\} [\Pi_{t'}(n_{t'}(w, x, y, z), x, y, z) - \Pi_t(w, x, y, z)]
\end{aligned}$$

The value function for the firm is analogous to that of the worker with a few exceptions. The flow value of the match is the total output produced $f_t(x, y, z)$ net of the wage paid w , the outside option of the firm is zero and not unemployment, and the firm does not care about the terms of the worker's next job, just if the worker leaves. Summing the above two expressions and applying the identity in equation (3.1) yields the total surplus generated by a match of a worker with ability x and a firm of productivity y with a match-specific productivity of z at time t .

$$\begin{aligned}
(r + \delta_t + \eta_t)S_t(w, x, y, z) &= f_t(x, y, z) - b_t(x) - \beta \lambda_{0,t} \int \int_{y', z' \in \mathcal{M}_{0,t}(x)} S_t(x, y', z') v(y') \gamma(z') dy' dz' \\
&+ \lambda_{1,t} \int \int_{y', z' \in \mathcal{M}_{10,t}(x, y, z)} [\beta S_t(x, y', z') - S_t(x, y, z)] v(y') \gamma(z') dy' dz' \\
&+ \eta_t \mathbf{1}\{\theta_{t'} \notin \mathcal{N}_{0,t'}(x, y, z)\} [W_{t'}(n_{t'}(w, x, y, z), x, y, z) - U_{t'}(x) + \Pi_{t'}(n_{t'}(w, x, y, z), x, y, z)]
\end{aligned}$$

Transferable utility means the final term is the surplus in period t' . Inspection of the sets $\mathcal{M}_{0,t}(x)$, $\mathcal{M}_{10,t}(x)$, and $\mathcal{N}_{0,t'}(x)$ reveals the surplus equation can be expressed in a simpler way. Following the notation of Lise and Robin (2017) we denote $A^+ := \max\{A, 0\}$. The surplus is independent of the wage rate, which validates the assumption of transferable utility.

$$(r + \delta_t + \eta_t)S_t(x, y, z) = f_t(x, y, z) - b_t(x) - \beta\lambda_{0,t} \int \int S_t(x, y', z')^+ v(y')\gamma(z')dy'dz' \\ + \lambda_{1,t} \int \int [\beta S_t(x, y', z') - S_t(x, y, z)]^+ v(y')\gamma(z')dy'dz' + \eta_t S_{t'}(x, y, z)^+$$

Appendix 3.3: Proofs of Lemma 1, Proposition 1 and Lemma 2

Lemma 1

Given the regularity condition imposed on f that $\lim_{z \rightarrow \bar{z}} f_t(x, y, z) = \infty$, and taking the limit of the right-hand side of equation (3.4) implies:¹⁴

$$\lim_{z \rightarrow \bar{z}} ((r + \delta_t + \eta_t)S_t(x, y, z)) = \infty + C_t(x) + D_t(x, y) + E_t(x, y) \\ \text{where } C_t(x) = -b_t(x) - \beta\lambda_{0,t} \int \int S_t(x, y', z')^+ v(y')\gamma(z')dy'dz' \\ \text{and } D_t(x, y) = \lambda_{1,t} \lim_{z \rightarrow \bar{z}} \left(\int_{\underline{y}}^{\bar{y}} \int_{\underline{z}}^{\bar{z}} \{\beta S_t(x, y', z') - S_t(x, y, z)\}^+ \gamma(z')dz'v(y')dy' \right) \\ \text{and } E_t(x, y) = \eta_t \lim_{z \rightarrow \bar{z}} (\eta_t S_{t'}(x, y, z)^+)$$

$C_t(x)$ is a constant for given x , and thus the limit properties of $S_t(x, y, z)$ are independent of this term. Further, it is assumed that $S_t : (\underline{x}, \bar{x}) \times (\underline{y}, \bar{y}) \times (\underline{z}, \bar{z}) \rightarrow \mathbb{R}$.

- (i) Assume $\lim_{z \rightarrow \bar{z}} S_t(x, y, z)$ is equal to a finite number. Then $D_t(x, y)$ would equal a finite number. $E_t(x, y) = \infty$ for $\lim_{z \rightarrow \bar{z}} S_{t'}(x, y, z) = \infty$ and $E_t(x, y)$ is equal to a finite number in all other situations. Thus, irrespective of the feasible value that $E_t(x, y)$ takes, $\lim_{z \rightarrow \bar{z}} S_t(x, y, z) = \infty$, which is inconsistent with our assumption.
- (ii) Assume $\lim_{z \rightarrow \bar{z}} S_t(x, y, z) = -\infty$. Then $D_t(x, y) = \infty$ and $E_t(x, y) = \infty$ for $\lim_{z \rightarrow \bar{z}} S_{t'}(x, y, z) = \infty$ and $E_t(x, y)$ is equal to a finite number in all other situations. Again, $\lim_{z \rightarrow \bar{z}} S_t(x, y, z) = \infty$, which is inconsistent with our assumption.

¹⁴The term $E_t(x, y)$ is indexed by t , as by definition t' is the period that arrives immediately after t .

(iii) Finally, assume $\lim_{z \rightarrow \bar{z}} S_t(x, y, z) = \infty$. Then $D_t(x, y)$ would equal a finite number. $E_t(x, y) = \infty$ for $\lim_{z \rightarrow \bar{z}} S_t(x, y, z) = \infty$ and $E_t(x, y)$ is equal to a finite number in all other situations. Thus, irrespective of the feasible value that $E_t(x, y)$ takes, $\lim_{z \rightarrow \bar{z}} S_t(x, y, z) = \infty$, which is consistent with our assumption. *Q.E.D.*

Proposition 1

To prove Proposition 1, it is enough to show that for any (x, y) there is a z such that $S_t(x, y, z) \geq 0$. For fixed x and y , the fact that $S_t(x, y, z)$ is positive translates to the condition that:

$$\begin{aligned} f_t(x, y, z) + N_1(z) + N_2(z) &\geq N_0 \quad \text{where} \quad N_0 = b_t(x) + \beta \lambda_{0,t} E_{y',z'} [\max \{S_t(x, y', z'), 0\}] \\ &\quad \text{and} \quad N_1(z) = \lambda_{1,t} E_{y',z'} [\max \{\beta S_t(x, y', z') - S_t(x, y, z), 0\}] \\ &\quad \text{and} \quad N_2(z) = \eta_t S_t(x, y, z) \end{aligned}$$

As $z \rightarrow \bar{z}$, $f_t(x, y, z) \rightarrow \infty$ and from Lemma 1: as $z \rightarrow \bar{z}$, $S_t(x, y, z) \rightarrow \infty$ which means $N_1(z) \rightarrow 0$ and $N_2(z) \rightarrow \infty$. Thus collectively, the left-hand side of the above expression tends to infinity as z tends to its limit and the right-hand side is, for fixed x , constant. Therefore there is a z which satisfies $f_t(x, y, z) + N_1(z) + N_2(z) > N_0$. This z will satisfy $S_t(x, y, z) \geq 0$. *Q.E.D.*

Lemma 2

For fixed x, y, y', z' , the condition $S_t(x, y, z) > S_t(x, y', z')$ can be translated into:

$$f_t(x, y, z) + N_1(z) + N_2(z) > (r + \delta_t + \eta_t) S_t(x, y', z') + N_0$$

where $N_0, N_1(z)$ and $N_2(z)$ are defined as before.

Only the left-hand side varies with z . From Lemma 1, as z tends to \bar{z} , the left-hand side tends to infinity. Therefore there is a z which satisfies $f_t(x, y, z) + N_1(z) + N_2(z) > (r + \delta_t + \eta_t) S_t(x, y, z) + N_0$. This z will satisfy $S_t(x, y, z) > S_t(x, y', z')$. *Q.E.D.*

Appendix 3.4: New Entrant's Wages

The wage a worker receives at time t , when hired from unemployment, is such that he takes a share β of the total surplus generated from the match.

$$(r + \delta_t + \eta_t) (W_t(\phi_{0,t}(x, y, z), y, z) - U_t(x)) = (r + \delta_t + \eta_t) \beta S_t(x, y, z)$$

Computing the option value of employment, derived in Section 3.6, evaluated at $w = \phi_{0,t}(x, y, z)$ gives:

$$\begin{aligned}
(r + \delta_t + \eta_t) (W_t(\phi_{0,t}(x, y, z), y, z) - U_t(x)) &= \phi_{0,t}(x, y, z) - b_t(x) \\
+ \lambda_{1,t} \int \int_{y', z' \in \mathcal{M}_{10,t}(x, y, z)} & [W_t(\phi_{0,t}(x, y', z'), x, y', z') - W_t(\phi_{0,t}(x, y, z), x, y, z)] v(y') \gamma(z') dy' dz' \\
+ \lambda_{1,t} \int \int_{y', z' \in \mathcal{M}_{11,t}(x, y, z)} & [W_t(\phi_{1,t}(x, y', z', y, z), x, y', z') - W_t(\phi_{0,t}(x, y, z), x, y, z)] v(y') \gamma(z') dy' dz' \\
+ \lambda_{1,t} \int \int_{y', z' \in \mathcal{M}_{2,t}(\phi_{0,t}(x, y, z), x, y, z)} & [W_t(\phi_{1,t}(x, y, z, y', z'), x, y, z) \\
& - W_t(\phi_{0,t}(x, y, z), x, y, z)] v(y') \gamma(z') dy' dz' \\
- \beta \lambda_{0,t} \int \int_{y', z' \in \mathcal{M}_{0,t}(x)} & S_t(x, y', z') v(y') \gamma(z') dy' dz' \\
+ \eta_t 1\{\theta_{t'} \notin \mathcal{N}_{0,t'}(x, y, z)\} & [W_{t'}(\phi_{0,t'}(x, y, z), x, y, z) - U_{t'}(x)]
\end{aligned}$$

By applying the wage identities defined by equations (3.2) and (3.3), we get:

$$\begin{aligned}
(r + \delta_t + \eta_t) \beta S_t(x, y, z) &= \phi_{0,t}(x, y, z) \\
+ \lambda_{1,t} \beta \int \int_{y', z' \in \mathcal{M}_{10,t}(x, y, z)} & [S_t(x, y', z') - S_t(x, y, z)] v(y') \gamma(z') dy' dz' \\
+ \lambda_{1,t} (1 - \beta) S_t(x, y, z) \int \int_{y', z' \in \mathcal{M}_{11,t}(x, y, z)} & v(y') \gamma(z') dy' dz' \\
+ \lambda_{1,t} \int \int_{y', z' \in \mathcal{M}_{2,t}(\phi_{0,t}(x, y, z), x, y, z)} & [S_t(x, y', z') - \beta S_t(x, y, z)] v(y') \gamma(z') dy' dz' \\
- b_t(x) - \beta \lambda_{0,t} \int \int_{y', z' \in \mathcal{M}_{0,t}(x)} & S_t(x, y', z') v(y') \gamma(z') dy' dz' \\
+ \eta_t 1\{\theta_{t'} \notin \mathcal{N}_{0,t'}(x, y, z)\} \beta S_{t'}(x, y', z') &
\end{aligned}$$

Substituting out the common terms in the above expression and in equation (3.4), which defines the surplus, and rearranging yields:

$$\begin{aligned}
\phi_{0,t}(x,y,z) &= f_t(x,y,z) - (1-\beta)(r + \delta_t + \eta_t)S_t(x,y,z) \\
&\quad - (1-\beta)\lambda_{1,t}S_t(x,y,z) \int \int_{y',z' \in \mathcal{M}_{10,t}(x,y,z)} v(y')\gamma(z')dy'dz' \\
&\quad - (1-\beta)\lambda_{1,t}S_t(x,y,z) \int \int_{y',z' \in \mathcal{M}_{11,t}(x,y,z)} v(y')\gamma(z')dy'dz' \\
&\quad - \lambda_{1,t} \int \int_{y',z' \in \mathcal{M}_{2,t}(\phi_{0,t}(x,y,z),x,y,z)} [S_t(x,y',z') - \beta S_t(x,y,z)] v(y')\gamma(z')dy'dz' \\
&\quad + \eta_t(1-\beta)1\{\theta_{t'} \notin \mathcal{N}_{0,t'}(x,y,z)\}S_{t'}(x,y',z')
\end{aligned}$$

In this instance, the set $\mathcal{M}_{2,t}(x,y,z)$ is simple to define:

$$\begin{aligned}
\mathcal{M}_{2,t}(\phi_{0,t}(x,y,z),x,y,z) &\equiv \{y',z' | S(x,y,z) > S_t(x,y',z') > W_t(\phi_{0,t}(x,y,z),x,y,x) - U_t(x)\} \\
\mathcal{M}_{2,t}(x,y,z) &\equiv \{y',z' | S_t(x,y,z) > S_t(x,y',z') > \beta S_t(x,y,z)\}
\end{aligned}$$

Our wage equation simplifies further to:

$$\begin{aligned}
\phi_{0,t}(x,y,z) &= f_t(x,y,z) - (1-\beta)(r + \delta_t + \eta_t)S_t(x,y,z) \\
&\quad - (1-\beta)\lambda_{1,t}S_t(x,y,z) \int \int_{y',z' \in \mathcal{M}_{1,t}(x,y,z)} v(y')\gamma(z')dy'dz' \\
&\quad - \lambda_{1,t} \int \int_{y',z' \in \mathcal{M}_{2,t}(x,y,z)} [S_t(x,y',z') - \beta S_t(x,y,z)] v(y')\gamma(z')dy'dz' \\
&\quad + \eta_t(1-\beta)1\{\theta_{t'} \notin \mathcal{N}_{0,t'}(x,y,z)\}S_{t'}(x,y',z')
\end{aligned}$$

Appendix 3.5: Wages with Outside Options

We substitute $\phi_{1,t}(x,y,z,y',z')$ into the option value of employment presented earlier. To review, $\phi_{1,t}(x,y,z,y',z')$ represents the wage a worker of type x in period t working for a

firm of type y with match draw z earns if his best outside offer is the pair (y', z') :

$$\begin{aligned}
& (r + \delta_t + \eta_t) (W_t(\phi_{1,t}(x, y, z, y', z'), y, z) - U_t(x)) = \phi_{1,t}(x, y, z, y', z') - b_t(x) \\
& + \lambda_{1,t} \int \int_{y'', z'' \in \mathcal{M}_{10,t}(x, y, z)} [W_t(\phi_{0,t}(x, y'', z''), x, y'', z'') \\
& \quad - W_t(\phi_{1,t}(x, y, z, y', z'), x, y, z)] v(y'') \gamma(z'') dy'' dz'' \\
& + \lambda_{1,t} \int \int_{y'', z'' \in \mathcal{M}_{11,t}(x, y, z)} [W_t(\phi_{1,t}(x, y'', z''), y, z), x, y'', z'') \\
& \quad - W_t(\phi_{1,t}(x, y, z, y', z'), x, y, z)] v(y'') \gamma(z'') dy'' dz'' \\
& + \lambda_{1,t} \int \int_{y'', z'' \in \mathcal{M}_{2,t}(\phi_{1,t}(x, y, z, y', z'), x, y, z)} [W_t(\phi_{1,t}(x, y, z, y'', z''), x, y, z) \\
& \quad - W_t(\phi_{1,t}(x, y, z, y', z'), y, z)] v(y'') \gamma(z'') dy'' dz'' \\
& - \beta \lambda_{0,t} \int \int_{y'', z'' \in \mathcal{M}_{0,t}(x)} S_t(x, y'', z'') v(y'') \gamma(z'') dy'' dz'' \\
& + \eta_t \left[1\{\theta_{t'} \in \mathcal{N}_{1,t'}(x, y, z, y', z')\} (W_{t'}(\phi_{1,t'}(x, y, z, y', z'), y, z) - U_{t'}(x)) \right. \\
& + 1\{\theta_{t'} \in \mathcal{N}_{2,t'}(x, y, z, y', z')\} (W_{t'}(\phi_{0,t'}(x, y, z), x, y, z) - U_{t'}(x)) \\
& \left. + 1\{\theta_{t'} \in \mathcal{N}_{3,t'}(x, y, z, y', z')\} (W_{t'}(\phi_{1,t'}(x, y, z, y, z), x, y, z) - U_{t'}(x)) \right]
\end{aligned}$$

Applying the same wage identities, we get:

$$\begin{aligned}
& (r + \delta_t + \eta_t) S_t(x, y', z') = \phi_{1,t}(x, y, z, y', z') - b_t(x) \\
& + \lambda_{1,t} \int \int_{y'', z'' \in \mathcal{M}_{10,t}(x, y, z)} [\beta S_t(x, y'', z'') - S_t(x, y', z')] v(y'') \gamma(z'') dy'' dz'' \\
& + \lambda_{1,t} \int \int_{y'', z'' \in \mathcal{M}_{11,t}(x, y, z)} [S_t(x, y, z) - S_t(x, y', z')] v(y'') \gamma(z'') dy'' dz'' \\
& + \lambda_{1,t} \int \int_{y'', z'' \in \mathcal{M}_{2,t}(\phi_{1,t}(x, y, z, y', z'), x, y, z)} [S_t(x, y'', z'') - S_t(x, y', z')] v(y'') \gamma(z'') dy'' dz'' \\
& - \beta \lambda_{0,t} \int \int_{y'', z'' \in \mathcal{M}_{0,t}(x)} S_t(x, y'', z'') v(y'') \gamma(z'') dy'' dz'' \\
& + \eta_t \left[1\{\theta_{t'} \in \mathcal{N}_{1,t'}(x, y, z, y', z')\} S_{t'}(x, y', z') + 1\{\theta_{t'} \in \mathcal{N}_{2,t'}(x, y, z, y', z')\} \beta S_{t'}(x, y, z) \right. \\
& \left. + 1\{\theta_{t'} \in \mathcal{N}_{3,t'}(x, y, z, y', z')\} S_{t'}(x, y, z) \right]
\end{aligned}$$

Substituting in the value of $S_t(x, y', z')$ from equation (3.4) gives:

$$\begin{aligned}
\phi_{1,t}(x, y, z, y', z') &= f_t(x, y', z') \\
&\quad - \lambda_{1,t} \int \int_{y'', z'' \in \mathcal{M}_{11,t}(x, y, z)} [S_t(x, y, z) - S_t(x, y', z')] v(y'') \gamma(z'') dy'' dz'' \\
&\quad - \lambda_1 \int \int_{y'', z'' \in \mathcal{M}_{2,t}(\phi_1(x, y, z, y', z'), x, y, z)} [S(x, y'', z'') - S(x, y', z')] v(y'') \gamma(z'') dy'' dz'' \\
&\quad + \eta_t \mathbf{1}\{\theta_{t'} \in \mathcal{N}_{2,t'}(x, y, z, y', z')\} [S_{t'}(x, y', z') - \beta S_{t'}(x, y, z)] \\
&\quad + \eta_t \mathbf{1}\{\theta_{t'} \in \mathcal{N}_{3,t'}(x, y, z, y', z')\} [S_{t'}(x, y', z') - S_{t'}(x, y, z)] \Big]
\end{aligned}$$

As only a worker's last job is important, the set $\mathcal{M}_2(\cdot)$ can be defined without the wage:

$$\begin{aligned}
\mathcal{M}_{2,t}(\phi_1(x, y, z, y', z'), x, y, z) &\equiv \{y'', z'' \mid S(x, y, z) > S(x, y'', z'') > W(\phi_1(x, y, z, y', z'), y, z) - U(x)\} \\
\mathcal{M}_{2,t}(x, y', z') &= \{y'', z'' \mid S(x, y, z) > S(x, y'', z'') > S(x, y', z')\}
\end{aligned}$$

$$\begin{aligned}
\phi_{1,t}(x, y, z, y', z') &= f_t(x, y', z') \\
&\quad - \lambda_{1,t} \int \int_{y'', z'' \in \mathcal{M}_{11,t}(x, y, z)} [S_t(x, y, z) - S_t(x, y', z')] v(y'') \gamma(z'') dy'' dz'' \\
&\quad - \lambda_1 \int \int_{y'', z'' \in \mathcal{M}_{2,t}(x, y, z)} [S(x, y'', z'') - S(x, y', z')] v(y'') \gamma(z'') dy'' dz'' \\
&\quad + \eta_t \mathbf{1}\{\theta_{t'} \in \mathcal{N}_{2,t'}(x, y, z, y', z')\} [S_{t'}(x, y', z') - \beta S_{t'}(x, y, z)] \\
&\quad + \eta_t \mathbf{1}\{\theta_{t'} \in \mathcal{N}_{3,t'}(x, y, z, y', z')\} [S_{t'}(x, y', z') - S_{t'}(x, y, z)] \Big]
\end{aligned}$$

Appendix 3.6: Proof of Proposition 3

To verify that the set $\mathcal{M}_{1,t}^{w^-}(w, x, y, z)$, as defined in the main body of the text, is non-empty for some (t, w, x, y, z) , we provide an example. Assume t is such that $\mu_t = 0$, which in the context of our application is either at the pre-announcement of the policy or after full implementation. Further, assume $w = \phi_{1,t}(x, y, z, y, z)$. This wage rate could arise because of a re-negotiation after the implementation of a policy or because of competing job offers of identical value. Inspection of equation (3.6) coupled with the matching set $\mathcal{M}_{2,t}(x, y, z)$ defined above reveals that under these assumptions a worker receives a wage equal to his marginal product, $w = f_t(x, y, z)$.

Then for any firm and match draw (y', z') such that the offer is strictly preferred, $S_t(x, y', z') > S_t(x, y, z)$, the new wage offer is:

$$\begin{aligned} \phi_{1,t}(x, y', z', y, z) &= f_t(x, y, z) \\ &- \lambda_{1,t} \int \int_{y'', z'' \in \mathcal{M}_{11,t}(x, y, z)} [S_t(x, y', z') - S_t(x, y, z)] v(y'') \gamma(z'') dy'' dz'' \\ &- \lambda_{1,t} \int \int_{y'', z'' \in \mathcal{M}_{2,t}(\phi_{1,t}(x, y', z', y, z), x, y', z')} [S(x, y'', z'') - S(x, y, z)] v(y'') \gamma(z'') dy'' dz'' < w \end{aligned}$$

Q.E.D.

Appendix 3.7: Solving the ODE Defining Labour Market Dynamics

The ordinary differential equation (ODE) defining unemployment for $t \in \tau_i$ is written in standard form:

$$\dot{u}_t(x) + \left(\delta_t + \lambda_{0,t} \int \int_{y, z \in \mathcal{M}_{0,t}(x)} v(y') \gamma(z') dy dz \right) u_t(x) = \delta_t \ell(x)$$

Multiplying by the integrating factor gives:

$$\begin{aligned} \frac{d}{dt} \left\{ u_t(x) \exp \left[\left(\delta_t + \lambda_{0,t} \int \int_{y, z \in \mathcal{M}_{0,t}(x)} v(y') \gamma(z') dy dz \right) (t - t_i) \right] \right\} = \\ \delta_t \ell(x) \exp \left[\left(\delta_t + \lambda_{0,t} \int \int_{y, z \in \mathcal{M}_{0,t}(x)} v(y') \gamma(z') dy dz \right) (t - t_i) \right] \end{aligned}$$

Integrating both sides with respect to t yields the particular solution given below, where $C(x)$ is the constant of integration:

$$\begin{aligned} u_t(x) &= \frac{\delta_t \ell(x)}{\delta_t + \lambda_{0,t} \int \int_{y, z \in \mathcal{M}_{0,t}(x)} v(y') \gamma(z') dy dz} \\ &+ \frac{C(x)}{\exp \left[\left(\delta_t + \lambda_{0,t} \int \int_{y, z \in \mathcal{M}_{0,t}(x)} v(y') \gamma(z') dy dz \right) (t - t_i) \right]} \end{aligned}$$

Substituting in the initial condition when $t = t_i$ and unemployment is equal to u_{t_i} , which is known and given by equation (3.9), the constant of integration can be solved, where $u_{ss,t}$ is the contemporaneous steady-state unemployment rate and the solution to equation (3.7).

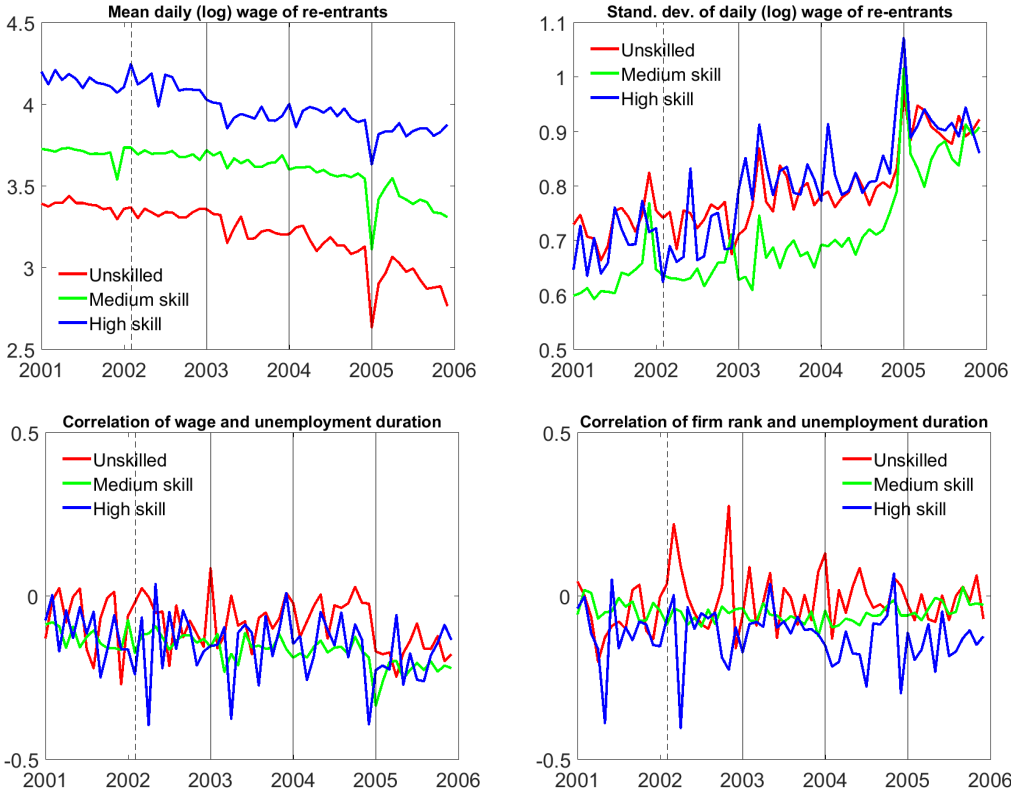
$$C(x) = u_{t_i}(x) - u_{ss,t}(x)$$

By substituting back into the particular solution one gets the more convenient ODE defining the unemployment rate.

$$u_t(x) = u_{ss,t}(x) \left(1 - \exp \left[\left(\delta_t + \lambda_{0,t} \int \int_{y,z \in \mathcal{M}_{0,t}(x)} v(y') \gamma(z') dy dz \right) (t_i - t) \right] \right) \\ + u_{ti}(x) \exp \left[\left(\delta_t + \lambda_{0,t} \int \int_{y,z \in \mathcal{M}_{0,t}(x)} v(y') \gamma(z') dy dz \right) (t_i - t) \right]$$

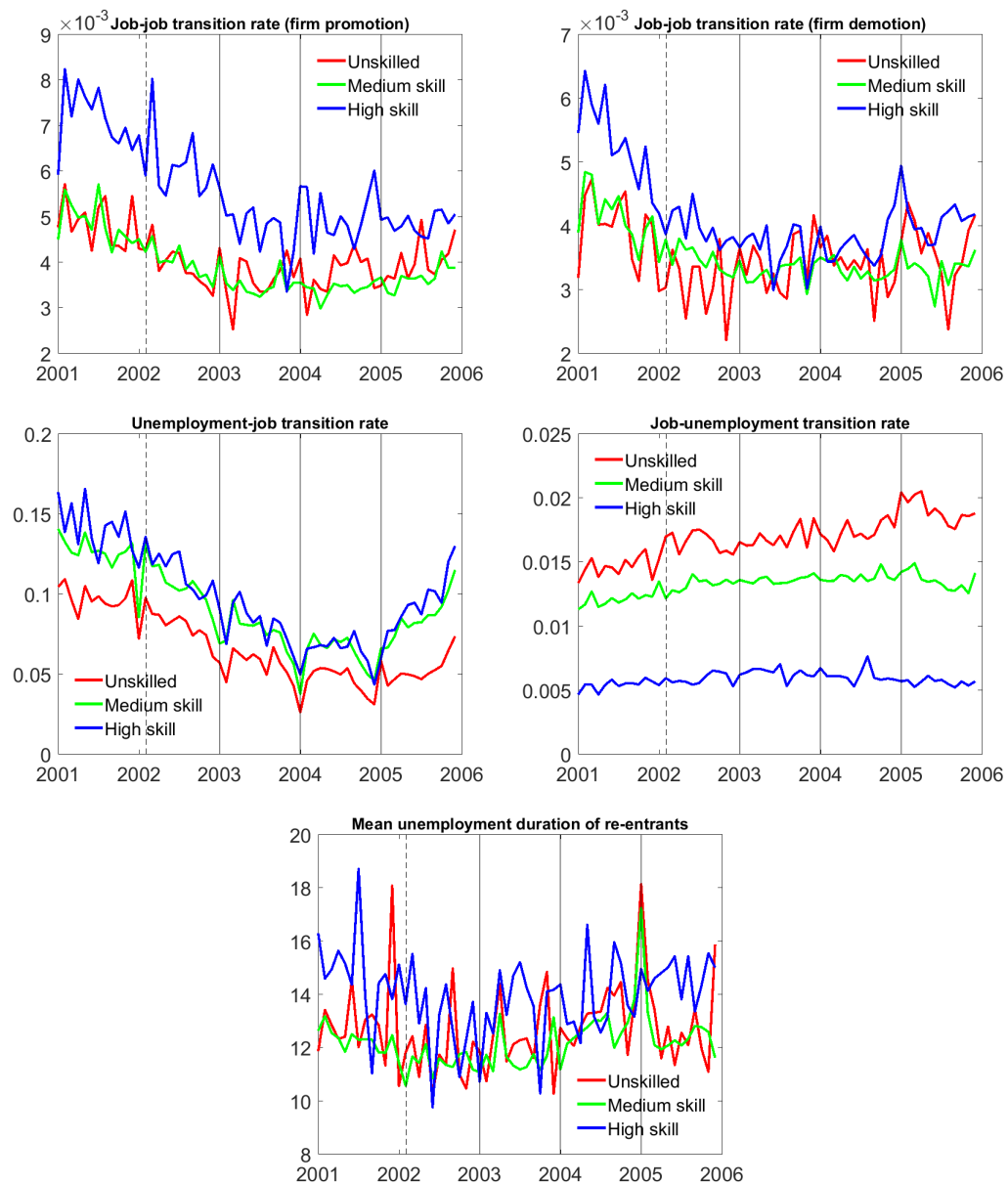
Appendix 3.8: Data Series

Figure A3.1 Wage moments of new hires and correlations 2001-2005



Notes: Log real re-entry wages refer to the natural log of daily wages in Euros for new hires, which are deflated by the Consumer Price Index. The monthly series are based on SIAB data and are seasonally adjusted.

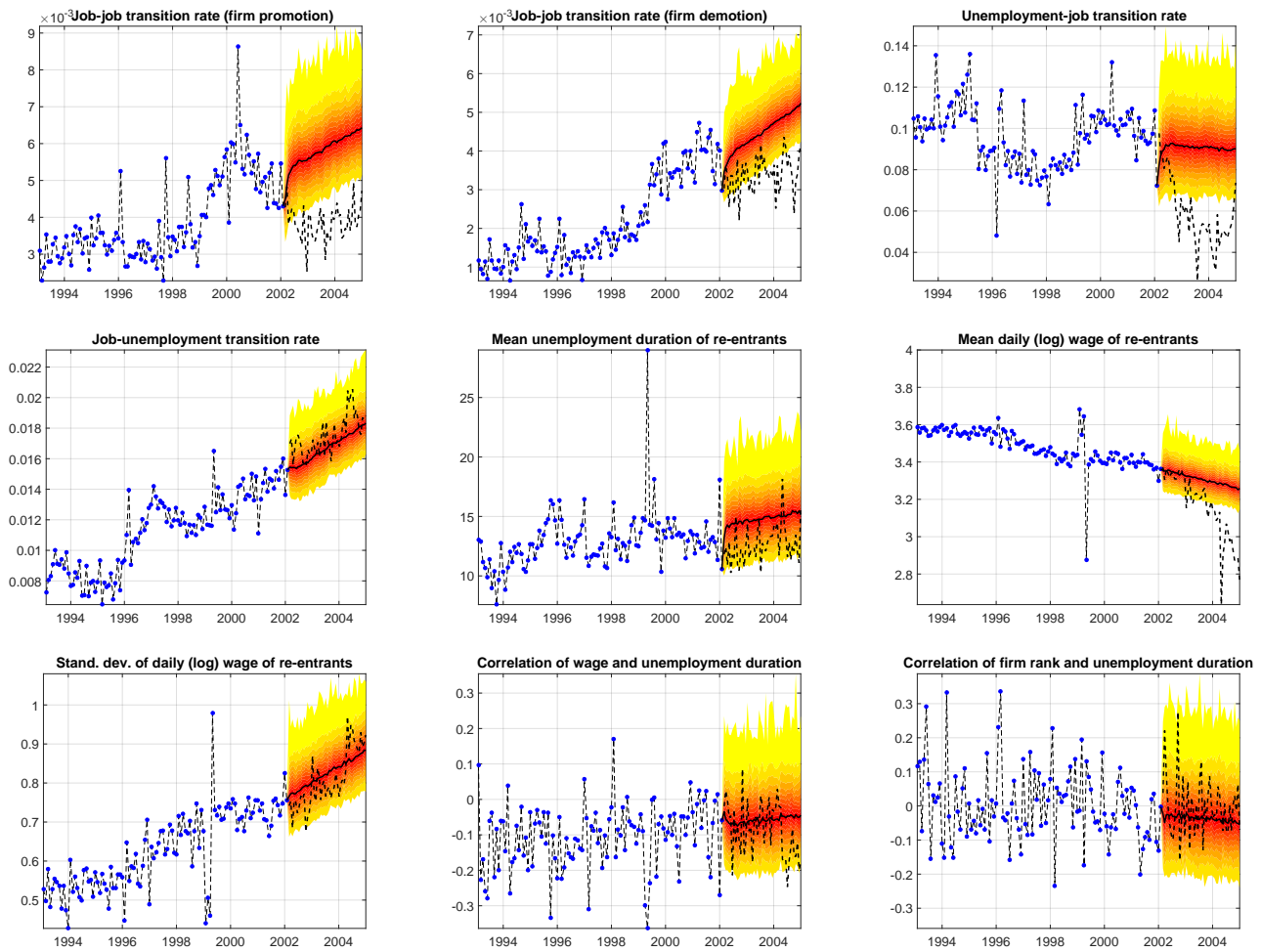
Figure A3.2 Transition rates and unemployment duration 2001-2005



Notes: The monthly series are based on SIAB data and are seasonally adjusted. Firms are ranked based on their average 75th-percentile real wage for full-time employees during the period January 2001 to December 2005.

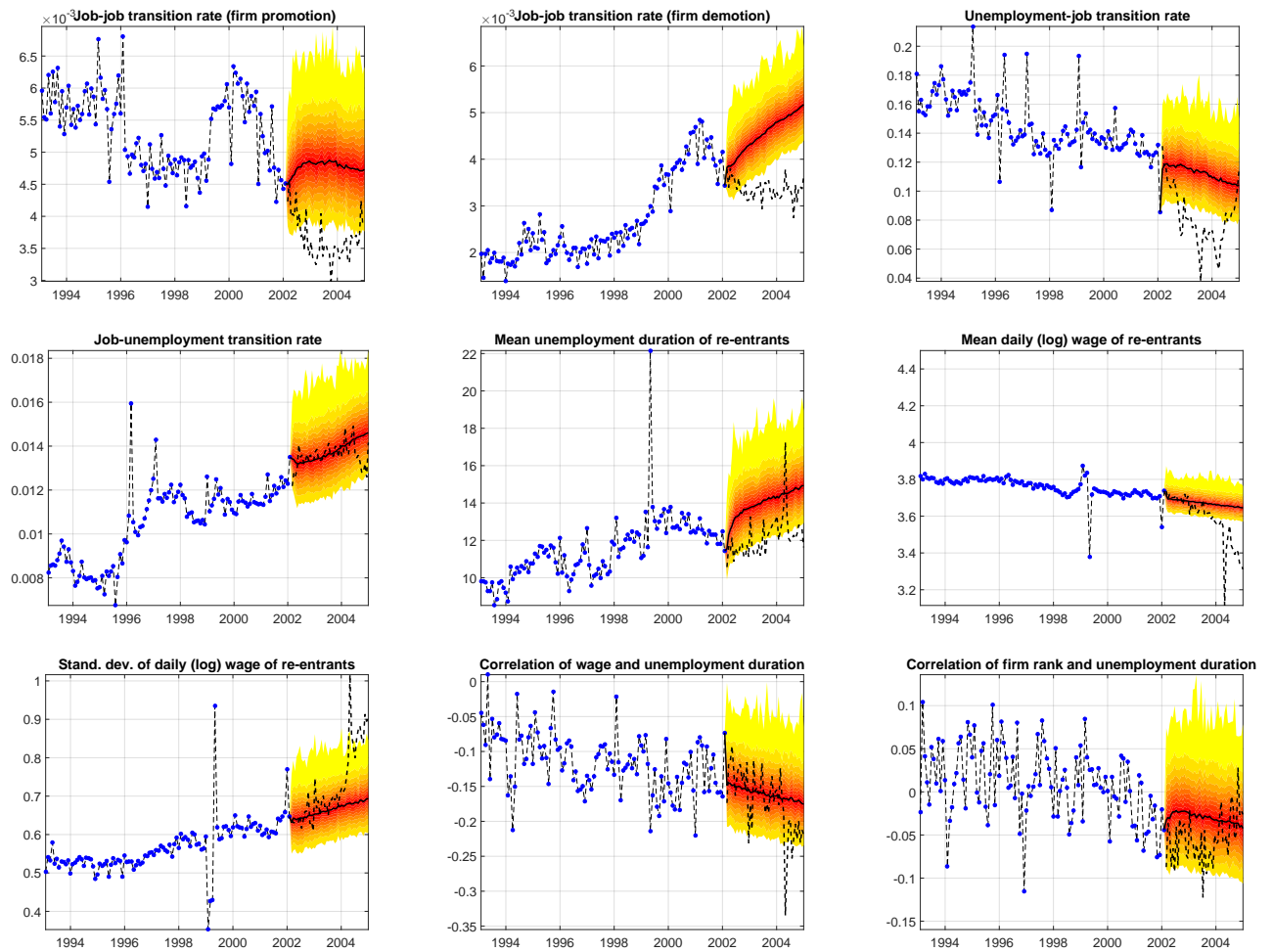
Appendix 3.9: Forecasts

Figure A3.3 Forecast for low-skill workers



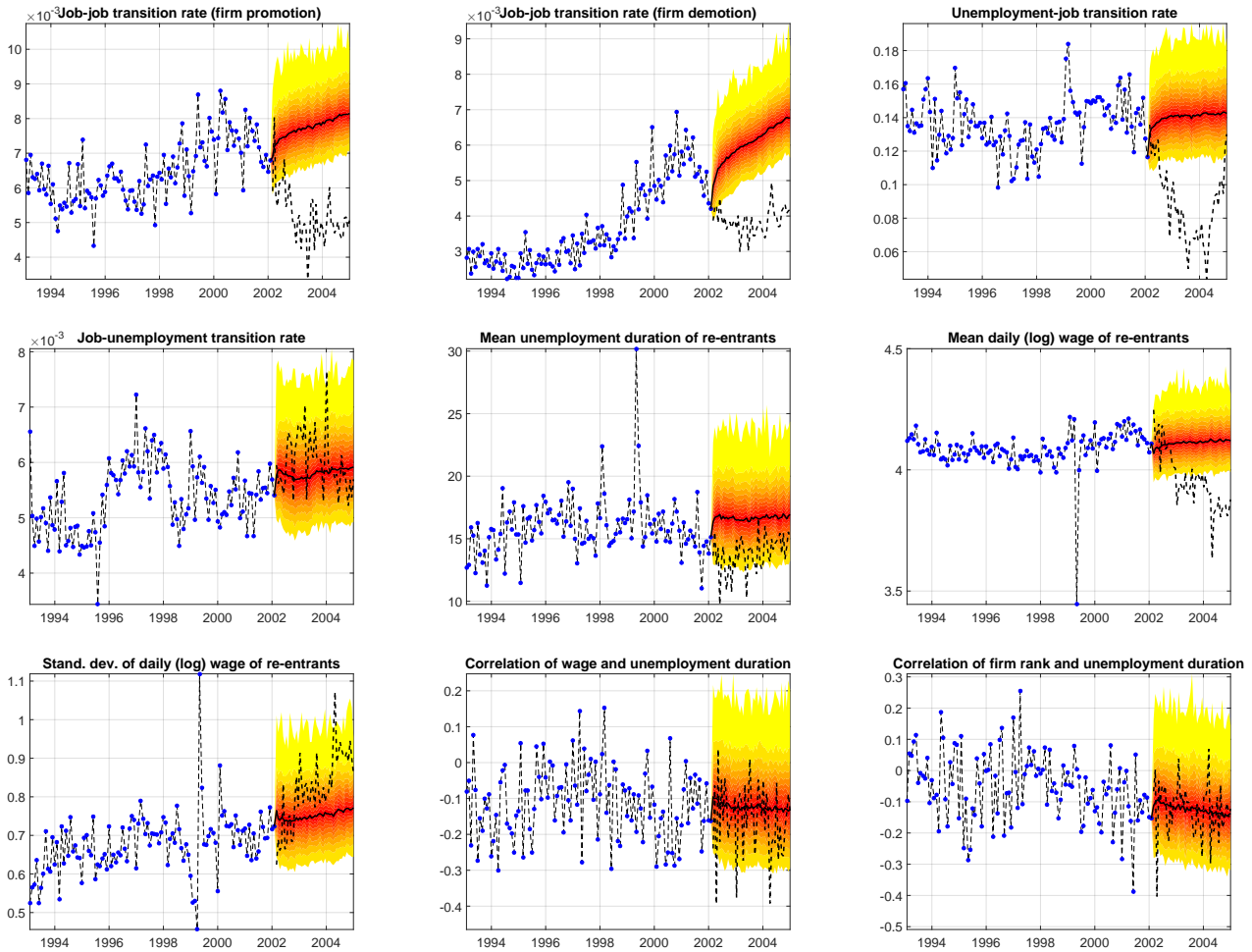
Notes: All transition rates are monthly. The black dotted line represents the data, the blue points are those that the forecast inference is based upon, the solid black line is the forecast and the heat map represents a 95-percent confidence interval.

Figure A3.4 Forecast for medium-skill workers



Notes: All transition rates are monthly. The black dotted line represents the data, the blue points are those that the forecast inference is based upon, the solid black line is the forecast and the heat map represents a 95-percent confidence interval.

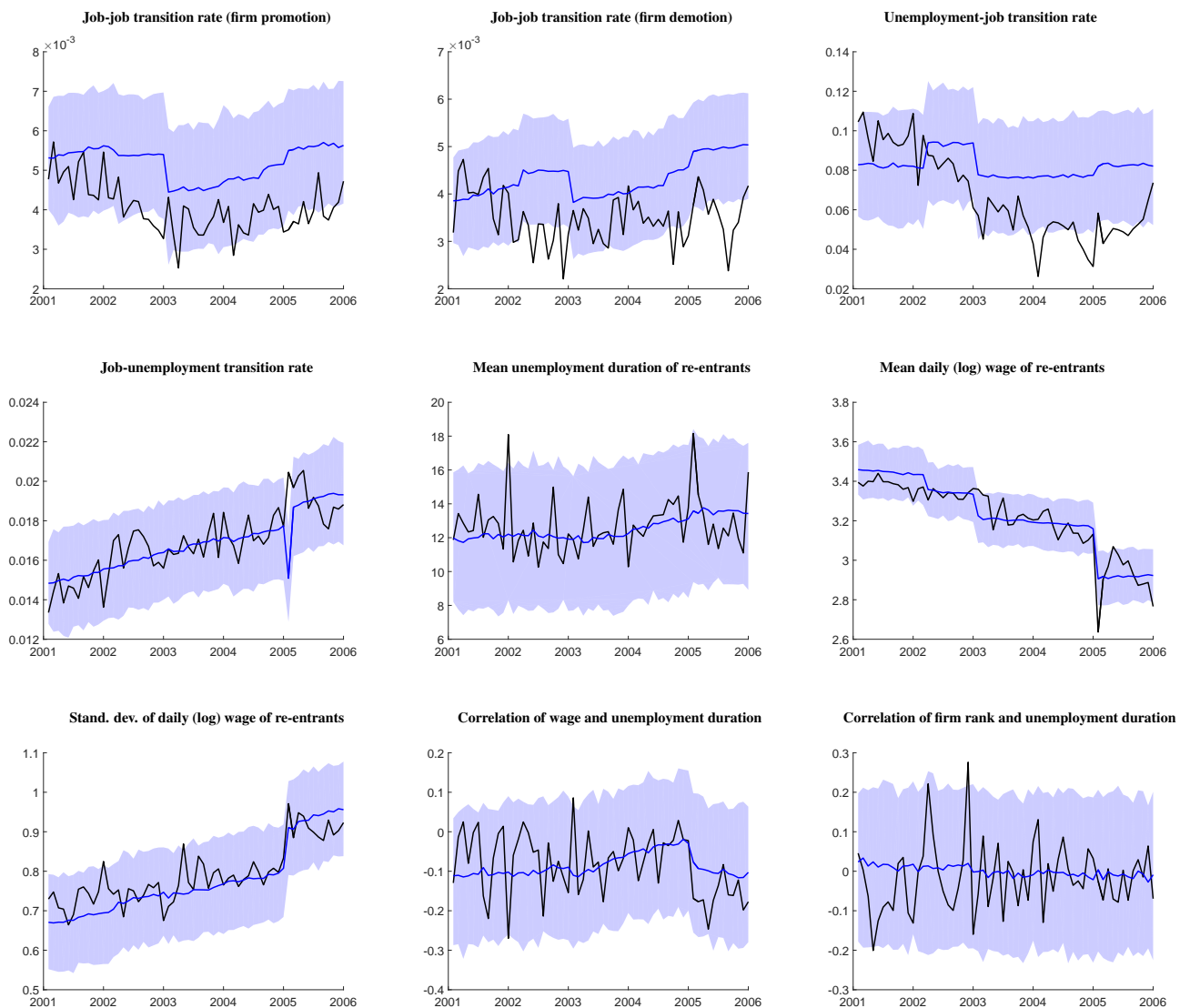
Figure A3.5 Forecast for high-skill workers



Notes: All transition rates are monthly. The black dotted line represents the data, the blue points are those that the forecast inference is based upon, the solid black line is the forecast and the heat map represents a 95-percent confidence interval.

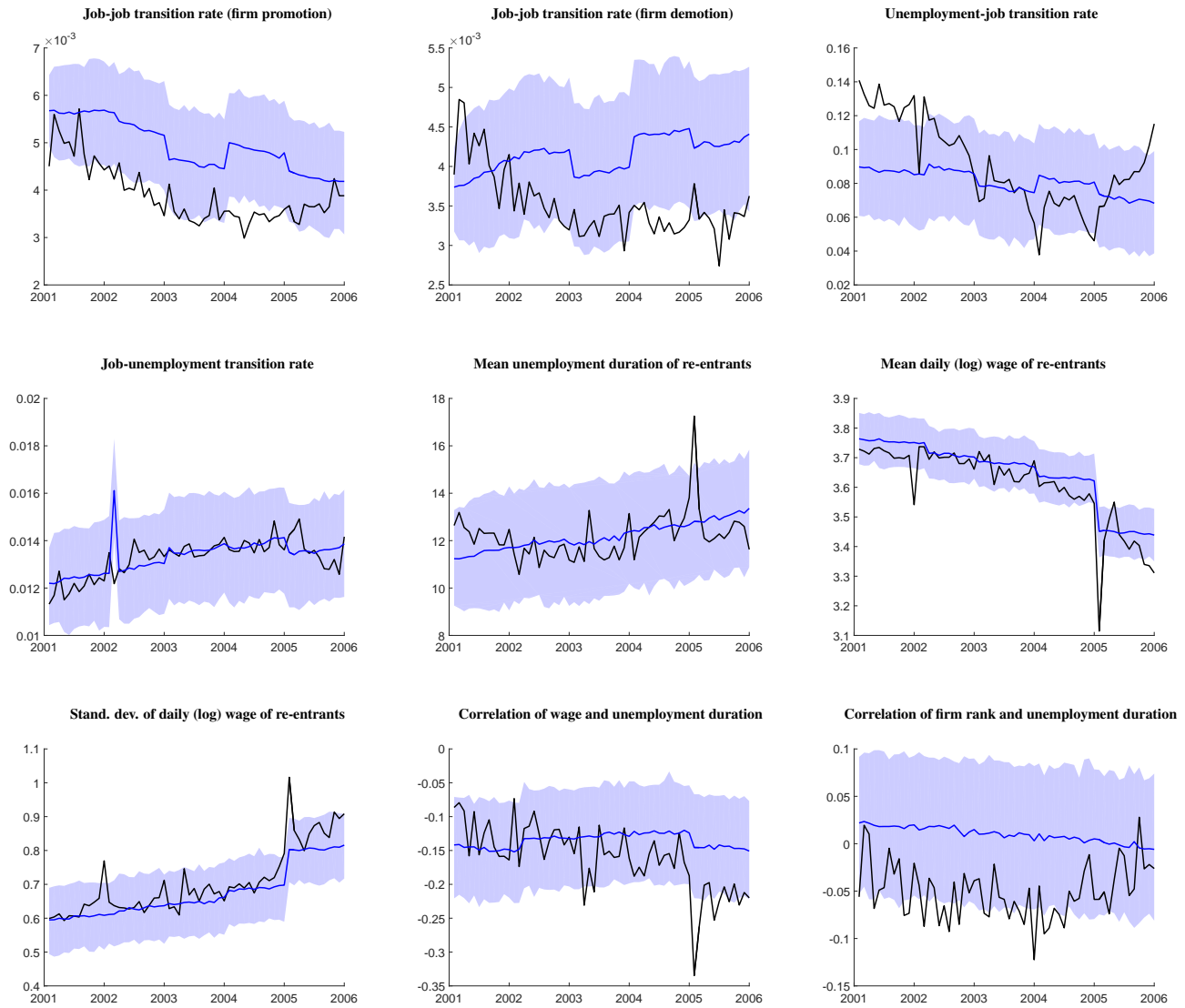
Appendix 3.10: The Fit of the Model

Figure A3.6 Simulated series for the low-skilled



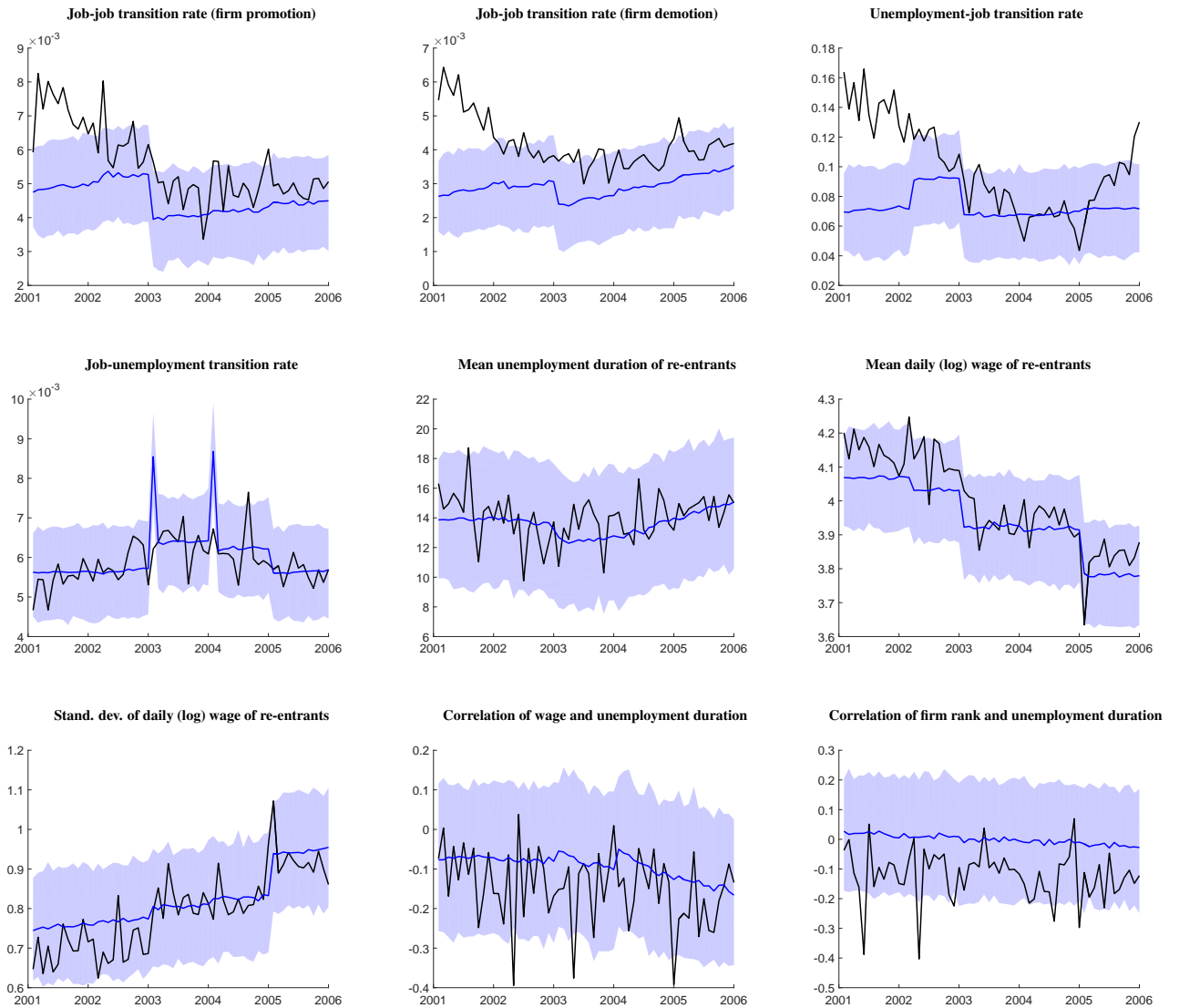
Notes: The solid black line represents the data and the blue line the simulations, 95-percent confidence intervals are represented by the shaded area and obtained by repeated re-simulations.

Figure A3.7 Simulated series for the medium-skilled



Notes: The solid black line represents the data and the blue line the simulations, 95-percent confidence intervals are represented by the shaded area and obtained by repeated re-simulations.

Figure A3.8 Simulated series for the high-skilled



Notes: The solid black line represents the data and the blue line the simulations, 95-percent confidence intervals are represented by the shaded area and obtained by repeated re-simulations.

Appendix 3.11: Steady-State Revisited

Further to Section 3.3.7, the pool of employed workers are divided into a type that has not received credible outside offers so that their threat point in wage bargaining is unemployment. A second type are the employed who received credible offers and therefore re-negotiated their wage using employment in another firm as leverage. The measure of the first employment type only varies with x, y and z , the productivity triple of the current match. The second measure, however, varies with x, y and z and similarly with y' and z' , the second best offer the worker has received since he left unemployment. We also impose stability on these two measures and call them $e_0(x, y, z)$ and $e_1(x, y, z, y', z')$, respectively.

Firstly, we equalise the flow in and out of $e_0(x, y, z)$ for all x, y and z . Workers exit to unemployment $u(x)$ if they exogenously lose their job, with probability δ . They can also exit to employment with a higher outside option. Exit is either to a different firm, using the current employer as leverage (if $y', z' \in \mathcal{M}_1(x, y, z)$) or they stay with the same employer, using the firm attempting to poach for leverage (if $y', z' \in \mathcal{M}_2(\phi_0(x, y, z), x, y, z)$).

$$\begin{aligned} e_0(x, y, z) & \left[\delta + \lambda_1 \int \int_{y', z' \in \{\mathcal{M}_1(x, y, z) \cup \mathcal{M}_2(\phi_0(x, y, z), x, y, z)\}} v(y') \gamma(z') dy' dz' \right] \\ & = \lambda_0 u(x) v(y) \gamma(z) \mathbf{1}\{y, z \in \mathcal{M}_0(x)\} \end{aligned}$$

This expression can be computed directly, by defining the set

$y', z' \in \{\mathcal{M}_1(x, y, z) \cup \mathcal{M}_2(\phi_0(x, y, z), x, y, z)\}$, and using the fact that $\beta \in (0, 1)$ as well as the identity given by equation (3.2).

$$\begin{aligned} \{\mathcal{M}_1(x, y, z) \cup \mathcal{M}_2(\phi_0(x, y, z), x, y, z)\} & = \{y', z' | S(x, y', z') > S(x, y, z) \\ & \cup S(x, y, z) > S(x, y', z') > \beta S(x, y, z)\} \\ & = \{y', z' | S(x, y', z') > \beta S(x, y, z)\} \end{aligned}$$

Thus, the steady-state measure $e_0(x, y, z)$ can be directly computed. To solve for $e_1(x, y, z, y', z')$ one needs to implement an iterative solution. The steady-state condition defining $e_1(x, y, z, y', z')$, for which indicator functions are used rather than matching sets, is given by:

$$\begin{aligned} e_1(x, y, z, y', z') & \left[\delta + \lambda_1 \int \int \mathbf{1}\{S(x, y'', z'') > S(x, y', z')\} v(y'') \gamma(z'') dy'' dz'' \right] \\ & = \lambda_1 v(y) \gamma(z) \mathbf{1}\{S(x, y, z) > S(x, y', z')\} e(x, y', z') \\ & + \lambda_1 e_0(x, y, z) v(y') \gamma(z') \mathbf{1}\{S(x, y, z) > S(x, y', z') > \beta S(x, y, z)\} \\ & + \lambda_1 v(y') \gamma(z') \int \int \mathbf{1}\{S(x, y, z) > S(x, y', z') > S(x, y'', z'')\} e(x, y, z, y'', z'') dy'' dz'' \end{aligned}$$

Appendix 3.12: Wage Projection

The data are simulated such that for an individual i we have his wage w_i , his unobserved type x_i , the type of his employer y_i , his match specific quality z_i , if applicable his best outside offer that includes firm and match components y'_i and z'_i , and the strata he belongs to, which equals $k = 1$ for low-skilled, $k = 2$ for medium-skilled and $k = 3$ for high-skilled workers. We then estimate the below relationship, where $\{k = n\}$ is a dummy variable taking the value one if the skill group is type n and zero otherwise. Since our production function accounts for circle sorting, we follow Gautier and Teulings (2006) and include a square term for each parameter. This improves the fit compared to a linear specification with an R^2 -value of approximately 0.8 to 0.9 in both pre- and post-reform projections. Higher order polynomials add little explanatory power and including them does not change the results significantly.

$$\begin{aligned} \log w_i = & \rho_0 + \sigma_1 x_i + \sigma_2 x_i^2 + \tau_1 y_i + \tau_2 y_i^2 + \upsilon_1 z_i + \upsilon_2 z_i^2 \\ & + \phi_1 y'_i + \phi_2 y_i'^2 + \chi_1 z'_i + \chi_2 z_i'^2 + \psi_1 \{k = 1\} + \psi_2 \{k = 2\} + \varepsilon_i \end{aligned}$$

After carrying out this regression we project wages on to $(\tilde{x}_i, \tilde{y}_i, \tilde{z}_i, \tilde{f}_i)$ by means of ordinary least squares, where the vector is defined as below and estimates are denoted by hats.

$$\begin{aligned} \tilde{x}_i &= \hat{\sigma}_1 x_i + \hat{\sigma}_2 x_i^2 + \hat{\psi}_1 \{k = 1\} + \hat{\psi}_2 \{k = 2\} \\ \tilde{y}_i &= \hat{\tau}_1 y_i + \hat{\tau}_2 y_i^2 \\ \tilde{z}_i &= \hat{\upsilon}_1 z_i + \hat{\upsilon}_2 z_i^2 \\ \tilde{f}_i &= \hat{\phi}_1 y'_i + \hat{\phi}_2 y_i'^2 + \hat{\chi}_1 z'_i + \hat{\chi}_2 z_i'^2 \end{aligned}$$

Differences in strata are assigned to worker differences, which may under-report firm, match and frictional variation. For example, systematic differences in firm quality might arise depending on which skill group firms hire from.

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