Firm growth and worker turnover in frictional labour markets

A thesis submitted for the degree of Doctor of Philosophy in Economics

by

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Summary

This dissertation contributes to the analysis of firm heterogeneity, turnover, and worker reallocation in frictional labour markets. Chapter 1 presents empirical evidence using German longitudinal matched employer-employee data on the relationship between worker flows and employer characteristics. In particular, the analysis distinguishes between employer-to-employer reallocations and movements into and out of non-employment. It also documents the relationship between worker movements and establishment wage, size and age. The empirical results constitute a motivation for the following chapters.

Chapter 2 analyses equilibrium in a labour market characterised by a stationary growth economy with heterogeneous firms and frictional unemployment. The model extends the Coles and Mortensen (2016) framework in two directions: it introduces vintage effects and endogenous worker search effort. New start-up firms are created with a productivity drawn from a technology frontier which grows over time. However, as a given firm's productivity is fixed, its quality declines relative to the market average. In addition, workers can choose their search intensity.

Chapter 3 provides a quantitative exploration of the theoretical model presented in Chapter 2. It estimates the parameters of the model using simulated minimum distance and evaluates its performance in capturing some features of the data: in particular, the model is able to match the establishment size distribution and the relationship between hires and employment.

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Chapter 1

Establishment heterogeneity and worker reallocation in Germany

1.1 Introduction

This chapter explores the empirical relationship between labour turnover and establishment heterogeneity using a rich matched employer-employee dataset from Germany. In doing so, it examines the direction of worker flows along several establishment-level dimensions, suggesting the importance of establishment age for understanding worker mobility patterns.

Firm productivity differences are large and persistent, as documented by a growing body of empirical literature (Syverson, 2004, and Foster, Haltiwanger and Syverson, 2008). There are several factors that may account for these differentials, as competition effects, managerial practices, human capital or R&D investments. Syverson (2011) provides a thorough review of the empirical literature on productivity differentials and their sources, which spans across numerous fields. What is common across all the surveyed studies is the magnitude and duration of productivity dispersion across producers. Recent studies also focus on productivity dynamics, and in particular on the reallocation aspect of productivity growth (Lentz and Mortensen, 2008). Bartelsman, Haltiwanger and Scarpetta (2009), observing cross-country productivity differentials, document the importance of entry and exit patterns as sources of aggregate productivity growth: new, more productive firms enter the market and substitute less productive exiting firms, contributing, together with within-firm reallocation of resources, to overall productivity growth.

Interestingly, there is also evidence of a tight relationship between productivity and wages, and between productivity and size. Faggio, Salvanes, and Van Reenen (2010) show that there has been an upward trend in within-industry productivity dispersion between 1984 and 2001 in the UK, paralleled by an increase in wage inequality over the same period of time. The clear link between wages and productivity has been already emphasised by previous studies: for example Baily, Hulten and Campbell (1992) document a strong correlation between plant-level productivity and plant-level wages in the US. In addition, Bartelsman et al. (2009) find evidence of significant firm heterogeneity, both in productivity and in size, across several markets and countries.

From the theoretical side, several models with heterogeneity in productivity and its implications for firm-size dynamics have been developed. For example, Jovanovic (1982) models equilibrium under a Schumpeterian selection mechanism, where the efficient firms grow and survive, while the inefficient ones decline and fail. Hopenayn (1992) develops a more tractable version of the entry and exit model of Jovanovic (1982), which allows to analyse the equilibrium firm size distribution, conditional on age cohorts. Search models of the labour market provide a significant contribution to the analysis of job reallocation and its relationship with firm productivity, wages and size. A canonical approach is the Burdett and Mortensen (1998) (henceforth BM), a model with on-the-job search that is able to generate wage dispersion even for ex-ante identical firms and workers. The model predicts that workers climb the job ladder by moving from lower paying to higher paying employers. The model also implies a *large firm-wage* effect: larger firms pay higher wages inducing workers to leave their current employment, thus attracting a larger share of their hires from other firms. Moreover, by offering higher wages, they increase their retention rates. Moscarini and Postel-Vinay (2012, 2013) extend the BM model to a stochastic environment and evaluate its quantitative performance. Their key insight is that large firms are typically more productive, thus, by paying more, they can attract workers from smaller employers. This, in turn, has an impact on their hiring strategy in the presence of expansion or contraction phases: as they can easily 'poach' workers from other firms, when the economy expands and the rate of unemployment falls, they can directly rely on the pool of employed workers. On the other hand, small firms find it hard to grow using the poaching channel. However, small firms are less affected by an economic contraction, as during a downturn they can hire from the larger pool of unemployed. Because in Moscarini and Postel-Vinay (2013) equilibrium requires a *Rank Preserving* structure, a larger firm will always offer a higher wage. Coles and Mortensen (2016) overcome this limitation with a dynamic version of the BM model that allows for firm turnover dynamics. Young firms are born small but, conditional on survival, can quickly grow large, while large firms may experience negative shocks and shrink.

Empirical evidence tests the implications of search and matching models for worker reallocation across firms. Moscarini and Postel-Vinay (2012) empirically support their theoretical prediction that large firms are more cyclically sensitive and manage to grow quickly during expansions. More recently, Haltiwanger, Hyatt, Kahn and McEntarfer (2018) investigate whether workers move from low to high wage, and from small to large firms. They use U.S. linked employer-employee data that distinguish between flows from employment and from non-employment, in order to test whether large firms are indeed growing because they 'poach' workers from other firms. Their findings suggest that workers move up the job ladder, from low to high wage firms, and these movements are procyclical. However, contrary to Moscarini and Postel-Vinay (2012), they do not find evidence that workers move from small to large firms. The cyclical sensitivity of large firms is driven also by flows to and from non-employment, and not mainly by poaching flows.

The present Chapter uses German longitudinal matched employer-employee data in order to analyse worker reallocation across several dimensions. In particular, it explores the direction of worker flows along establishment size and wage, which, as previous literature documents, have a strong link with productivity. The availability of spell data allows to analyse not only worker reallocation in terms of establishment hiring and separation flows, but also to distinguish between employment-to-employment flows and movements into and out of non-employment. Findings show that workers tend indeed to move from low to high wage establishments, but that the relationship between worker movements and establishment size is more complex. Small establishments can be either very productive, young and fast-growing, or mature and declining, suggesting that establishment age is an important factor to take into account.

The Chapter is structured as follows: Section 1.2 provides an overview of the data and presents some preliminary descriptive statistics; Section 1.3 illustrates the relationship between worker flows and employment growth, and between those flows and establishment wage, age and size; Section 1.4 analyses worker transition probabilities; Section 1.5 considers worker heterogeneity; Section 1.6 concludes.

1.2 Data

1.2.1 LIAB overview

This study uses the Linked-Employer-Employee Data longitudinal model 1993-2010 (LIAB LM 9310) from the IAB. Data access was provided via on-site use at the Research Data Centre (FDZ) of the German Federal Employment Agency (BA) at the Institute for Employment Research (IAB) and subsequently remote data access. The LIAB combines establishment information from the IAB Establishment Panel, with information on individuals from the Integrated Employment Biographies (IEB). The first data source, the IAB Establishment Panel, is an annual survey, carried out since 1993, of establishments in Germany with at least one employee liable for social security contributions. The unit of observation is the establishment, which is defined as a regionally and economically separate unit, so it is possible that more establishments belong to the same firm. However, the data do not allow to identify multiplant firms[1].

The sample is stratified according to establishment size, industry and federal state, and it contains about 15,000 establishments every year. As a result of the stratification, large establishments, small federal states and small industries are overrepresented in the sample. Thus, every establishment is given an individual weighting factor to correct for the sample structure. Descriptive statistics that aim at being representative of the population of German establishments need to use weighted data[2]. The data contain information on number of employees, industry, total sales, investment. As regards the individual data, the Employment Statistics Register is an administrative panel based on the notifications of employers for health, pension, and unemployment insurances. The entire IEBs comprise information about employment subject to social security, marginal part-time employment, unemployment and social benefits, registered jobseekers and participants in employment or training measures. Civil servants, self-employed and family workers are excluded. Information on individuals include age, sex, nationality, education, daily wage, employment status and occupation, among the other. All individuals who were employed at least one day at one of the establishments of the IAB in a certain period, are identified and selected for the LIAB panel. As both data sources contain a unique firm identification number,

[1]For further information about the IAB Establishment Panel, see Fischer, Janik, Muller and Schmucker (2009).

[2]The sample weights are structured according to the distribution of the establishments in the population. See Fischer et al. (2009) for a detailed description of the sample design and the weighting procedure.

it is possible to match the establishment with the individual information. Thus, the LIAB includes 1,883,198 workers in total, which potentially can be linked to 146,781 establishments-year observations during the period 1993-2010. However, only 75,505 establishment-year observations are linked to the IAB survey, which amount to 9,678 distinct establishments[3].

1.2.2 Descriptive statistics

I restrict the dataset only to establishments located in West Germany. All establishments in the public sector have been excluded[4]. Moreover, only establishments that are observed in the dataset for at least two consecutive years have been selected, as it is not possible to distinguish between panel attrition and true death of an establishment. Therefore, the analysis does not focus on entry and exit, but only on continuing establishments. As regards the worker side, only individuals with age between 20 and 60 years old have been selected. Unfortunately, the LIAB does not contain information on employee working hours. However, since it is possible to distinguish between full-time and part-time workers, part-time workers are excluded from the sample and only the daily wage of full-time workers has been considered[5]. The resulting sample after all the restrictions has a total of 3,361 distinct establishments, which is almost a third of the total number of establishments available in the LIAB that can be linked to the IAB survey. Table 1.1 reports the descriptive statistics[6]. The number of establishment-year observations for the period 2001-2009 is 16,187, while every year, on average, there are 1,949 distinct establishments in the sample. As explained above, the random sample is stratified by establishment size and industry, so that it is disproportional with respect to the number of employees and the branch of the economy. Thus,

[3]See Alda, Bender and Gartner (2005) for additional information about the LIAB dataset.

[4]The exclusion is due to differences both as regards the economic situation and the wage determination between East and West Germany. Appendix 1.C extends the analysis to establishments located in the East, as well as public establishments.

[5]Dustmann, Ludsteck and Schönberget (2009) find no change in the variance of hours among full-time male workers.

[6]Detailed descriptive statistics by area and industry can be found in Appendix 1.C.

Table 1.1: Descriptive statistics

	Sample	**Weighted**
Number of distinct establishments	3,361	3,361
Establishment-year observations	16,187	16,187
Mean employees	162	13
	(661)	(76)
Median employees	19	5
Mean employees (full-time)	134	10
	(587)	(65)
Median employees (full-time)	13	3
Mean daily log wage (raw, full-time)	4.300	4.074
	(0.447)	(0.488)
Mean daily log wage (imputed, full-time)	4.310	4.078
	(0.459)	(0.494)

Note: The first column corresponds to the sample statistics, without weights; the second column uses sample weights. The reported averages are simple averages over annual cross-sections of establishments. The number of employees is calculated by aggregating the number of workers covered by the social security system. Standard deviations are in brackets. Source: Author's tabulations from LIAB data collapsed at annual level, 2001-2009.

weighted and unweighted statistics differ considerably, as illustrated in Table 1.1. For example, the average establishment in the sample employs 162 workers, but when using sample weights, its size shrinks considerably. As the dataset oversamples large establishments, in what follows I will only show the weighted results. For descriptive purposes, Table 1.1 reports both the average number of all employees liable to social security and the average number of those employees who work full-time. Another major disadvantage of the LIAB is that wages are top-censored at the contribution limit to the social security system. This contribution limit changes every year. As this censoring affects the distribution of the average wage, I impute the censored wages using Tobit regressions following Card, Heining and Kline (2013)[7]. Table 1.1 shows the log of establishment average daily wage, both censored and after the imputation. The average daily wage is calculated by dividing total earnings by the duration of the job spell for each worker, and then taking the average at the establishment level.

The establishment age is derived from the IAB survey questions. The dataset

[7]See Appendix 1.B for details.

Table 1.2: Summary statistics by age of establishment

	Start-up	**Young**	**Mature**
Mean employees	7	6	11
	(36)	(39)	(73)
Establishment share	12.60%	15.45%	71.95%
Employment share	9.10%	8.95%	81.94%
Log average wage	3.988	3.972	4.116
	(0.485)	(0.565)	(0.474)

Note: 'Start-up' indicates that the establishment is 5 or less years old; 'Young' indicates that the establishment has age $\in (5, 10]$; 'Mature' indicates that the establishment is more than 10 years old. Sample weights are used. Standard deviations are in brackets. Top coded wages are imputed with Tobit predicted values. Source: Author's tabulations from LIAB data, 2001-2009.

provides the foundation year of the establishment, given it was founded in 1990 or later. Therefore, I classify establishments according to three classes of age, where 'Mature' indicates that the establishment is more than 10 years old; 'Young' are those establishments with age between 5 and 10 years old; 'Start-up' are those establishments with 5 or less than 5 years old[8]. Table 1.2 shows that mature establishments are the largest, they represent the majority of the German establishments, they employ the largest share of full-time workers and they pay the highest wage. In addition, there is no stark difference between establishments with less than 5 years old and those with age between 5 and 10 years.

Table 1.3 shows that small establishments are the majority and together they employ the largest proportion of workers. In addition, it confirms the tendency of large establishments to offer higher wages, i.e. the employer-size wage premium. However, while average wage monotonically increases with size, it does not show the same pattern across age classes.

[8]The classification is for expositional convenience only. Generally, US firms that are less than one or two years old are defined as true start-ups (Haltiwanger, Jarmin and Miranda, 2013), while there is no consensus as regards German establishments. As I restrict attention to continuing establishments, those with age between one and two years represent only 2% of the population (Table 1.D.1 in Appendix).

Table 1.3: Summary statistics by number of employees

	1-19	**20-99**	**100-999**	**$\geqslant$1000**
Establishment share	92.57%	6.12%	/	/
Employment share	40.68%	22.32%	29.03%	7.97%
Log average wage	4.047	4.437	4.575	4.798
	(0.493)	(0.312)	(0.323)	(0.166)

Note: Due to data confidentiality rules, cells with a low share must be replaced by '/'. Sample weights are used. Standard deviations are in brackets. The number of employees is calculated by aggregating the number of workers covered by the social security system. Top coded wages are imputed with Tobit predicted values. Source: Author's tabulations from LIAB data, 2001-2009.

1.3 Growth and worker flows

1.3.1 Worker Flows

The dataset is in spell format, and it provides information on the start and end dates of each employment spell. Thus, it is possible to calculate worker flows and distinguish the employer-to-employer transitions from movements into and out of non-employment[9]. Table 1.4 shows the average annual hiring and separation rates, weighted by employment size. Hiring and separation rates are calculated following Davis, Haltiwanger and Schuh (1996) as

$$h_{et} = \frac{H_{et}}{0.5(N_{et} + N_{et-1})} \tag{1.1}$$

and

$$s_{et} = \frac{S_{et}}{0.5(N_{et} + N_{et-1})}, \tag{1.2}$$

where N_{et} is the number of workers employed in establishment e in period t, H_{et} is the number of workers hired and S_{et} is the number of separations. As in Faberman (2017), $N_{et-1} = N_{et} - H_{et} + S_{et}$. I use a cumulative measure of

[9] One disadvantage of the LIAB is the lack of explicit information on registered unemployed, which makes it difficult to identify the exact length of unemployment periods. Since I am more interested in extracting the job-to-job component from establishment hiring and separation, the analysis does not distinguish between unemployment and non-participation. Thus, the non-employment status refers to both unemployment and non-participation.

hiring and separations: instead of selecting all workers who were employed by an establishment at a single point in time t each year, I computed the cumulative number of full-time workers at each establishment during the interval between $t-1$ and t, so to exploit the spell nature of the dataset. Thus, H_{et} is the number of distinct full-time workers hired by the establishment e during the time between $t-1$ and t. Also separations S_{et} are computed in this way[10]. As explained above, these measures refer only to establishments that are observed in the sample for at least two consecutive years.

To identify employer-to-employer transitions (henceforth EE transitions), or quits from an establishment to another, I record all employment interruptions that do not contain a non-employment spell. If the spell is recorded as ending but the worker starts a job at another establishment before 7 days, I consider the spell as a voluntary quit or EE transition[11]. Thus, quits in period t correspond to all workers who left the establishment during the interval between period $t-1$ and t. I will discuss below in this Section the implications of such assumption.

The average annual hiring and separation rates are respectively 17.14% and 17.01%, indicating that, on average, a considerable proportion of employees is hired or leaves the establishment during a year, though the average net employment growth is close to zero. Table 1.4 also reports a slightly higher job creation rate with respect to job destruction. Job creation (destruction) is defined as in Davis et al. (1996), as the sum of all new jobs created (destroyed):

$$JC_t = \sum_{e \in E^+} \frac{H_{et} - S_{et}}{0.5(N_{et} + N_{et-1})}, \tag{1.3}$$

and

[10] The cumulative measure does not take into account temporary layoffs: thus, if a worker temporarily leaves and then she is hired again by the establishment during the year, I do not record the separation nor the corresponding hiring.

[11] A worker may also voluntarily quit to unemployment. However, following the convention I identify voluntary quits as EE transitions.

$$JD_t = \sum_{e \in E^-} \left| \frac{H_{et} - S_{et}}{0.5(N_{et} + N_{et-1})} \right|. \tag{1.4}$$

The average net employment growth, or job reallocation (JR) is the difference between job creation and job destruction. Equivalently, it is the difference between hires and separations. Usually hires and separations (worker flows) are larger than job flows (JC and JD), because an establishment can either create or destroy jobs in a given period, while at the same time having workers who leave and join jobs.

The EE transitions, both in terms of hires from and quits to employment, are a small proportion of the total hires and separations. However, I considered a very strict measure of worker reallocation. It is possible that a worker may take a break longer than 7 days between ending up the job at the previous establishment and starting a new job. All these inter-spell gaps of more than a week are recorded as transitions to and from non-employment. Appendix 1.A shows the employment-to-employment flow rates when the time gap is extended to 30 days. The disadvantage of this second measure is that it may include also true spells of non-employment and not only gaps between a job and another. The one-week approach, on the other hand, may leave out some true employer-to-employer transitions with a break between jobs.

Table 1.4: Average worker flow rates

Hiring	0.1714
	(0.2114)
Separation	0.1701
	(0.1942)
JC	0.0644
	(0.1545)
JD	0.0631
	(0.1366)
JR	0.0013
	(0.2251)
Quit to employment	0.0359
	(0.0771)
Hiring from employment	0.0353
	(0.0790)

Note: Both employment and sample weights are used. Flow rates are annual averages on full-time, permanent workers covered by social security. Standard deviations are in brackets. Source: Author's tabulations from LIAB data, 2001-2009.

The assumption of identifying as voluntary all EE transitions with less than one-week inter-job spells is clearly strong, as the administrative data do not allow to observe the reason for leaving the employer. Thus, what follows considers indirect evidence for the importance of this assumption. In particular, the IAB survey provides information on the number of workers who were recruited and those who left the establishments in the first six months of the calendar year. Establishments are also asked for the cause of leaving, so that it is possible to distinguish between voluntary and involuntary separations.

Table 1.5 reports descriptive statistics for those employers of the sample who answered the survey questions on separations. These establishments are, on average, larger, and pay higher salaries.

Table 1.6 shows worker flow rates according to the IAB establishment survey. As the IAB panel considers only workers entering or leaving the establishments in the first six months of the year, the reported flows are doubled, to get approximate yearly measures. In addition, the flows refer to all employees liable for social security, and not just full-time workers.

I consider two alternative measures for voluntary separations: the stricter, 'Resign', indicates all resignations on the part of the employee; the broader one 'Tot Quit' includes, together with all resignations, also terminations of contracts by mutual agreement and transfers to other establishments within the organisation. 'Dismissal', on the other hand, illustrates all dismissals on the part of the employer, i.e. non-voluntary separations. The reported total hiring and separation flow rates are slightly different than those calculated from administrative data (in Table 1.4), and indicate a negative job reallocation rate. Both the total quit and resign rates are higher than the quit rate in Table 1.4. This may be due to several reasons: first, as already pointed out, separations here apply to all workers liable for social security, thus they include also part-time workers, while the main analysis uses only full-time workers, in order to obtain consistent estimates of worker flows across wage classes. The IAB panel, on the other hand, does not contain any information on voluntary separations of full-time employees. Moreover, these measures have been calculated by doubling the rates, as the number of employees leaving the establishment refers to the first six months of the calendar year only, therefore it does not account for seasonal movements. Another source of measurement error is that the IAB hires and separations count every accession and separation without considering recalls. The hiring and separation rates calculated using administrative data (Table 1.4), on the other hand, exclude temporary layoffs, i.e. do not record the separation nor the hiring of a worker who temporarily leaves and then is hired a second time by the same establishment during the year. Including all accessions and separations would inflate the flow rate, as the measure is calculated by dividing total hires (separations) in period t by the average number of workers in period t and $t-1$ (equations (1.1) and (1.2)), albeit here the average hiring rate is lower than the one observed using administrative data (14% compared to 17%). Finally, while the survey measures of the IAB panel allow to disentangle the 'voluntary' component of separations, they do not contain any information on the destination of these flows: as individuals are not tracked in the

Table 1.5: Descriptive statistics, IAB survey

	Sample	**Weighted**
Number of distinct establishments	2,436	2,436
Establishment-year observations	8,298	8,298
Mean employees	284	31
	(843)	(137)
Median employees	67	9
Mean employees (reported, 30 June)	295	27
	(920)	(143)
Median employees (reported, 30 June)	62	6
Mean employees (full-time)	237	24
	(750)	(117)
Median employees (full-time)	53	5
Mean daily log wage (raw, full-time)	4.422	4.163
	(0.374)	(0.423)
Mean daily log wage (imputed, full-time)	4.493	4.167
	(0.389)	(0.429)

Note: The first column corresponds to the sample statistics, without weights; the second column uses sample weights. The reported averages are simple averages over annual cross-sections of establishments. The number of employees is calculated by aggregating the number of workers covered by the social security system, while the '30 June' averages are those reported by the establishments in the IAB panel at that date. Standard deviations are in brackets. Source: Author's tabulations from LIAB data collapsed at annual level, 2001-2009.

survey, it is not possible to check whether the worker who quits ends in another establishment or into non-employment. Therefore, the IAB survey does not allow to contribute to the analysis on EE transitions provided in this Chapter.

Table 1.6: Average worker flow rates, IAB survey

Hiring	0.1438
	(0.3249)
Separation	0.1736
	(0.3134)
Tot Quit	0.0756
	(0.2000)
Dismissal	0.0739
	(0.2145)
Resign	0.0621
	(0.1850)

Note: Both employment (reported by the establishment at 30 June each year) and sample weights are used. Flow rates are annual averages on all permanent workers covered by social security. Standard deviations are in brackets. Source: Author's tabulations from LIAB data, 2001-2009.

1.3.2 The relationship between employment growth and worker turnover

Figure 1.1 shows the relationship between net employment growth rate and worker flows at the establishment level. The horizontal axis represents the establishment growth rate, while the hiring and separation rates are measured on the vertical axis. The graph illustrates how establishment hiring and separation rates vary with the employment growth rate. Similarly to Davis, Faberman and Haltiwanger (2012) for the U.S. and Bellmann, Gerner and Upward (2018) for Germany, I first partition the establishment growth rate in 38 bins, with narrower bins as growth approaches zero, and I add a zero-width bin for no employment growth. Then I regress the hire (separation) rate on a vector of dummy variables corresponding to the 39 bins:

$$h_{et} = \alpha_e + \sum_{g=1}^{G} \beta_g D_{et}^{g} + \epsilon_{et} \tag{1.5}$$

Here h_{et} represents the hiring (separation) rate of establishment e in year t, G=39 is the total number of bins and α_e is the establishment fixed effect[12]. β represents

[12] As I consider data in pooled cross-sectional form (every observation is an establishment-year

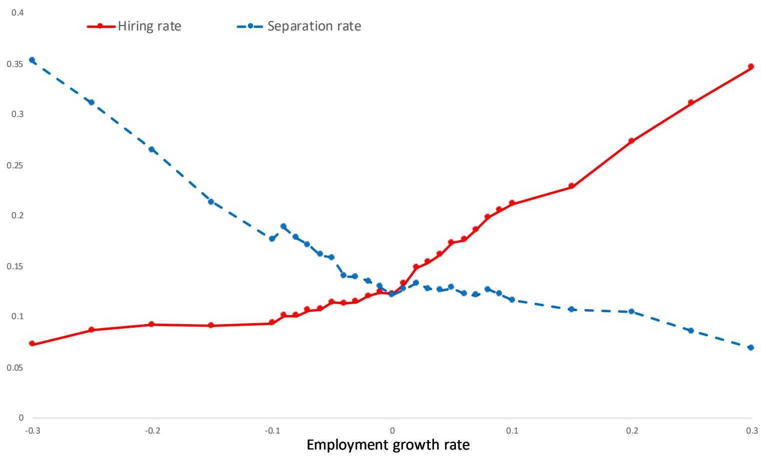
the hiring (separation) response of an increase in the employment growth rate. Figure 1.1 shows that stable establishments with zero net employment growth still exhibit positive worker flows (hiring and separation rates are approximately 12%), suggesting a high degree of worker turnover. Moreover, the hiring (separation) rate sharply increases with the employment growth rate to the right (left) of zero. As observed by Davis et al. (2012), hires rise more rapidly than job creation. The same is true for separations and job destruction. This indicates that growing establishments are more likely to replace workers who separate. However, when contracting, there is a fall in hiring together with an increase in separations. While in Davis et al. (2012) the hiring is almost flat to the left of zero, Figure 1.1 shows that establishments rely on worker attrition when they shrink, in particular for small contractions. This is in line with theoretical models that take into account establishment hiring costs. Coles and Mortensen (2016) develop a stochastic version of the Burdett and Mortensen (1998) model with endogenous quit turnover and costly hiring: a worker who quits represents a sunk cost for the establishment. Thus, when the establishment shrinks, it tends to reduce its hires instead of relying only on layoffs.

When expanding, differently from Davis et al. (2012), establishments increase hires but experience also a reduction in separations. This indicates that expanding establishments try to increase their retention rates instead of relying only on new hires. However, the reduction in separations to the right of zero is less than the reduction in hires to the left of zero, which is in line with Davis et al. (2012). They suggest that growing establishments tend to rely on new hires who are also more likely to leave, generating the need for replacement hires.

Figure 1.2 distinguishes the quit response to growth rate from the overall separations. Stable establishments (with zero net job reallocation) still experience quits. For positive growth rates, separations continue to fall with employment growth, while quits are flat. On the other hand, when establishments shrink,

pair), I use establishment fixed effects to exploit within-establishment variation over time.

Figure 1.1: WORKER FLOW RATES AS A FUNCTION OF ESTABLISHMENT-LEVEL GROWTH

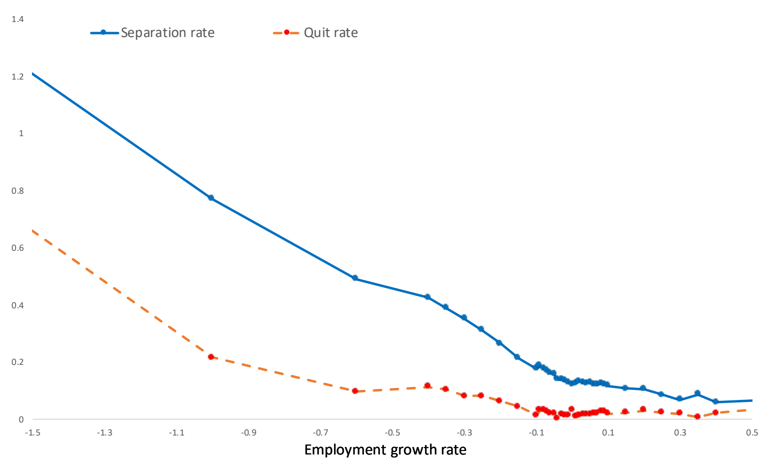


Note: Estimates of a regression of hiring (separation) rate on employment growth rate with robust standard errors clustered at establishment level, surviving establishments only. Both employment and sample weights used. The horizontal axis shows the establishment employment growth rate. Source: Author's tabulations from LIAB data, 2001-2009.

quits increase, in particular for small contractions, even if voluntary separation is not the main channel through which employers reduce their size. However, as I did not use survey data, I cannot distinguish between voluntary quits and layoffs, since my measure of quits relies on employment-to-employment transitions. In addition, as highlighted above, my measure for employer-to-employer transitions is very strict. Thus, I may possibly neglect a proportion of voluntary separations to non-employment or those quits that involve more than seven days breaks between a worker's previous and current job. Figure 1.A.1 in the Appendix shows equivalent estimates of Figure 1.2 but using a wider time window for inter-spell gaps, i.e. 30 days. Though the proportion of quits to total separations is larger, qualitatively Figure 1.A.1 shows a similar pattern in the relationship between quit rate and employment growth rate, in particular the sharper increase in quits for small employment contractions.

Bellmann et al. (2018) perform a similar analysis to the one presented in Figures 1.1 and 1.2 for the worker flows in Germany. Results, however, are slightly different. The amount of turnover for establishments with zero net employment growth is smaller (around 5%), and they observe a sharper increase in separations for declining establishments and a correspondingly sharper increase in hires for expanding establishments. Though they find that establishments rely less both on the hiring margin when contracting and on the retention channel when expanding, the basic pattern of the hiring and separation responses to net employment growth is similar to what observed in Figures 1.1 and 1.2. However, Bellmann et al. (2018) use the IAB survey data on hires and separations, which are subject to the measurement errors highlighted above. For this reason, I decided to base my analysis on the social security data, which should provide more robust results.

Figure 1.2: Separation and quit rates as a function of establishment-level growth



Note: Estimates of regressions of separation and quit rates on employment growth rate with robust standard errors clustered at establishment level, surviving establishments only. Both employment and sample weights used. The horizontal axis shows the establishment employment growth rate. Source: Author's tabulations from LIAB data, 2001-2009.

Because the analysis on worker flows presented so far does not take into account establishment characteristics, such as size or age, Table 1.7 shows worker and job flow rates according to different establishment size classes. Small establishments are growing (job reallocation is positive) and are those with the highest turnover: both the hiring and separation rates are about 20% and the job creation, JC, is very high. Small establishments experience a large job destruction (JD), but the balance between JC and JD is positive. Both job creation and destruction decline with establishment size, but the decline in job creation is sharper. Worker flows decrease on average with establishment size. Large establishments are more stable, with the employment growth slightly negative. It is interesting to notice the behaviour of the employment-to-employment transitions: both the proportion of hiring and separations from and to employment with respect to total hiring is smaller in small establishments than in larger ones. It seems that small establishments rely less on EE transitions and prefer to hire workers from the pool of non-employed individuals. However, the same pattern is observed for separations. On net, small establishments are growing by hiring non-employed workers, while they lose on net workers who quit to other establishments. On the contrary, a large proportion of hires made by large establishments comes from other employers. Thus, this table seems to confirm the results highlighted by Moscarini and Postel-Vinay (2012) that large establishments grow by poaching workers from other establishments, while small establishments need to rely on the pool of non-employed to grow.

Table 1.7: Average worker flow rates by size

	Hiring	Separation	JC	JD	JR	EE (hire)	EE (quit)	NE (hire)	NE (sep.)
1-19									
	0.2142	0.2042	0.1003	0.0902	0.0100	0.0288	0.0322	0.1855	0.1724
	(0.2694)	(0.2566)	(0.2065)	(0.1866)	(0.3092)	(0.0875)	(0.0940)	(0.2552)	(0.2341)
20-99									
	0.1745	0.1757	0.0562	0.0573	-0.0011	0.0383	0.0404	0.1364	0.1357
	(0.1797)	(0.1540)	(0.1247)	(0.1093)	(0.1842)	(0.0680)	(0.0685)	(0.1560)	(0.1268)
100-999									
	0.1444	0.1497	0.0401	0.0454	-0.0054	0.0441	0.0425	0.1004	0.1074
	(0.1620)	(0.1428)	(0.1035)	(0.0850)	(0.1469)	(0.0851)	(0.0695)	(0.1280)	(0.1008)
$\geqslant$1000									
	0.0725	0.0795	0.0166	0.0236	-0.0070	0.0265	0.0182	0.0460	0.0614
	(0.0564)	(0.0389)	(0.0406)	(0.0345)	(0.0602)	(0.0379)	(0.0233)	(0.0325)	(0.0270)

Note: Both employment and sample weights are used. Flow rates are annual averages on full-time, permanent workers covered by social security. Standard deviations are in brackets. Source: Author's tabulations from LIAB data, 2001-2009.

When classifying establishments according to size, it is important to consider that there is high within-size class heterogeneity: for example, some small establishments may be growing and have high productivity, while others may decline, and pay low wages in order to hire replacement workers from the non-employment pool. An important factor to take into account when considering worker turnover is then establishment age. Table 1.8 classifies worker flow rates by establishment age. Start-up establishments experience more worker turnover, and they grow more. Their job creation is very high. On the other hand, mature establishments decline. While the behaviour of hires and separations by age resembles the one by size (total worker flows fall with age), the EE transitions reflect a positive net employer reallocation rate for start-up and young establishments, while mature establishments lose on net workers both towards non-employment and other establishments.

Table 1.9 shows a sharper difference in worker flows when classified by both establishment age and size. Small, start-up establishments have an average hiring rate very high compared to the separation rate, and grow more. On the other hand mature establishments, regardless of their size, lose on net workers and shrink. Small establishments, regardless of the age, gain workers on net from non-employment. However, small start-ups experience also net positive employment-to-employment transitions, while small mature establishments lose workers on net through poaching. In addition, both small and large mature establishments lose on net workers (net job reallocation is negative): small mature establishments lose workers to other establishments, while large establishments lose workers to non-employment.

Table 1.8: Average worker flow rates by age

	Hiring	Separation	JC	JD	JR	EE (hire)	EE (quit)	NE (hire)	NE (sep.)
Start-up									
	0.2887	0.2480	0.1188	0.0781	0.0407	0.0487	0.0474	0.2405	0.2016
	(0.2850)	(0.2537)	(0.2249)	(0.1664)	(0.3112)	(0.0831)	(0.0875)	(0.2716)	(0.2235)
Young									
	0.2258	0.2002	0.0976	0.0720	0.0256	0.0431	0.0390	0.1829	0.1613
	(0.2495)	(0.2241)	(0.1987)	(0.1582)	(0.2803)	(0.0911)	(0.0787)	(0.2282)	(0.2035)
Mature									
	0.1524	0.1581	0.0547	0.0605	-0.0058	0.0330	0.0343	0.1195	0.1241
	(0.1909)	(0.1803)	(0.1363)	(0.1301)	(0.2052)	(0.0769)	(0.0756)	(0.1723)	(0.1556)

Note: Both employment and sample weights are used. Flow rates are annual averages on full-time, permanent workers covered by social security. Standard deviations are in brackets. Source: Author's tabulations from LIAB data, 2001-2009.

Table 1.9: Average worker flow rates by size and age

	Start-up and small	**Mature and small**	**Mature and large**
Hiring	0.3002	0.1943	0.1156
	(0.3174)	(0.2542)	(0.1331)
Separation	0.2468	0.1956	0.1226
	(0.2823)	(0.2516)	(0.1111)
JR	0.0534	-0.0013	-0.0070
	(0.3754)	(0.2910)	(0.1274)
Net EE flows	0.0076	-0.0066	0.0045
	(0.1358)	(0.1200)	(0.0933)
Net NE flows	0.0450	0.0051	-0.0116
	(0.3523)	(0.2591)	(0.0702)

Notes: Both employment and sample weights are used. Flow rates are annual averages on full-time, permanent workers covered by social security. Standard deviations are in brackets. As establishments with more than 1000 employees represent less than one percent of the population, I label 'Large' those establishments that have more than 100 employees. Source: Author's tabulations from LIAB data, 2001-2009.

Table 1.10 compares flow rates at high and low wage establishments. I used the average establishment wage and classified establishments as 'Low wage' if they are in the bottom quintile of the distribution, 'High wage' if they are at the top quintile. At a first glance, results may look counterintuitive, as low wage establishments have positive job reallocation, differently from high wage establishments. However, a closer look at the composition of those hires and separations reveals that net EE transitions are positive for high wage and negative for low wage establishments. The opposite holds for net reallocation to and from non-employment. Interestingly, Haltiwanger et al. (2018) obtain similar results with US data for the period 1998-2011: low wage establishments lose on net workers to other employers, while establishments that pay high wages are able to attract workers through poaching. Table 1.D.2 in Appendix compares again flow rates by wage, but considering only the period 2001-2007, in order to check for business cycle composition effects, as the economic downturn could affect the job reallocation of high wage establishments. However, results are invariant to the choice of the time period[13]. Table 1.D.3 in Appendix shows also worker flow rates decomposed by

[13]During the time period considered in the analysis, the German labour market underwent deep structural changes due to the Hartz reforms, enacted in Germany between 2003 and 2005 (Carrillo-Tudela, Launov and Robin, 2018). Unfortunately, the time span is limited to the years

establishment wage, size and age.

Table 1.11 documents flow rates according to establishment wage, conditional on age. Start-up establishments, irrespective of their wage, have positive job reallocation. On the other hand, mature establishments that offer a high wage decline. This is due to the negative net NE flows: on average, the flows from non-employment are smaller than the flows to non-employment. This is not the case for high-wage start-ups, which have positive NE flows. The table shows no difference in the direction of worker flows for low wage establishments, according to their age. Low wage establishments, both start-up and mature, lose workers on net through poaching and gain workers on net from non-employment.

2001-2009, thus it is not possible to check whether the results of Table 1.10 are influenced by those reforms.

Table 1.10: Average worker flow rates by wage

	Hiring	Separation	JC	JD	JR	EE (hire)	EE (quit)	NE (hire)	NE (sep.)
Low wage									
	0.3022	0.2590	0.1283	0.0851	0.0432	0.0302	0.0400	0.2725	0.2193
	(0.3102)	(0.2799)	(0.2403)	(0.1788)	(0.3340)	(0.0850)	(0.0893)	(0.2909)	(0.2486)
High wage									
	0.1035	0.1171	0.0353	0.0489	-0.0136	0.0422	0.0381	0.0614	0.0792
	(0.1264)	(0.1339)	(0.1056)	(0.1255)	(0.1742)	(0.0920)	(0.0823)	(0.0811)	(0.0854)

Note: 'Low wage' are establishments in the bottom quintile of the wage distribution, 'High wage' are those in the top quintile. Both employment and sample weights are used. Flow rates are annual averages on full-time, permanent workers covered by social security. Standard deviations are in brackets. Source: Author's tabulations from LIAB data, 2001-2009.

Table 1.11: Average worker flow rates by wage conditional on firm age

	Hiring	Separation	JR	Net EE flows	Net NE flows
Start-up					
Low wage					
	0.3980	0.3629	0.0351	-0.0282	0.0633
	(0.3301)	(0.3106)	(0.3760)	(0.1226)	(0.3379)
High wage					
	0.2002	0.1592	0.0410	0.0057	0.0342
	(0.2423)	(0.1646)	(0.2627)	(0.0925)	(0.2372)
Mature					
Low wage					
	0.2700	0.2291	0.0409	-0.0073	0.0483
	(0.2934)	(0.2626)	(0.3063)	(0.1108)	(0.2838)
High wage					
	0.0977	0.1154	-0.0177	0.0039	-0.0216
	(0.1151)	(0.1330)	(0.1697)	(0.1197)	(0.0922)

Note: Both employment and sample weights are used. Flow rates are annual averages on full-time, permanent workers covered by social security. Standard deviations are in brackets. Source: Author's tabulations from LIAB data, 2001-2009.

1.4 Transition probabilities

As in Haltiwanger et al. (2018), Tables 1.12 1.13 and 1.14 present transition probabilities by size of the establishment. The total row and column percentages in Table 1.12 show that small establishments are more likely to be a destination than an origin. Also large establishments are more likely to be a destination, but the discrepancy between the row total and the column total is smaller (45% probability of being a destination against 42% probability of being an origin). The diagonal shows that most worker reallocations happen within a size class. However, medium sized establishments tend to lose workers to both small and large employers. Table 1.13 shows the probability for a worker of coming from a small, medium or large employer, conditional on ending up in a given size establishment. Also this table shows that the majority of transitions is inside a given size. A striking result is that conditional on ending in a large establishment, the least probable event is that the worker was coming from a small establishment

Table 1.12: Worker transition probabilities

		Origin			
		Small	**Medium**	**Large**	**Total**
Destination	**Small**	0.1547	0.1034	0.0816	0.3397
	Medium	0.0630	0.0859	0.0662	0.2150
	Large	0.0582	0.1145	0.2726	0.4453
	Total	0.2758	0.3038	0.4204	1

Note: Both employment and sample weights are used. Flow rates are annual averages on full-time, permanent workers covered by social security. Standard deviations are in brackets. Source: Author's tabulations from LIAB data, 2001-2009.

(13% against 26% and 61%). Again, the results seem to confirm Haltiwanger et al. (2018) findings: there is no evidence of a systematic worker reallocation from small to large establishments. In order to check if some of these findings are related to age differences, I also decompose the destination by age class and calculate again the transition probabilities, conditional on destination (Table 1.14). In Table 1.14, a small, start-up establishment has higher chances to 'poach' workers from medium and large establishments than an equivalently small, but mature establishment (conditional on ending in a small start-up, there is a 62% probability of coming from another size class). On the other hand, conditional on landing a job at a large establishment, the probability of coming from another size class is around 40%, regardless of establishment age. Overall, there is no evidence of large establishments poaching workers from small employers. This is because small establishments are heterogeneous: they can be young and growing, or mature. The role of establishment age helps to clarify the direction of worker reallocation: small start-ups do indeed poach workers from their mature counterparts.

The results presented so far are based on private establishments located in West Germany. In order to make sure that the evidence is not artificially affected by sample selection, Appendix 1.C presents results based on the whole sample of German establishments, private and public, including also those establishments located in the East. Appendix 1.C shows that, apart from some negligible discrepancies in magnitudes, the direction of worker flows is not affected by the sample

Table 1.13: Worker transition probabilities conditional on destination

		Origin		
		Small	**Medium**	**Large**
Destination	**Small**	0.4553	0.3045	0.2402
	Medium	0.2929	0.3993	0.3079
	Large	0.1306	0.2571	0.6122

Note: Both employment and sample weights are used. Flow rates are annual averages on full-time, permanent workers covered by social security. Standard deviations are in brackets. Source: Author's tabulations from LIAB data, 2001-2009.

Table 1.14: Worker transition probabilities classified by establishment age

			Origin		
			Small	**Medium**	**Large**
Destination	**Small**	Start-up	0.3798	0.3902	0.2300
		Young	0.4202	0.2853	0.2945
		Mature	0.4781	0.2923	0.2295
	Medium	Start-up	0.2692	0.4472	0.2836
		Young	0.2683	0.3918	0.3400
		Mature	0.3004	0.3912	0.3084
	Large	Start-up	0.1247	0.2848	0.5905
		Young	0.1271	0.2871	0.5858
		Mature	0.1313	0.2526	0.6161

Note: Both employment and sample weights are used. Flow rates are annual averages on full-time, permanent workers covered by social security. Standard deviations are in brackets. Source: Author's tabulations from LIAB data, 2001-2009.

Table 1.15: Worker transition probabilities, manufacturing sector

		Origin			
		Small	**Medium**	**Large**	**Total**
Destination	**Small**	0.0608	0.0532	0.0374	0.1514
	Medium	0.0564	0.0812	0.0692	0.2069
	Large	0.0754	0.1733	0.3930	0.6417
	Total	0.1927	0.3077	0.4996	1

Note: Both employment and sample weights are used. Flow rates are annual averages on full-time, permanent workers covered by social security. Standard deviations are in brackets. Source: Author's tabulations from LIAB data, 2001-2009.

choice.

This Chapter also explores data along some alternative directions. In particular, Tables 1.15 and 1.16 show the transition probabilities across size classes of establishments in the manufacturing sector[14]. The row and column totals indicate that small establishments are more likely to be an origin, while large establishments are more likely to be a destination (15% against 19% and 64% against 50%). However, Table 1.16 shows that conditional on ending in a large establishment, the least probable event is that a worker is coming from a small establishment (12% probability against 27% and 61%). Also in the manufacturing sector, most reallocations are within each size class. Table 1.17 confirms that, among small establishments, a start-up has a higher poaching rate from medium and large establishments than a mature employer (62% against 58% probability of coming from another size class). Moreover, there is no evidence in support of the theory that large establishments poach workers from small employers, regardless of the age[15].

[14] To increase the sample size, I also consider manufacturing establishments located in the East.

[15] Appendix 1.C analyses also worker flows according to size, age and wage of manufacturing establishments. In addition, it provides evidence on worker reallocation in the trade sector.

Table 1.16: Worker transition probabilities conditional on destination, manufacturing sector

		Origin		
		Small	**Medium**	**Large**
Destination	**Small**	0.4017	0.3515	0.2467
	Medium	0.2727	0.3926	0.3347
	Large	0.1175	0.2700	0.6125

Note: Both employment and sample weights are used. Flow rates are annual averages on full-time, permanent workers covered by social security. Standard deviations are in brackets. Source: Author's tabulations from LIAB data, 2001-2009.

Table 1.17: Worker transition probabilities classified by establishment age, manufacturing sector

			Origin		
			Small	**Medium**	**Large**
Destination	**Small**	Start-up	0.3805	0.4425	0.1770
		Young	0.3590	0.3949	0.2462
		Mature	0.4201	0.3196	0.2603
	Medium	Start-up	0.2315	0.4382	0.3303
		Young	0.3327	0.3747	0.2926
		Mature	0.2694	0.3893	0.3413
	Large	Start-up	0.1347	0.2899	0.5754
		Young	0.1132	0.3600	0.5268
		Mature	0.1173	0.2606	0.6222

Note: Both employment and sample weights are used. Flow rates are annual averages on full-time, permanent workers covered by social security. Standard deviations are in brackets. Source: Author's tabulations from LIAB data, 2001-2009.

1.5 Worker and establishment heterogeneity

Up to now the analysis has focused on the behaviour of worker flows according to different characteristics of the establishments. This section considers also the impact of worker heterogeneity on separation flow rates. In order to do so, I estimate a probit model where the latent dependent variable is defined by

$$s^*_{iet} = \alpha + \beta X_{it} + \gamma Y_t + \phi Z_{et} + \delta D_t + \epsilon_{iet}, \tag{1.6}$$

where s_{iet} is equal to one if a worker i separates from an establishment e in quarter t with $s^*_{iet} \geqslant 0$ and zero otherwise. Similarly to Bachmann and Bechara (2010), in order to account for establishment-size specific differences, I estimate two sets of regressions, one for establishments with more than 100 employees and one for small establishments that have no more than 19 employees. X_{it} is a set of worker characteristics. They include age, sex, education, earnings and nationality. Y_t is a vector indicating GDP in quarter t and one-quarter lagged GDP, so to capture business cycle effects, while Z_{et} indicates establishment age classes-dummy variables for the three age categories 'Start-up', 'Young' and 'Mature', defined above. I also include quarter dummy variables D_t. For the regressions of this section I convert the data into a quarterly panel[16].

1.5.1 Results: worker separation rates

It is possible to compare the probit estimates of Table 1.18 with the results of tables 1.7 and 1.8. The probability of a worker to separate falls with establishment age. This is in line with what observed above, because worker turnover is higher at start-up and young establishments. However, the impact of establishment age on the worker propensity to leave has a different effect depending on whether the

[16] In transforming the dataset I record a separation in quarter t if the worker separates at least once during that quarter.

worker is employed at a small or large establishment. As expected, the probability of a separation decreases with wage. However, the impact of an increase in earnings is higher for large establishments. As regards workers characteristics, I find that worker age reduces the probability of a separation for both classes of establishment size. In particular, this effect is U-shaped, indicating that young and older employees are more likely to separate than middle-aged worker. A possible explanation is that older employees have a higher separation rate due to retirement decisions. Finally, large establishments are initially more cyclically sensitive than small establishments, while lagged GDP is significant only for small employers. These results suggest that the effect of worker characteristics, apart from education, is invariant to the establishment size. On the other hand, establishment age shows a differential pattern by size.

1.5.2 Results: worker quits and transition to non-employment

I decompose worker separations into separations to other establishments (quits) and separations to non-employment. The results are presented in Table 1.19. The effect of worker wage on separations at small establishments is driven by the quit response. This is in line with theoretical models that include worker search effort and endogenous quits: workers at firms who pay more want to leave less, irrespective of establishment size. The age of the establishment has a stronger impact on quits than on separations to non-employment. An interesting result is that an increase in worker earnings reduces only the probability of a quit, but not the probability of separating to non-employment from small firms. In addition, separations to non-employment show a countercyclical behaviour at both small and large establishments, contrary to quits. The suggestion that separations may be influenced also by retirement decisions seems to be confirmed by the behaviour of separations to non-employment. Indeed, while at small establishments quits fall

Table 1.18: Probit estimations, separations from small vs large establishments

	(1) Separation (small)	(2) Separation (large)
GDP_t	0.0013	-0.0013***
	(0.001)	(0.000)
GDP_{t-1}	-0.0051***	0.0008
	(0.001)	(0.001)
Age	-0.0083***	-0.0086***
	(0.000)	(0.000)
Age^2	0.0097***	0.010***
	(0.000)	(0.000)
Education:		
Apprentice	-0.0097***	-0.0015
	(0.002)	(0.001)
Upper secondary school	-0.0076*	0.0119***
	(0.003)	(0.002)
University	-0.0049	0.0131***
	(0.005)	(0.002)
Nationality	-0.0178***	-0.0069***
	(0.005)	(0.001)
Female	-0.0151***	0.0029**
	(0.002)	(0.001)
Wage	-0.0057***	-0.0201***
	(0.002)	(0.003)
Establishment age:		
Young	-0.0118***	0.0018
	(0.004)	(0.006)
Mature	-0.0237***	-0.0130**
	(0.004)	(0.005)
N	172,522	3,521,716
region	Yes	Yes
quarter	Yes	Yes
sector	Yes	Yes
pseudo-R^2	0.0406	0.0591

Note: Table reports marginal effects from a probit specification. Robust standard errors clustered at establishment level are in parentheses. 'Small' indicates < 19 employees; 'Large' indicates $\geqslant 100$ employees. Establishments with more than 1000 employees are excluded from the analysis. 'Nationality' is an indicator variable = 1 if the worker is German and 0 otherwise. Region and industry dummy variables are included. *, **, *** indicates statistical significance at the 10, 5, and 1% levels, respectively. Both employment and sample weights are used. Source: Author's calculations from LIAB data, 2001-2009, transformed into a quarterly dataset.

linearly with worker age, separations to non-employment present the U-shaped pattern already illustrated in Table 1.18.

Table 1.19: Probit estimations, EE vs NE transitions, small vs large establishments

	Small establishments		Large establishments	
	(1)	(2)	(3)	(4)
	EE (quit)	NE (separation)	EE (quit)	NE (separation)
GDP_t	0.0013	-0.0015**	-0.0002	-0.0012***
	(0.001)	(0.000)	(0.000)	(0.000)
GDP_{t-1}	-0.0020**	-0.0006	0.0002	0.0008***
	(0.000)	(0.000)	(0.000)	(0.000)
Age	-0.0009***	-0.0051***	-0.0016***	-0.0044***
	(0.000)	(0.000)	(0.000)	(0.000)
Age^2	-0.0002	0.0068***	0.0012***	0.0058***
	(0.000)	(0.000)	(0.000)	(0.000)
Education:				
Apprentice	-0.0055***	-0.0016	-0.0006	-0.0006
	(0.001)	(0.002)	(0.001)	(0.001)
Upper secondary school	0.0010	-0.0046**	0.0107***	0.0003
	(0.003)	(0.002)	(0.002)	(0.001)
University	0.0022	-0.0022	0.0116***	0.0010
	(0.003)	(0.002)	(0.002)	(0.001)
Nationality	-0.0027	-0.0149***	0.0002	-0.0059***
	(0.003)	(0.003)	(0.001)	(0.001)
Female	-0.0025*	-0.0086***	0.0015	0.0013***
	(0.001)	(0.001)	(0.001)	(0.000)
Wage	-0.0065***	0.0013	-0.0109***	-0.0059***
	(0.001)	(0.001)	(0.002)	(0.001)
Establishment age:				
Young	-0.0069**	-0.0046**	-0.0010	0.0020
	(0.002)	(0.002)	(0.004)	(0.002)
Mature	-0.0124***	-0.0096***	-0.0087**	-0.0030**
	(0.002)	(0.002)	(0.004)	(0.002)
N	172,522	172,522	3,521,716	3,521,716
region	Yes	Yes	Yes	Yes
quarter	Yes	Yes	Yes	Yes
sector	Yes	Yes	Yes	Yes
pseudo-R^2	0.0382	0.0601	0.0509	0.1022

Note: Marginal effects from a probit specification for (1) and (2) 'Small', (3) and (4) 'Large' establishments. 'Small' indicates < 19 employees; 'Large' indicates $\geqslant$100 employees. Establishments with more than 1000 employees are excluded from the analysis. 'Nationality' is an indicator variable = 1 if the worker is German and 0 otherwise. Region and industry dummy variables are included. Robust standard errors clustered at firm level are reported in parentheses. *, **, *** indicates statistical significance at the 10, 5, and 1% levels, respectively. Both employment and sample weights are used. Source: Author's calculations from LIAB data, 2001-2009, transformed into a quarterly dataset.

1.6 Conclusions

This Chapter used LIAB matched employer-employee data to analyse worker turnover across several establishment dimensions. In particular, the analysis focused on the direction of worker reallocations by wage, size and age of the establishments. I first document the relationship between hires, separations and job-to-job quits with the employment growth rate. Findings show that, during a contraction, there is an increase in quits, even if voluntary separation is not the main channel through which employers reduce their size.

There is a tendency of workers to reallocate from low to high wage establishments, consistent with the Burdett and Mortensen (1998) job ladder model. However, workers do not move from small to large employers. These results seem to confirm the empirical evidence found by Haltiwanger et al. (2018).

The probit analysis of separations controlling for worker heterogeneity suggests again that establishment age is a major determinant in workers' movements. There is evidence that quits react to a wage increase regardless of establishment size. This is in line with theoretical models that consider worker search effort and endogenous quits. In addition, the establishment age has a stronger impact on quits than on separations to non-employment. Overall, the empirical analysis suggests that a theoretical model of on-the-job search aimed at capturing worker reallocations across firms, should include an endogenous worker search margin and firm turnover.

Appendix

1.A Identifying employment-to-employment transitions using worker level data

Although the LIAB contains information on the start and end dates of each employment spell, it is possible that a worker, after quitting the current job, takes a break before starting to work at a new establishment. Thus, it is necessary to make some assumptions as regards the length of the inter-spell gaps between employment. The measure of employment-to-employment flow rate identified in the Chapter is very strict, as it allows non-employment breaks of up to 7 days. Table 1.A.1 shows employment-to-employment quit and hire flow rates corresponding to a non-employment time-window of up to 30 days. In this Section I reproduce some of the main results of the Chapter using the 30-days measure. Table 1.A.2 replicates Table 1.7 classifying flow rates according to establishment size. Qualitatively the results are very similar, as small establishments still grow by gaining on net non-employed workers and losing workers who quit to other establishments. Moreover, for large establishments there is more tendency to hire from the employment pool. Large establishments decline mainly by losing workers through the non-employment channel. On the other hand, flow rates by establishment age differ according to the measure used. Table 1.A.3 replicates Table 1.8 using the 30-days measure of employment-to-employment transitions. Start-ups lose on net workers through poaching, as mature establishments. The composition of hires and separations in high and low wage establishments of Table 1.A.4 is similar to the one observed in Table 1.10: high wage establishments are gaining on net workers through employer-to-employer transitions, and losing them to non-employment, while the opposite is true for low wage establishments. Overall, changing the window of time for recording a quit to or a hire from employment does not affect the main qualitative findings across size and wage. On the other hand, results differ for the age category. However, using the 30-days measure implies the possibility that some workers are wrongly recorded as quitting while they were moving to non-employment, while the measure used in the main Chapter is more reliable in identifying those movements.

As regards the relationship between employment-to-employment transitions and establishment growth, Figure 1.A.1 replicates Figure 1.2 but using the 30-days measure of quits. The key features of Figure 1.2 are invariant to the choice of measure: when establishments shrink, quits exhibit a sharp increase, in particular for small employment contractions. When employment grows, establishments still experience positive quits. For small employment increases, there is also an increase in quits, which may confirm the greater separation propensity of expanding establishments found in Davis et al. (2012).

Table 1.A.1: Employment-to-employment transition rates - 30 days gap

Quit to employment	0.0568
	(0.1084)
Hiring from employment	0.0519
	(0.0977)

Note: Both employment and sample weights are used. Flow rates are annual averages on full-time, permanent workers covered by social security. Standard deviations are in brackets. A quit to or hire from employment is identified when a worker moves from an establishment to another, allowing for a maximum of 30 days lag between the employment spells. Source: Author's tabulations from LIAB data, 2001-2009.

Table 1.A.2: Average worker flow rates by size - 30 days gap

	Hiring	Separation	EE (hire)	EE (quit)	NE (hire)	NE (sep.)
1-19						
	0.2142	0.2042	0.0512	0.0640	0.1646	0.1429
	(0.2694)	(0.2566)	(0.1200)	(0.1443)	(0.2351)	(0.2017)
20-99						
	0.1745	0.1757	0.0559	0.0607	0.1192	0.1166
	(0.1796)	(0.1540)	(0.0810)	(0.0875)	(0.1396)	(0.1043)
100-999						
	0.1444	0.1497	0.0566	0.0552	0.0883	0.0951
	(0.1620)	(0.1428)	(0.0908)	(0.0812)	(0.1090)	(0.0823)
⩾1000						
	0.0725	0.0795	0.0296	0.0215	0.0429	0.0581
	(0.0564)	(0.0389)	(0.0388)	(0.0241)	(0.0296)	(0.0255)

Note: Both employment and sample weights are used. Flow rates are annual averages on full-time, permanent workers covered by social security. Standard deviations are in brackets. A quit to or hire from employment is identified when a worker moves from an establishment to another, allowing for a maximum of 30 days lag between the employment spells. Source: Author's tabulations from LIAB data, 2001-2009.

Table 1.A.3: Average worker flow rates by age - 30 days gap

	Hiring	Separation	EE (hire)	EE (quit)	NE (hire)	NE (sep.)
Start-up						
	0.2887	0.2480	0.0744	0.0811	0.2154	0.1695
	(0.2850)	(0.2537)	(0.1106)	(0.1267)	(0.2534)	(0.1930)
Young						
	0.2258	0.2002	0.0634	0.0646	0.1629	0.1378
	(0.2495)	(0.2241)	(0.1138)	(0.1122)	(0.2083)	(0.1754)
Mature						
	0.1524	0.1581	0.0482	0.0533	0.1051	0.1063
	(0.1909)	(0.1803)	(0.0938)	(0.1054)	(0.1546)	(0.1310)

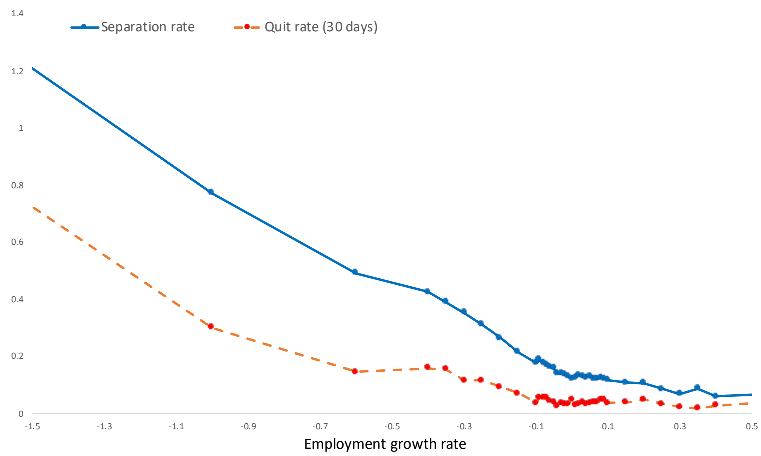
Note: Both employment and sample weights are used. Flow rates are annual averages on full-time, permanent workers covered by social security. A quit to or hire from employment is identified when a worker moves from an establishment to another, allowing for a maximum of 30 days lag between the employment spells. Standard deviations are in brackets. Source: Author's tabulations from LIAB data, 2001-2009.

Table 1.A.4: Average worker flow rates by wage - 30 days gap

	Hiring	Separation	EE (hire)	EE (quit)	NE (hire)	NE (sep.)
Low wage						
	0.3022	0.2589	0.0581	0.0757	0.2456	0.1853
	(0.3102)	(0.2799)	(0.1168)	(0.1380)	(0.2700)	(0.2186)
High wage						
	0.1033	0.1169	0.0468	0.0434	0.0566	0.0737
	(0.1264)	(0.1336)	(0.0939)	(0.0858)	(0.0781)	(0.0792)

Note: 'Low wage' are establishments in the bottom quintile of the wage distribution, 'High wage' are those in the top quintile. Both employment and sample weights are used. Flow rates are annual averages on full-time, permanent workers covered by social security. A quit to or hire from employment is identified when a worker moves from an establishment to another, allowing for a maximum of 30 days lag between the employment spells. Standard deviations are in brackets. Source: Author's tabulations from LIAB data, 2001-2009.

Figure 1.A.1: Separation and quit rates as a function of establishment-level growth - 30 days gap



Note: Estimates of regressions of separation and quit rates on employment growth rate with robust standard errors clustered at establishment level, surviving establishments only. A quit to employment is identified when a worker moves from an establishment to another, allowing for a maximum of 30 days lag between the employment spells. Both employment and sample weights used. The horizontal axis shows the establishment employment growth rate. Source: Author's tabulations from LIAB data, 2001-2009.

1.B Tobit imputation for wage data

A major disadvantage of the dataset is that wages are top censored at the maximum level for social security contributions. In Germany, if the gross wage is higher than the contribution limit, only the amount up to the limit is liable. This limit is updated every year. As the exact wage is not necessary to calculate the contribution, employers do not report wages in excess of the threshold. Thus, workers with wages above the contribution limit are assigned the same wage. In order to overcome this loss of information, I follow Card et al. (2013) and use Tobit regressions to impute wages above the contribution limit. First, I obtained a person-establishment-year record for every full-time worker, with her corresponding daily wage. I group education into 5 classes corresponding to (1) missing; (2) lower secondary school or less, and no vocational qualification; (3) lower secondary school with vocational qualification; (4) upper secondary school; (5) university degree. I also generate as in Card et. al (2013) four age group with 10-year length (20-29, 30-39, 40-49, 50-60). Then, for each combination of year, education level, sex and age range, I fit a separate Tobit regression, which uses the following variables as regressors: age, number of full-time employees at the current establishment and its square, and mean years of schooling. Then, after I obtain the estimates, I replace the censored values with the sum of the predicted values from the Tobit model and a random component drawn from a truncated Normal (as generally it is assumed that log wages follow a Normal distribution)[17]. Once obtained the imputed wages, I computed the average wage paid by each establishment in order to produce the results of Section 1.3.

[17] See Card et al. (2013) for a more detailed explanation.

1.C Robustness analyses

The results presented in the Chapter are based on private establishments located in West Germany. This section explores the data based on a less restrictive selection of observations. Table 1.C.1 shows descriptive statistics for a sample which includes both the public sector and establishments located in the East. The average employer size is smaller than the one observed in Table 1.1, both when considering all workers covered by social security and full-time workers only. Table 1.C.2 shows that this is due to the inclusion of East establishments, which on average are smaller than West establishments. Public establishments, on the other hand, are larger (Table 1.C.3), though there are relatively few observations in the sample. Table 1.C.1 shows also that the average wage is lower in the whole sample, which, as expected, is due to the inclusion of the East (Table 1.C.2). Public sector salaries are, on average, higher (1.C.3).

Table 1.C.6 shows that, similarly to Table 1.2, mature establishments are the largest on average. They are the majority of all German establishments and employ the largest share of full-time workers. On average, they pay a higher salary than their younger counterparts. Table 1.C.6 shows a slightly more pronounced difference between Start-up and Young establishments, which is due to the inclusion of East establishments in the sample (Table 1.C.8). Table 1.C.10 shows also that public establishments are almost exclusively mature. As expected, there is less dispersion in public salaries compared to the private sector, and mature public establishments do not pay, on average, higher wages.

The statistics by number of employees (Tables 1.C.7, 1.C.9 and 1.C.11) confirm that small establishments are the majority and they employ the largest share of workers. In addition, as highlighted in Table 1.3, wages monotonically increase with size, supporting the size-wage premium. By observing the composition of establishments in East and West Germany (Table 1.C.9), there is no striking difference by location. Also wages offered by East establishments monotonically increase with size, but on average salaries are lower for every size category. There is less concentration of small public establishments, on the other hand, even if they still represent the vast majority of establishments in the public sector (Table 1.C.11). There is evidence of a size-wage premium also in the public sector, though there is more wage dispersion in private establishments.

Table 1.C.16 shows the average worker flow rates in the whole sample of German establishments. Though the magnitude of worker reallocations is higher (hiring, separation, and JR rates are higher here than in Table 1.4), the difference is negligible. Differently from Table 1.C.16, the difference between poaching hire and quit rates is positive, while the net employment-to-employment reallocation is negative when considering only private West establishments.

As in Table 1.7, Table 1.C.17 shows that worker flows, job creation and job destruction rates decrease with size. Worker flows are driven mainly by flows in and out of non-employment for small establishments, while large establishments gain workers through poaching but lose workers on net to non-employment. Also the results by age (Table 1.C.18) are largely consistent with those in Section 1.3. The only difference is that here mature establishments lose workers on net through non-employment, but gain workers through employment-to-employment reallocations, albeit the gain is relatively small. Mature, west private establishments, on the other hand, lose on net workers both through the EE and the NE channel (Table 1.8). Overall, their job reallocation is slightly negative as in Table 1.C.18.

The different choice of sample does not change the results on the relationship between flow rates and age and size considered together. Table 1.C.19 shows that the direction of worker flows is the same as in Table 1.9. Small, start-up establishments grow more than mature establishments of any size. Moreover, the sign of net EE flows of small establishments depends on the age: start-up have positive EE flows, but their mature counterparts lose workers on net through poaching.

The composition of worker flows according to wage supports the results for West private establishments (Table 1.C.20 compared to Table 1.10): net EE transitions are positive for high wage and negative for low wage establishments, while net reallocation to and from non-employment is positive for low wage establishments and negative for high wage establishments. The same analysis, conditional on age, confirms the results of Section 1.3 (Table 1.C.21 compared to Table 1.11).

Tables 1.C.22, 1.C.23 and 1.C.24 show the transition probabilities calculated on the whole sample, to be compared respectively to Tables 1.12, 1.13 and 1.14. Results largely confirm those presented in Section 1.4. Though the majority of worker reallocations takes place within each size class, small establishments are more likely to be a destination than an origin. Table 1.C.23 shows that conditional on ending up in a large establishment, there is only a 15% probability that the worker is coming from a small establishment (compared to 29% and 56% from medium and large, respectively). This probability is only slightly smaller for west private establishments (13% in Table 1.13). Overall, these results confirm that there is no evidence of a systematic reallocation from small to large establishments. Conditional on age (Table 1.C.24), the transition probabilities confirm that there is no evidence of large establishments poaching workers from small ones: conditional on ending in a large establishment, the probability of coming from a small one is between 14% and 15%, for all ages.

This Section also explores the direction of worker flows across employer characteristics for private establishments located in the East only. East establishments are on average smaller and offer a lower salary (Table 1.C.4). The magnitude of worker flows is higher than in West establishments (Table 1.C.25 compared to Table 1.4), but this is mainly due to flows in and out of employment, while EE transitions are similar in magnitude. Table 1.C.26 confirms that both job creation and destruction decline with establishment size, but the decomposition between EE and NE

Table 1.C.1: Descriptive statistics, whole sample

	Sample	**Weighted**
Number of distinct establishments	7,328	7,328
Establishment-year observations	39,126	39,126
Mean employees	128	14
	(498)	(74)
Median employees	20	5
Mean employees (full-time)	101	10
	(419)	(61)
Median employees (full-time)	14	3
Mean daily log wage (raw, full-time)	4.200	4.046
	(0.437)	(0.478)
Mean daily log wage (imputed, full-time)	4.205	4.049
	(0.443)	(0.483)

Note: The first column corresponds to the sample statistics, without weights; the second column uses sample weights. The reported averages are simple averages over annual cross-sections of establishments. The number of employees is calculated by aggregating the number of workers covered by the social security system. Standard deviations are in brackets. Source: Author's tabulations from LIAB data collapsed at annual level, 2001-2009.

transitions is different in East and West establishments: large establishments located in the East lose workers on net through poaching, while they gain workers on net from non-employment. In particular, the decline of establishments with more than 1,000 employees is due to the net flows towards other establishments. This evidence is not consistent with an establishment-size ladder, where large establishments are growing more by poaching workers from their smaller counterparts. Table 1.C.27 also reflects some differences between East and West establishments. Here, mature establishments do not decline, but do experience negative poaching from other establishments. These results are confirmed by Table 1.C.28: mature establishments, regardless of their size, experience negative EE flows. Also the transition probabilities in Tables 1.C.31 1.C.32 and 1.C.33, apart from some minor differences, are consistent with those for West establishments. Overall, the analysis on private establishments located in the East reinforces the results shown in Sections 1.3 and 1.4. The rest of this Section presents evidence on worker flows for the manufacturing and trade sectors also.

Table 1.C.2: Descriptive statistics: West vs. East

	West		East	
	Sample	Weighted	Sample	Weighted
Number of distinct establishments	3,683	3,683	3,751	3,751
Establishment-year observations	18,710	18,710	20,416	20,416
Mean employees	174	14	85	13
	(673)	(80)	(238)	(52)
Median employees	23	5	17	4
Mean employees (full-time)	138	10	68	11
	(573)	(66)	(184)	(42)
Median employees (full-time)	15	3	13	3
Mean daily log wage (raw, full-time)	4.340	4.103	4.072	3.879
	(0.431)	(0.487)	(0.401)	(0.408)
Mean daily log wage (imputed, full-time)	4.349	4.107	4.072	3.879
	(0.442)	(0.492)	(0.402)	(0.409)

Note: 'Sample' corresponds to sample statistics, without weights; the 'Weighted' columns use sample weights. The reported averages are simple averages over annual cross-sections of establishments. The number of employees is calculated by aggregating the number of workers covered by the social security system. Standard deviations are in brackets. Source: Author's tabulations from LIAB data collapsed at annual level, 2001-2009.

Table 1.C.3: Descriptive statistics: private vs. public

	Private		Public	
	Sample	Weighted	Sample	Weighted
Number of distinct establishments	6,605	6,605	723	723
Establishment-year observations	33,941	33,941	5,185	5,185
Mean employees	111	13	237	38
	(474)	(68)	(626)	(141)
Median employees	15	5	81	12
Mean employees (full-time)	93	10	151	22
	(423)	(59)	(392)	(86)
Median employees (full-time)	12	3	48	6
Mean daily log wage (raw, full-time)	4.153	4.022	4.511	4.462
	(0.442)	(0.476)	(0.218)	(0.286)
Mean daily log wage (imputed, full-time)	4.158	4.025	4.514	4.465
	(0.450)	(0.481)	(0.222)	(0.289)

Note: 'Sample' corresponds to sample statistics, without weights; the 'Weighted' columns use sample weights. The reported averages are simple averages over annual cross-sections of establishments. The number of employees is calculated by aggregating the number of workers covered by the social security system. Standard deviations are in brackets. Source: Author's tabulations from LIAB data collapsed at annual level, 2001-2009.

Table 1.C.4: Descriptive statistics, East private establishments

	Sample	**Weighted**
Number of distinct establishments	3,350	3,350
Establishment-year observations	17,622	17,622
Mean employees	66	11
	(180)	(41)
Median employees	13	4
Mean employees (full-time)	56	10
	(157)	(36)
Median employees (full-time)	11	3
Mean daily log wage (raw, full-time)	4.012	3.854
	(0.392)	(0.397)
Mean daily log wage (imputed, full-time)	4.013	3.855
	(0.392)	(0.398)

Note: The first column corresponds to the sample statistics, without weights; the second column uses sample weights. The reported averages are simple averages over annual cross-sections of establishments. The number of employees is calculated by aggregating the number of workers covered by the social security system. Standard deviations are in brackets. Source: Author's tabulations from LIAB data collapsed at annual level, 2001-2009.

Table 1.C.5: Descriptive statistics by industry

	Agriculture/Mining/ Energy/Water		Manufacturing		Trade		Transport/ Communication		Finance/ Business services		Other services	
	Sample	Weighted	Sample	Weighted	Sample	Weighted	Sample	Weighted	Sample	Weighted	Sample	Weighted
Number of distinct establishments	312	312	1,698	1,698	1,146	1,146	276	276	960	960	1,339	1,339
Establishment-year observations	1,734	1,734	10,435	10,435	5,413	5,413	1,267	1,267	4,415	4,415	6,446	6,446
Mean employees	91	11	186	27	38	11	173	17	117	11	90	10
	(233)	(40)	(725)	(148)	(91)	(26)	(492)	(77)	(485)	(65)	(267)	(43)
Median employees	22	4	28	7	10	5	23	6	14	4	13	4
Mean employees (full-time)	85	10	169	23	27	7	139	14	90	9	61	6
	(217)	(38)	(668)	(135)	(65)	(19)	(410)	(64)	(394)	(54)	(195)	(31)
Median employees (full-time)	19	3	25	5	6	3	19	4	10	2	8	2
Mean daily log wage (raw, full-time)	4.108	3.894	4.233	4.135	4.099	4.045	4.188	4.061	4.240	4.081	3.996	3.814
	(0.457)	(0.484)	(0.401)	(0.422)	(0.439)	(0.442)	(0.447)	(0.514)	(0.512)	(0.557)	(0.480)	(0.468)
Mean daily log wage (imputed, full-time)	4.111	3.895	4.239	4.138	4.103	4.048	4.194	4.069	4.249	4.086	3.998	3.815
	(0.463)	(0.485)	(0.410)	(0.426)	(0.446)	(0.447)	(0.456)	(0.526)	(0.526)	(0.566)	(0.483)	(0.469)

Note: 'Sample' corresponds to sample statistics, without weights; the 'Weighted' columns use sample weights. The reported averages are simple averages over annual cross-sections of establishments. The number of employees is calculated by aggregating the number of workers covered by the social security system. Standard deviations are in brackets. Source: Author's tabulations from LIAB data collapsed at annual level, 2001-2009.

Table 1.C.6: SUMMARY STATISTICS BY AGE OF ESTABLISHMENT, WHOLE SAMPLE

	Start-up	**Young**	**Mature**
Mean employees	7	7	12
	(38)	(39)	(68)
Establishment share	11.40%	16.38%	72.22%
Employment share	8.19%	10.46%	81.35%
Log average wage	3.952	3.947	4.087
	(0.479)	(0.518)	(0.469)

Note: 'Start-up' indicates that the establishment is 5 or less years old; 'Young' indicates that the establishment has age $\in (5, 10]$; 'Mature' indicates that the establishment is more than 10 years old. Sample weights are used. Standard deviations are in brackets. Top coded wages are imputed with Tobit predicted values. Source: Author's tabulations from LIAB data, 2001-2009.

Table 1.C.7: SUMMARY STATISTICS BY NUMBER OF EMPLOYEES, WHOLE SAMPLE

	1-19	**20-99**	**100-999**	**$\geqslant$1000**
Establishment share	91.47%	7.07%	/	/
Employment share	40.49%	24.07%	28.75%	6.69%
Log average wage	4.017	4.366	4.503	4.730
	(0.481)	(0.343)	(0.362)	(0.241)

Note: Due to data confidentiality rules, cells with a low share must be replaced by '/'. Sample weights are used. Standard deviations are in brackets. The number of employees is calculated by aggregating the number of workers covered by the social security system. Top coded wages are imputed with Tobit predicted values. Source: Author's tabulations from LIAB data, 2001-2009.

Table 1.C.8: SUMMARY STATISTICS BY AGE OF ESTABLISHMENT: WEST VS. EAST

		West			**East**	
	Start-up	Young	Mature	Start-up	Young	Mature
Mean employees	7	6	12	8	8	12
	(37)	(42)	(74)	(40)	(31)	(45)
Establishment share	11.76%	14.56%	73.67%	10.34%	21.67%	67.99%
Employment share	8.18%	8.25%	83.57%	8.21%	16.79%	75.00%
Log average wage	3.995	3.983	4.149	3.810	3.875	3.892
	(0.485)	(0.563)	(0.471)	(0.431)	(0.409)	(0.404)

Note: 'Start-up' indicates that the establishment is 5 or less years old; 'Young' indicates that the establishment has age $\in (5, 10]$; 'Mature' indicates that the establishment is more than 10 years old. Sample weights are used. Standard deviations are in brackets. Top coded wages are imputed with Tobit predicted values. Source: Author's tabulations from LIAB data, 2001-2009.

Table 1.C.9: Summary statistics by number of employees: West vs. East

	West				East			
	1-19	20-99	100-999	$\geqslant$1000	1-19	20-99	100-999	$\geqslant$1000
Establishment share	91.87%	6.66%	/	/	90.30%	8.25%	/	/
Employment share	38.92%	22.87%	30.33%	7.88%	41.84%	28.06%	26.77%	3.32%
Log average wage	4.073	4.461	4.592	4.788	3.849	4.144	4.242	4.473
	(0.491)	(0.305)	(0.305)	(0.165)	(0.405)	(0.324)	(0.388)	(0.336)

Note: Due to data confidentiality rules, cells with a low share must be replaced by '/'. Sample weights are used. Standard deviations are in brackets. The number of employees is calculated by aggregating the number of workers covered by the social security system. Top coded wages are imputed with Tobit predicted values. Source: Author's tabulations from LIAB data, 2001-2009.

Table 1.C.10: Summary statistics by age of establishment: private vs. public

	Private			Public		
	Start-up	Young	Mature	Start-up	Young	Mature
Mean employees	7	6	11	22	30	22
	(37)	(37)	(66)	(106)	(103)	(85)
Establishment share	11.98%	17.16%	70.87%	1.20%	2.80%	96.00%
Employment share	9.10%	11.32%	79.58%	1.19%	3.81%	95.01%
Log average wage	3.949	3.942	4.058	4.471	4.435	4.465
	(0.479)	(0.518)	(0.467)	(0.196)	(0.209)	(0.292)

Note: 'Start-up' indicates that the establishment is 5 or less years old; 'Young' indicates that the establishment has age $\in (5, 10]$; 'Mature' indicates that the establishment is more than 10 years old. Sample weights are used. Standard deviations are in brackets. Top coded wages are imputed with Tobit predicted values. Source: Author's tabulations from LIAB data, 2001-2009.

Table 1.C.11: Summary statistics by number of employees: private vs. public

	Private				Public			
	1-19	20-99	100-999	$\geqslant$1000	1-19	20-99	100-999	$\geqslant$1000
Establishment share	92.15%	6.58%	/	/	79.53%	15.78%	/	/
Employment share	42.77%	23.53%	27.11%	6.58%	21.16%	27.82%	43.00%	8.03%
Log average wage	3.996	4.338	4.476	4.738	4.434	4.570	4.629	4.691
	(0.479)	(0.347)	(0.383)	(0.252)	(0.297)	(0.224)	(0.189)	(0.179)

Note: Due to data confidentiality rules, cells with a low share must be replaced by '/'. Sample weights are used. Standard deviations are in brackets. The number of employees is calculated by aggregating the number of workers covered by the social security system. Top coded wages are imputed with Tobit predicted values. Source: Author's tabulations from LIAB data, 2001-2009.

Table 1.C.12: Summary statistics by age of establishment, East private establishments

	Start-up	**Young**	**Mature**
Mean employees	8	8	10
	(40)	(29)	(38)
Establishment share	10.71%	22.43%	66.86%
Employment share	9.35%	18.36%	72.30%
Log average wage	3.804	3.870	3.858
	(0.430)	(0.406)	(0.389)

Note: 'Start-up' indicates that the establishment is 5 or less years old; 'Young' indicates that the establishment has age $\in (5, 10]$; 'Mature' indicates that the establishment is more than 10 years old. Sample weights are used. Standard deviations are in brackets. Top coded wages are imputed with Tobit predicted values. Source: Author's tabulations from LIAB data, 2001-2009.

Table 1.C.13: Summary statistics by number of employees, East private establishments

	1-19	**20-99**	**100-999**	**$\geqslant$1000**
Establishment share	91.18%	7.63%	/	/
Employment share	45.68%	27.76%	24.07%	2.48%
Log average wage	3.829	4.106	4.175	4.417
	(0.395)	(0.317)	(0.399)	(0.393)

Note: Due to data confidentiality rules, cells with a low share must be replaced by '/'. Sample weights are used. Standard deviations are in brackets. The number of employees is calculated by aggregating the number of workers covered by the social security system. Top coded wages are imputed with Tobit predicted values. Source: Author's tabulations from LIAB data, 2001-2009.

Table 1.C.14: Summary statistics by age of establishment and by industry

	Agriculture/Mining/ Energy/Water			**Manufacturing**			**Trade**		
	Start-up	Young	Mature	Start-up	Young	Mature	Start-up	Young	Mature
Establishment share	8.40%	11.77%	79.84%	6.26%	11.68%	82.06%	12.36%	15.62%	72.01%
Employment share	8.14%	14.31%	77.56%	3.85%	6.51%	89.64%	8.57%	10.75%	80.68%
Log average wage	3.910	3.960	3.883	4.239	4.043	4.144	3.962	4.020	4.068
	(0.454)	(0.473)	(0.490)	(0.436)	(0.457)	(0.418)	(0.451)	(0.472)	(0.438)
	Transport/ Communication			**Finance/ Business services**			**Other services**		
	Start-up	Young	Mature	Start-up	Young	Mature	Start-up	Young	Mature
Establishment share	12.81%	18.71%	68.48%	12.06%	22.89%	65.06%	15.12%	17.82%	67.06%
Employment share	10.04%	11.69%	78.27%	14.87%	15.60%	69.53%	14.35%	15.37%	70.28%
Log average wage	3.969	3.846	4.153	3.996	3.994	4.136	3.760	3.710	3.855
	(0.540)	(0.473)	(0.511)	(0.565)	(0.622)	(0.539)	(0.453)	(0.486)	(0.463)

Note: Due to data confidentiality rules, cells with a low share must be replaced by '/'. 'Start-up' indicates that the establishment is 5 or less years old; 'Young' indicates that the establishment has age $\in (5, 10]$; 'Mature' indicates that the establishment is more than 10 years old. Sample weights are used. Standard deviations are in brackets. Top coded wages are imputed with Tobit predicted values. Source: Author's tabulations from LIAB data, 2001-2009.

Table 1.C.15: Summary statistics by number of employees and by industry

	Agriculture/Mining/ Energy/Water				**Manufacturing**				**Trade**			
	1-19	20-99	100-999	⩾1000	1-19	20-99	100-999	⩾1000	1-19	20-99	100-999	⩾1000
Establishment share	90.16%	9.04%	/	/	82.55%	/	3.85%	/	94.06%	5.19%	0.75%	0%
Employment share	50.24%	27.85%	19.30%	2.60%	19.21%	22.88%	42.00%	15.91%	57.65%	24.32%	18.03%	0%
Log average wage	3.863	4.181	4.228	4.465	4.077	4.372	4.595	4.799	4.028	4.340	4.533	0
	(0.482)	(0.399)	(0.571)	(0.429)	(0.423)	(0.305)	(0.251)	(0.157)	(0.447)	(0.287)	(0.263)	(0)

	Transport/ Communication				**Finance/ Business services**				**Other services**			
	1-19	20-99	100-999	⩾1000	1-19	20-99	100-999	⩾1000	1-19	20-99	100-999	⩾1000
Establishment share	86.64%	11.32%	/	/	92.65%	6.01%	/	/	95.27%	4.08%	/	/
Employment share	30.99%	29.60%	33.69%	5.72%	41.09%	24.95%	27.03%	6.93%	55.52%	22.07%	19.73%	2.68%
Log average wage	4.036	4.253	4.440	4.664	4.055	4.508	4.371	4.779	3.796	4.178	4.246	4.434
	(0.547)	(0.271)	(0.286)	(0.104)	(0.561)	(0.437)	(0.561)	(0.395)	(0.466)	(0.368)	(0.433)	(0.324)

Note: Due to data confidentiality rules, cells with a low share must be replaced by '/'. Sample weights are used. Standard deviations are in brackets. The number of employees is calculated by aggregating the number of workers covered by the social security system. Top coded wages are imputed with Tobit predicted values. Source: Author's tabulations from LIAB data, 2001-2009.

Table 1.C.16: Average worker flow rates, whole sample

Hiring	0.1799
	(0.2241)
Separation	0.1760
	(0.1984)
JC	0.0671
	(0.1647)
JD	0.0632
	(0.1355)
JR	0.0039
	(0.2323)
Quit to employment	0.0351
	(0.0755)
Hiring from employment	0.0361
	(0.0864)

Note: Both employment and sample weights are used. Flow rates are annual averages on full-time, permanent workers covered by social security. Standard deviations are in brackets. Source: Author's tabulations from LIAB data, 2001-2009.

Table 1.C.17: Average worker flow rates by size, whole sample

	Hiring	Separation	JC	JD	JR	EE (hire)	EE (quit)	NE (hire)	NE (sep.)
1-19									
	0.2164	0.2056	0.1009	0.0902	0.0108	0.0292	0.0312	0.1874	0.1750
	(0.2758)	(0.2566)	(0.2106)	(0.1844)	(0.3108)	(0.0897)	(0.0930)	(0.2599)	(0.2357)
20-99									
	0.1820	0.1780	0.0615	0.0575	0.0039	0.0410	0.0382	0.1412	0.1402
	(0.2035)	(0.1625)	(0.1521)	(0.1086)	(0.2050)	(0.0956)	(0.0665)	(0.1728)	(0.1383)
100-999									
	0.1583	0.1594	0.0438	0.0449	-0.0011	0.0424	0.0404	0.1160	0.1192
	(0.1819)	(0.1560)	(0.1166)	(0.0887)	(0.1594)	(0.0806)	(0.0656)	(0.1570)	(0.1241)
$\geqslant$1000									
	0.0860	0.0947	0.0178	0.0265	-0.0087	0.0275	0.0233	0.0585	0.0715
	(0.0930)	(0.0806)	(0.0446)	(0.0449)	(0.0703)	(0.0449)	(0.0370)	(0.0756)	(0.0596)

Note: Both employment and sample weights are used. Flow rates are annual averages on full-time, permanent workers covered by social security. Standard deviations are in brackets. Source: Author's tabulations from LIAB data, 2001-2009.

Table 1.C.18: Average worker flow rates by age, whole sample

	Hiring	Separation	JC	JD	JR	EE (hire)	EE (quit)	NE (hire)	NE (sep.)
Start-up									
	0.2992	0.2530	0.1238	0.0776	0.0462	0.0507	0.0491	0.2491	0.2048
	(0.2943)	(0.2550)	(0.2337)	(0.1620)	(0.3164)	(0.0871)	(0.0882)	(0.2775)	(0.2255)
Young									
	0.2425	0.2147	0.1024	0.0746	0.0278	0.0409	0.0385	0.2018	0.1765
	(0.2761)	(0.2343)	(0.2143)	(0.1601)	(0.2946)	(0.0939)	(0.0776)	(0.2561)	(0.2160)
Mature									
	0.1598	0.1632	0.0569	0.0603	-0.0034	0.0340	0.0333	0.1260	0.1302
	(0.2021)	(0.1839)	(0.1459)	(0.1288)	(0.2115)	(0.0851)	(0.0736)	(0.1815)	(0.1617)

Note: Both employment and sample weights are used. Flow rates are annual averages on full-time, permanent workers covered by social security. Standard deviations are in brackets. Source: Author's tabulations from LIAB data, 2001-2009.

Table 1.C.19: Average worker flow rates by size and age, whole sample

	Start-up and small	**Mature and small**	**Mature and large**
Hiring	0.3067	0.1942	0.1315
	(0.3267)	(0.2573)	(0.1550)
Separation	0.2483	0.1955	0.1350
	(0.2832)	(0.2499)	(0.1283)
JR	0.0583	-0.0013	-0.0035
	(0.3804)	(0.2903)	(0.1375)
Net EE flows	0.0106	-0.0052	0.0038
	(0.1364)	(0.1204)	(0.0880)
Net NE flows	0.0473	0.0038	-0.0074
	(0.3546)	(0.2588)	(0.0951)

Notes: Both employment and sample weights are used. Flow rates are annual averages on full-time, permanent workers covered by social security. Standard deviations are in brackets. As establishments with more than 1000 employees represent less than one percent of the population, I label 'Large' those establishments that have more than 100 employees. Source: Author's tabulations from LIAB data, 2001-2009.

Table 1.C.20: Average worker flow rates by wage, whole sample

	Hiring	Separation	JC	JD	JR	EE (hire)	EE (quit)	NE (hire)	NE (sep.)
Low wage									
	0.3334	0.2839	0.1364	0.0869	0.0494	0.0316	0.0419	0.3022	0.2425
	(0.3272)	(0.2818)	(0.2592)	(0.1785)	(0.3503)	(0.0865)	(0.0878)	(0.3069)	(0.2537)
High wage									
	0.1065	0.1201	0.0348	0.0485	-0.0136	0.0435	0.0368	0.0630	0.0834
	(0.1334)	(0.1267)	(0.1123)	(0.1141)	(0.1703)	(0.1019)	(0.0776)	(0.0803)	(0.0861)

Note: 'Low wage' are establishments in the bottom quintile of the wage distribution, 'High wage' are those in the top quintile. Both employment and sample weights are used. Flow rates are annual averages on full-time, permanent workers covered by social security. Standard deviations are in brackets. Source: Author's tabulations from LIAB data, 2001-2009.

Table 1.C.21: Average worker flow rates by wage conditional on firm age, whole sample

	Hiring	Separation	JR	Net EE flows	Net NE flows
Start-up					
Low wage					
	0.4399	0.3755	0.0643	-0.0251	0.0895
	(0.3425)	(0.3019)	(0.3989)	(0.1233)	(0.3607)
High wage					
	0.1794	0.1590	0.0204	0.0040	0.0155
	(0.2198)	(0.1707)	(0.2476)	(0.1072)	(0.2101)
Mature					
Low wage					
	0.2975	0.2595	0.0379	-0.0089	0.0466
	(0.3054)	(0.2692)	(0.3171)	(0.1110)	(0.2913)
High wage					
	0.1024	0.1180	-0.0157	0.0070	-0.0227
	(0.1274)	(0.1242)	(0.1670)	(0.1233)	(0.0923)

Note: Both employment and sample weights are used. Flow rates are annual averages on full-time, permanent workers covered by social security. Standard deviations are in brackets. Source: Author's tabulations from LIAB data, 2001-2009.

Table 1.C.22: Worker transition probabilities, whole sample

		Origin			
		Small	**Medium**	**Large**	**Total**
Destination	**Small**	0.1551	0.1048	0.0772	0.3372
	Medium	0.0725	0.0931	0.0753	0.2409
	Large	0.0633	0.1213	0.2373	0.4219
	Total	0.2909	0.3193	0.3898	1

Note: Both employment and sample weights are used. Flow rates are annual averages on full-time, permanent workers covered by social security. Standard deviations are in brackets. Source: Author's tabulations from LIAB data, 2001-2009.

Table 1.C.23: Worker transition probabilities conditional on destination, whole sample

		Origin		
		Small	**Medium**	**Large**
Destination	**Small**	0.4601	0.3108	0.2291
	Medium	0.3010	0.3865	0.3125
	Large	0.1499	0.2876	0.5625

Note: Both employment and sample weights are used. Flow rates are annual averages on full-time, permanent workers covered by social security. Standard deviations are in brackets. Source: Author's tabulations from LIAB data, 2001-2009.

Table 1.C.24: Worker transition probabilities classified by establishment age, whole sample

			Origin		
			Small	**Medium**	**Large**
Destination	**Small**	Start-up	0.4380	0.3438	0.2182
		Young	0.4713	0.2924	0.2363
		Mature	0.4617	0.3092	0.2291
	Medium	Start-up	0.2610	0.4418	0.2972
		Young	0.3036	0.4032	0.2931
		Mature	0.3063	0.3761	0.3175
	Large	Start-up	0.1538	0.3158	0.5304
		Young	0.1362	0.3526	0.5112
		Mature	0.1528	0.2796	0.5675

Note: Both employment and sample weights are used. Flow rates are annual averages on full-time, permanent workers covered by social security. Standard deviations are in brackets. Source: Author's tabulations from LIAB data, 2001-2009.

Table 1.C.25: Average worker flow rates, East private establishments

Hiring	0.2282
	(0.2736)
Separation	0.2161
	(0.2347)
JC	0.0862
	(0.1999)
JD	0.0741
	(0.1523)
JR	0.0121
	(0.2756)
Quit to employment	0.0322
	(0.0725)
Hiring from employment	0.0302
	(0.0778)

Note: Both employment and sample weights are used. Flow rates are annual averages on full-time, permanent workers covered by social security. Standard deviations are in brackets. Source: Author's tabulations from LIAB data, 2001-2009.

Table 1.C.26: Average worker flow rates by size, East private establishments

	Hiring	Separation	JC	JD	JR	EE (hire)	EE (quit)	NE (hire)	NE (sep.)
1-19									
	0.2441	0.2302	0.1098	0.0960	0.0139	0.0271	0.0279	0.2173	0.2029
	(0.3093)	(0.2739)	(0.2345)	(0.1903)	(0.3351)	(0.0943)	(0.0875)	(0.2893)	(0.2575)
20-99									
	0.2177	0.2065	0.0762	0.0650	0.0112	0.0338	0.0336	0.1844	0.1734
	(0.2418)	(0.1954)	(0.1820)	(0.1230)	(0.2412)	(0.0714)	(0.0606)	(0.2234)	(0.1752)
100-999									
	0.2238	0.2108	0.0672	0.0543	0.0129	0.0314	0.0359	0.1926	0.1755
	(0.2536)	(0.2117)	(0.1645)	(0.1129)	(0.2170)	(0.0574)	(0.0563)	(0.2433)	(0.1921)
$\geqslant$1000									
	0.1651	0.1720	0.0330	0.0399	-0.0069	0.0253	0.0424	0.1401	0.1302
	(0.2087)	(0.1999)	(0.0639)	(0.0835)	(0.1171)	(0.0279)	(0.0764)	(0.1987)	(0.1584)

Note: Both employment and sample weights are used. Flow rates are annual averages on full-time, permanent workers covered by social security. Standard deviations are in brackets. Source: Author's tabulations from LIAB data, 2001-2009.

Table 1.C.27: AVERAGE WORKER FLOW RATES BY AGE, EAST PRIVATE ESTABLISHMENTS

	Hiring	Separation	JC	JD	JR	EE (hire)	EE (quit)	NE (hire)	NE (sep.)
Start-up									
	0.3410	0.2829	0.1436	0.0855	0.0581	0.0524	0.0508	0.2893	0.2329
	(0.3193)	(0.2699)	(0.2617)	(0.1706)	(0.3495)	(0.0961)	(0.0872)	(0.2952)	(0.2411)
Young									
	0.2746	0.2426	0.1134	0.0814	0.0319	0.0343	0.0358	0.2406	0.2075
	(0.3127)	(0.2518)	(0.2386)	(0.1684)	(0.3221)	(0.0858)	(0.0758)	(0.2959)	(0.2374)
Mature									
	0.2019	0.2007	0.0719	0.0707	0.0012	0.0263	0.0288	0.1759	0.1724
	(0.2503)	(0.2228)	(0.1766)	(0.1452)	(0.2499)	(0.0723)	(0.0690)	(0.2360)	(0.2059)

Note: Both employment and sample weights are used. Flow rates are annual averages on full-time, permanent workers covered by social security. Standard deviations are in brackets. Source: Author's tabulations from LIAB data, 2001-2009.

Table 1.C.28: Average worker flow rates by size and age, East private establishments

	Start-up and small	**Mature and small**	**Mature and large**
Hiring	0.3375	0.2170	0.2019
	(0.3549)	(0.2880)	(0.2379)
Separation	0.2695	0.2186	0.1901
	(0.2994)	(0.2662)	(0.1959)
JR	0.0679	-0.0017	0.0118
	(0.4151)	(0.3091)	(0.1933)
Net EE flows	0.0152	-0.0047	-0.0046
	(0.1417)	(0.1210)	(0.0679)
Net NE flows	0.0531	0.0026	0.0161
	(0.3768)	(0.2791)	(0.1734)

Notes: Both employment and sample weights are used. Flow rates are annual averages on full-time, permanent workers covered by social security. Standard deviations are in brackets. As establishments with more than 1000 employees represent less than one percent of the population, I label 'Large' those establishments that have more than 100 employees. Source: Author's tabulations from LIAB data, 2001-2009.

Table 1.C.29: Average worker flow rates by wage, East private establishments

	Hiring	Separation	JC	JD	JR	EE (hire)	EE (quit)	NE (hire)	NE (sep.)
Low wage									
	0.3383	0.2930	0.1345	0.0892	0.0453	0.0297	0.0391	0.3091	0.2545
	(0.3305)	(0.2742)	(0.2641)	(0.1797)	(0.3551)	(0.0811)	(0.0805)	(0.3116)	(0.2515)
High wage									
	0.0855	0.1156	0.0264	0.0565	-0.0301	0.0304	0.0335	0.0553	0.0824
	(0.1078)	(0.1338)	(0.0776)	(0.1151)	(0.1492)	(0.0558)	(0.0770)	(0.0829)	(0.0985)

Note: 'Low wage' are establishments in the bottom quintile of the wage distribution, 'High wage' are those in the top quintile. Both employment and sample weights are used. Flow rates are annual averages on full-time, permanent workers covered by social security. Standard deviations are in brackets. Source: Author's tabulations from LIAB data, 2001-2009.

Table 1.C.30: Average worker flow rates by wage conditional on firm age, East private establishments

	Hiring	Separation	JR	Net EE flows	Net NE flows
Start-up					
Low wage					
	0.4532	0.3660	0.0873	-0.0125	0.0997
	(0.3417)	(0.2794)	(0.4080)	(0.1305)	(0.3724)
High wage					
	0.0931	0.1545	-0.0614	-0.0294	-0.0320
	(0.1468)	(0.1675)	(0.1911)	(0.1252)	(0.1329)
Mature					
Low wage					
	0.2982	0.2708	0.0274	-0.0086	0.0359
	(0.3068)	(0.2664)	(0.3212)	(0.1044)	(0.2943)
High wage					
	0.0809	0.1108	-0.0299	0.0000	-0.0300
	(0.0923)	(0.1301)	(0.1338)	(0.0796)	(0.0963)

Note: Both employment and sample weights are used. Flow rates are annual averages on full-time, permanent workers covered by social security. Standard deviations are in brackets. Source: Author's tabulations from LIAB data, 2001-2009.

Table 1.C.31: Worker transition probabilities, East private establishments

		Origin			
		Small	**Medium**	**Large**	**Total**
Destination	**Small**	0.1868	0.1252	0.0731	0.3851
	Medium	0.0999	0.1146	0.0857	0.3001
	Large	0.0568	0.1077	0.1502	0.3147
	Total	0.3434	0.3476	0.3090	1

Note: Both employment and sample weights are used. Flow rates are annual averages on full-time, permanent workers covered by social security. Standard deviations are in brackets. Source: Author's tabulations from LIAB data, 2001-2009.

Table 1.C.32: Worker transition probabilities conditional on destination, East private establishments

		Origin		
		Small	**Medium**	**Large**
Destination	**Small**	0.4851	0.3252	0.1897
	Medium	0.3327	0.3819	0.2854
	Large	0.1803	0.3422	0.4774

Note: Both employment and sample weights are used. Flow rates are annual averages on full-time, permanent workers covered by social security. Standard deviations are in brackets. Source: Author's tabulations from LIAB data, 2001-2009.

Table 1.C.33: Worker transition probabilities classified by establishment age, East private establishments

			Origin		
			Small	**Medium**	**Large**
Destination	**Small**	Start-up	0.4983	0.2949	0.2068
		Young	0.5010	0.3166	0.1824
		Mature	0.4764	0.3349	0.1887
	Medium	Start-up	0.2509	0.4381	0.3110
		Young	0.3544	0.4065	0.2391
		Mature	0.3410	0.3666	0.2923
	Large	Start-up	0.1837	0.3578	0.4585
		Young	0.1707	0.4266	0.4027
		Mature	0.1909	0.3354	0.4737

Note: Both employment and sample weights are used. Flow rates are annual averages on full-time, permanent workers covered by social security. Standard deviations are in brackets. Source: Author's tabulations from LIAB data, 2001-2009.

Table 1.C.34: Average worker flow rates, manufacturing sector

Hiring	0.1146
	(0.1437)
Separation	0.1230
	(0.1352)
JC	0.0408
	(0.1027)
JD	0.0492
	(0.1014)
JR	-0.0084
	(0.1576)
Quit to employment	0.0266
	(0.0649)
Hiring from employment	0.0287
	(0.0551)

Note: Both employment and sample weights are used. Flow rates are annual averages on full-time, permanent workers covered by social security. Standard deviations are in brackets. Source: Author's tabulations from LIAB data, 2001-2009.

Table 1.C.35: Average worker flow rates by size, manufacturing sector

	Hiring	Separation	JC	JD	JR	EE (hire)	EE (quit)	NE (hire)	NE (sep.)
1-19									
	0.1757	0.1807	0.0841	0.0891	-0.0050	0.0236	0.0310	0.1522	0.1497
	(0.2327)	(0.2263)	(0.1791)	(0.1735)	(0.2778)	(0.0818)	(0.0989)	(0.2192)	(0.2015)
20-99									
	0.1380	0.1358	0.0500	0.0478	0.0022	0.0307	0.0267	0.1075	0.1093
	(0.1514)	(0.1227)	(0.1023)	(0.0848)	(0.1498)	(0.0524)	(0.0553)	(0.1337)	(0.1042)
100-999									
	0.0929	0.1106	0.0256	0.0433	-0.0177	0.0305	0.0287	0.0625	0.0820
	(0.0917)	(0.0998)	(0.0586)	(0.0790)	(0.1091)	(0.0471)	(0.0627)	(0.0718)	(0.0687)
$\geqslant$1000									
	0.0664	0.0721	0.0172	0.0229	-0.0057	0.0266	0.0169	0.0398	0.0553
	(0.0527)	(0.0354)	(0.0407)	(0.0318)	(0.0588)	(0.0385)	(0.0244)	(0.0271)	(0.0228)

Note: Both employment and sample weights are used. Flow rates are annual averages on full-time, permanent workers covered by social security. Standard deviations are in brackets. Source: Author's tabulations from LIAB data, 2001-2009.

Table 1.C.36: Average worker flow rates by age, manufacturing sector

	Hiring	Separation	JC	JD	JR	EE (hire)	EE (quit)	NE (hire)	NE (sep.)
Start-up									
	0.1950	0.1542	0.0965	0.0557	0.0408	0.0493	0.0349	0.1458	0.1195
	(0.2050)	(0.1798)	(0.1714)	(0.1304)	(0.2391)	(0.0766)	(0.0845)	(0.1814)	(0.1584)
Young									
	0.1666	0.1411	0.0732	0.0477	0.0255	0.0360	0.0295	0.1307	0.1118
	(0.2061)	(0.1654)	(0.1598)	(0.1135)	(0.2130)	(0.0698)	(0.0653)	(0.1941)	(0.1466)
Mature									
	0.1074	0.1203	0.0360	0.0490	-0.0130	0.0272	0.0261	0.0802	0.0944
	(0.1328)	(0.1301)	(0.0918)	(0.0990)	(0.1475)	(0.0525)	(0.0639)	(0.1191)	(0.1081)

Note: Both employment and sample weights are used. Flow rates are annual averages on full-time, permanent workers covered by social security. Standard deviations are in brackets. Source: Author's tabulations from LIAB data, 2001-2009.

Table 1.C.37: Average worker flow rates by size and age, manufacturing sector

	Start-up and small	**Mature and small**	**Mature and large**
Hiring	0.3088	0.1549	0.0842
	(0.2979)	(0.2115)	(0.0830)
Separation	0.2475	0.1728	0.0992
	(0.2995)	(0.2177)	(0.0881)
JR	0.0614	-0.0179	-0.0150
	(0.3976)	(0.2596)	(0.0972)
Net EE flows	0.0148	-0.0088	0.0035
	(0.1929)	(0.1213)	(0.0666)
Net NE flows	0.0458	-0.0090	-0.0186
	(0.3630)	(0.2288)	(0.0564)

Notes: Both employment and sample weights are used. Flow rates are annual averages on full-time, permanent workers covered by social security. Standard deviations are in brackets. As establishments with more than 1000 employees represent less than one percent of the population, I label 'Large' those establishments that have more than 100 employees. Source: Author's tabulations from LIAB data, 2001-2009.

Table 1.C.38: Average worker flow rates by wage, manufacturing sector

	Hiring	Separation	JC	JD	JR	EE (hire)	EE (quit)	NE (hire)	NE (sep.)
Low wage									
	0.2138	0.1840	0.1078	0.0780	0.0298	0.0159	0.0172	0.1983	0.1671
	(0.2652)	(0.2175)	(0.2139)	(0.1605)	(0.2972)	(0.0563)	(0.0570)	(0.2579)	(0.2047)
High wage									
	0.0755	0.0956	0.0219	0.0421	-0.0202	0.0302	0.0275	0.0453	0.0682
	(0.0718)	(0.0926)	(0.0547)	(0.0857)	(0.1103)	(0.0494)	(0.0660)	(0.0417)	(0.0551)

Note: 'Low wage' are establishments in the bottom quintile of the wage distribution, 'High wage' are those in the top quintile. Both employment and sample weights are used. Flow rates are annual averages on full-time, permanent workers covered by social security. Standard deviations are in brackets. Source: Author's tabulations from LIAB data, 2001-2009.

Table 1.C.39: Average worker flow rates by wage conditional on firm age, manufacturing sector

	Hiring	Separation	JR	Net EE flows	Net NE flows
Start-up					
Low wage					
	0.2534	0.1906	0.0628	0.0087	0.0541
	(0.2632)	(0.1856)	(0.3238)	(0.0900)	(0.2675)
High wage					
	0.1210	0.1161	0.0049	0.0141	-0.0092
	(0.1017)	(0.1328)	(0.1698)	(0.0796)	(0.1368)
Mature					
Low wage					
	0.2037	0.1792	0.0244	-0.0012	0.0259
	(0.2547)	(0.2179)	(0.2853)	(0.0771)	(0.2689)
High wage					
	0.0740	0.0954	-0.0214	0.0021	-0.0235
	(0.0703)	(0.0919)	(0.1091)	(0.0800)	(0.0587)

Note: Both employment and sample weights are used. Flow rates are annual averages on full-time, permanent workers covered by social security. Standard deviations are in brackets. Source: Author's tabulations from LIAB data, 2001-2009.

Table 1.C.40: Average worker flow rates, trade sector

Hiring	0.1574
	(0.1904)
Separation	0.1537
	(0.1683)
JC	0.0696
	(0.1602)
JD	0.0659
	(0.1322)
JR	0.0037
	(0.2288)
Quit to employment	0.0357
	(0.0745)
Hiring from employment	0.0380
	(0.0836)

Note: Both employment and sample weights are used. Flow rates are annual averages on full-time, permanent workers covered by social security. Standard deviations are in brackets. Source: Author's tabulations from LIAB data, 2001-2009.

Table 1.C.41: AVERAGE WORKER FLOW RATES BY SIZE, TRADE SECTOR

	Hiring	Separation	JC	JD	JR	EE (hire)	EE (quit)	NE (hire)	NE (sep.)
1-19									
	0.1616	0.1542	0.0872	0.0798	0.0074	0.0272	0.0298	0.1343	0.1248
	(0.2251)	(0.2083)	(0.1882)	(0.1623)	(0.2751)	(0.0804)	(0.0869)	(0.2067)	(0.1851)
20-99									
	0.1534	0.1623	0.0486	0.0575	-0.0089	0.0464	0.0432	0.1072	0.1194
	(0.1454)	(0.1214)	(0.1191)	(0.0940)	(0.1691)	(0.0930)	(0.0641)	(0.1041)	(0.0943)
100-999									
	0.1519	0.1388	0.0520	0.0389	0.0131	0.0557	0.0408	0.0963	0.0983
	(0.1358)	(0.0763)	(0.1172)	(0.0639)	(0.1479)	(0.0723)	(0.0422)	(0.0892)	(0.0555)

Note: Both employment and sample weights are used. Flow rates are annual averages on full-time, permanent workers covered by social security. Standard deviations are in brackets. Source: Author's tabulations from LIAB data, 2001-2009.

Table 1.C.42: Average worker flow rates by age, trade sector

	Hiring	Separation	JC	JD	JR	EE (hire)	EE (quit)	NE (hire)	NE (sep.)
Start-up									
	0.2244	0.1751	0.1256	0.0764	0.0492	0.0507	0.0391	0.1736	0.1363
	(0.2820)	(0.1906)	(0.2527)	(0.1440)	(0.3222)	(0.0963)	(0.0833)	(0.2652)	(0.1679)
Young									
	0.2047	0.1866	0.0994	0.0812	0.0182	0.0460	0.0379	0.1588	0.1488
	(0.2358)	(0.2043)	(0.2058)	(0.1565)	(0.2881)	(0.0982)	(0.0713)	(0.2146)	(0.1898)
Mature									
	0.1437	0.1470	0.0595	0.0627	-0.0032	0.0355	0.0350	0.1083	0.1124
	(0.1667)	(0.1596)	(0.1358)	(0.1272)	(0.2051)	(0.0799)	(0.0739)	(0.1394)	(0.1359)

Note: Both employment and sample weights are used. Flow rates are annual averages on full-time, permanent workers covered by social security. Standard deviations are in brackets. Source: Author's tabulations from LIAB data, 2001-2009.

Table 1.C.43: Average worker flow rates by size and age, trade sector

	Start-up and small	**Mature and small**	**Mature and large**
Hiring	0.2318	0.1407	0.1507
	(0.3198)	(0.1942)	(0.1307)
Separation	0.1761	0.1431	0.1364
	(0.2130)	(0.2017)	(0.0772)
JR	0.0556	-0.0025	0.0143
	(0.3653)	(0.2467)	(0.1436)
Net EE flows	0.0049	-0.0057	0.0162
	(0.1298)	(0.1054)	(0.0851)
Net NE flows	0.0508	0.0028	-0.0021
	(0.3382)	(0.2198)	(0.0811)

Notes: Both employment and sample weights are used. Flow rates are annual averages on full-time, permanent workers covered by social security. Standard deviations are in brackets. There are no establishments with more than 1000 employees in the trade sector, hence 'Large' here are those establishments that have more than 100 employees. Source: Author's tabulations from LIAB data, 2001-2009.

Table 1.C.44: Average worker flow rates by wage, trade sector

	Hiring	Separation	JC	JD	JR	EE (hire)	EE (quit)	NE (hire)	NE (sep.)
Low wage									
	0.2012	0.1710	0.1056	0.0754	0.0302	0.0164	0.0161	0.1849	0.1550
	(0.2736)	(0.2246)	(0.2302)	(0.1616)	(0.3083)	(0.0649)	(0.0610)	(0.2585)	(0.2148)
High wage									
	0.1351	0.1365	0.0524	0.0538	-0.0014	0.0649	0.0483	0.0702	0.0884
	(0.1479)	(0.1296)	(0.1255)	(0.1178)	(0.1878)	(0.1103)	(0.0797)	(0.0756)	(0.0920)

Note: 'Low wage' are establishments in the bottom quintile of the wage distribution, 'High wage' are those in the top quintile. Both employment and sample weights are used. Flow rates are annual averages on full-time, permanent workers covered by social security. Standard deviations are in brackets. Source: Author's tabulations from LIAB data, 2001-2009.

Table 1.C.45: Average worker flow rates by wage conditional on firm age, trade sector

	Hiring	Separation	JR	Net EE flows	Net NE flows
Start-up					
Low wage					
	0.2483	0.1868	0.0615	0.0025	0.0590
	(0.3659)	(0.2185)	(0.4125)	(0.0956)	(0.3864)
High wage					
	0.1298	0.1983	-0.0685	-0.0097	-0.0588
	(0.1690)	(0.2233)	(0.2608)	(0.1894)	(0.1152)
Mature					
Low wage					
	0.1764	0.1587	0.0177	-0.0018	0.0193
	(0.2335)	(0.2158)	(0.2538)	(0.0853)	(0.2396)
High wage					
	0.1359	0.1344	0.0015	0.0176	-0.0163
	(0.1485)	(0.1235)	(0.1859)	(0.1307)	(0.1062)

Note: Both employment and sample weights are used. Flow rates are annual averages on full-time, permanent workers covered by social security. Standard deviations are in brackets. Source: Author's tabulations from LIAB data, 2001-2009.

Table 1.C.46: Worker transition probabilities, trade sector

		Origin			
		Small	**Medium**	**Large**	**Total**
Destination	**Small**	0.2777	0.1402	0.0932	0.5111
	Medium	0.0960	0.1149	0.0726	0.2836
	Large	0.0451	0.0788	0.0814	0.2053
	Total	0.4188	0.3339	0.2472	1

Note: Both employment and sample weights are used. Flow rates are annual averages on full-time, permanent workers covered by social security. Standard deviations are in brackets. Source: Author's tabulations from LIAB data, 2001-2009.

Table 1.C.47: Worker transition probabilities conditional on destination, trade sector

		Origin		
		Small	**Medium**	**Large**
Destination	**Small**	0.5433	0.2743	0.1824
	Medium	0.3387	0.4052	0.2561
	Large	0.2197	0.3840	0.3963

Note: Both employment and sample weights are used. Flow rates are annual averages on full-time, permanent workers covered by social security. Standard deviations are in brackets. Source: Author's tabulations from LIAB data, 2001-2009.

1.D Additional tables

Table 1.D.1: Summary statistics, establishments with age $\leqslant 2$ years

Mean employees	7
	(22)
Establishment share	2.04%
Employment share	1.49%
Log average wage	4.028
	(0.444)

Note: Sample weights are used. Standard deviations are in brackets. Top coded wages are imputed with Tobit predicted values. Only full-time employees. Source: Author's tabulations from LIAB data, 2001-2009.

Table 1.D.2: Average worker flow rates by wage - LIAB 2001-2007

	Hiring	Separation	JC	JD	JR	EE (hire)	EE (quit)	NE (hire)	NE (sep.)
Low wage									
	0.2813	0.2421	0.1205	0.0813	0.0393	0.0253	0.0318	0.2564	0.2106
	(0.3001)	(0.2687)	(0.2256)	(0.1726)	(0.3167)	(0.0800)	(0.0810)	(0.2866)	(0.2492)
High wage									
	0.1043	0.1195	0.0364	0.0516	-0.0152	0.0436	0.0394	0.0607	0.0801
	(0.1333)	(0.1408)	(0.1162)	(0.1352)	(0.1885)	(0.1013)	(0.0870)	(0.0806)	(0.0855)

Note: 'Low wage' are establishments in the bottom quintile of the wage distribution, 'High wage' are those in the top quintile. Both employment and sample weights are used. Flow rates are annual averages on full-time, permanent workers covered by social security. Standard deviations are in brackets. Source: Author's tabulations from LIAB data, 2001-2007.

Table 1.D.3: Average worker flow rates by wage, size and age

	High wage		**Low wage**	
	Start-up and small	Mature and large	Mature and small	Mature and large
Hiring	0.1598	0.0924	0.2226	0.3278
	(0.1831)	(0.1112)	(0.2709)	(0.2201)
Separation	0.1813	0.0989	0.1996	0.3143
	(0.2593)	(0.0803)	(0.2505)	(0.2144)
JR	-0.0215	-0.0065	0.0230	0.0135
	(0.3185)	(0.1307)	(0.3033)	(0.1899)
Net EE flows	0.0240	0.0099	-0.0035	-0.0284
	(0.1260)	(0.1114)	(0.1072)	(0.0798)
Net NE flows	-0.0469	-0.0164	0.0265	0.0414
	(0.2748)	(0.0464)	(0.2844)	(0.1532)

Note: Both employment and sample weights are used. Flow rates are annual averages on full-time, permanent workers covered by social security. Standard deviations are in brackets. Source: Author's tabulations from LIAB data, 2001-2009.

Chapter 2

Equilibrium firm growth and worker reallocation

2.1 Introduction

Labour markets are characterised by significant amount of turnover. Davis, Haltiwanger and Schuh (1996) show that over ten per cent of the existing jobs in the US manufacturing sector are destroyed every year and replaced by the same amount through net creation. Moreover, Haltiwanger, Jarmin and Miranda (2013), analysing U.S. employment data, observe that start-up firms are responsible for only 3% of employment, but almost 20% of gross job creation. Their evidence is consistent with a framework where new firms with better technology gradually drive out of business pre-existing firms[1].

From the theoretical side, the framework of this Chapter is related to the vast research on vintage capital models in frictional labour markets, first introduced by Aghion and Howitt (1994). They study the effect of technological growth

[1]See also Hobijn and Jovanovic (2001) on the IT revolution that started in the 1970s, which favoured new firms and destroyed the old ones, suggesting a characterisation of the economy based on the Schumpeterian's idea of creative destruction.

on labour market reallocation and equilibrium unemployment. The authors extend the standard Diamond-Mortensen-Pissarides framework (Mortensen and Pissarides, 1994, Pissarides, 2000) by introducing an exogenous rate of technological progress. Newly created jobs are born with the most advanced technology, while existing jobs can acquire the technological innovation if the firm pays a fixed cost. If the firm fails to upgrade to the new standard, the existing jobs become obsolete, leading to endogenous job destruction, which in turn increases equilibrium unemployment[2]. Caballero and Hammour (1994, 1996) consider a vintage model with exogenous technological progress that is embodied in production units, or jobs. As firms cannot upgrade the existing units with the new technology, existing jobs will inevitably become outdated and consequently destroyed, leading to a continuous process of creation and destruction.

However, as Hornstein, Krusell and Violante (2007) point out, the framework analysed by this literature does not allow for heterogeneity in productivity: at the moment of creation, all vacant firms have the best technology possible. Thus, they enrich the Diamond-Mortensen-Pissarides (henceforth DMP) setting by introducing a non-degenerate distribution of vacancies across vintages. The effect of technological progress on labour market equilibrium is an increase in unemployment and unemployment duration.

Nevertheless, Hornstein et al. (2007), by using a DMP approach, do not consider the effect of technological growth and labour market frictions on job to job transitions, which are considerably large in the data (Fallick and Fleischman, 2004). In order to overcome this limitation, I use an efficiency wage structure as in Coles and Mortensen (2016). The CM setting constitutes a dynamic extension of the on-the-job search model by Burdett and Mortensen (1998). It introduces hiring costs, together with firm specific and aggregate productivity shocks, and captures equilibrium turnover as well as out of steady state dynamics. In addition, differently from the model of Hornstein et al. (2007), it allows to analyse the

[2]A similar framework is analysed by Mortensen and Pissarides (1998).

relationship between firm size and wages.

The approach of this paper, while it does not consider its out of steady state dynamic implications, enriches the CM setting by assuming that there is technological progress with vintage effects. New firms are created with a productivity drawn from a technology frontier. While the frontier grows over time, a given firm's productivity remains fixed, undergoing the process of obsolescence documented in the empirical literature. However, as in Hornstein et al. (2007), there is heterogeneity in firms' initial level of productivity. Not all start-ups are born with the highest technology possible, thus firms with low starting productivity may fail to grow. The model can thus capture interesting firm dynamics: there is a high likelihood of exit of young firms, but conditional on survival, start-up firms grow quickly over time and are responsible for a significant proportion of gross job creation (Haltiwanger et al., 2013).

The model considers two investment margins: firms' hiring costs, as in the CM framework, and workers' search intensity. Much of the existing literature that stems from the Burdett and Mortensen (1998) approach does not model worker search intensity. Generally, it is assumed that unemployed workers receive job offers at a higher rate than employed workers, but those job offers do not depend on the agents' relative search effort. The assumption is motivated by the fact that the job finding rate of the unemployed observed in the data is higher than the employer-to-employer transition rate. However, if the only decision of the worker is to accept or not a wage offer, this would imply that unemployed workers have access to a better search technology than the employed (Coles and Mortensen, 2016). In order to overcome this limitation, I introduce an endogenous search effort choice. Lentz (2010) introduces a contractable search intensity in a model with heterogeneous workers and firms. Here, on the other hand, search effort is endogenous as in Christensen, Lentz, Mortensen, Neumann and Werwatz (2005). As Christensen et al. (2005) point out, workers who currently earn less have more to gain by increasing their search effort, thus the model estimates a measure of search effort which is strictly decreasing in the rank of the employer's wage[3]. Differently from Christensen et al. (2005), here the offer arrival rate of each worker depends not only on individual search effort, but also on the aggregate effort by all workers, so that higher search effort by others will reduce the individual chances of getting a job offer, resulting in a congestion externality.

Here, as in CM, the firm does not respond to outside offers received by its employees. This assumption has consequences as regards the way workers form expectations on employment values. With no outside offer-matching, when the employee receives an outside offer, she forms rational expectations on future wages at the two firms and chooses the firm that offers the higher expected value. On the other hand, an outside offer-matching framework, when on-the-job search is unobservable, implies moral hazard: knowing employers can retain them by matching outside offers, workers employed at a low wage have an incentive to search more intensively. Moreover, a worker may even move to a lower paying firm if she expects the new employer to be more likely to match outside offers in the future (Postel-Vinay and Robin, 2004 and Kiraly, 2007).

The paper proceeds as follows: Section 2.2 describes the model; Section 2.3 illustrates optimal search behaviour by workers and firms in a stationary environment; Section 2.4 determines the wage equation and the stationary equilibrium; Section 2.5 describes the numerical implementation.; Section 2.6 concludes.

2.2 The Model

This paper considers a continuous time, infinite horizon economy. There is a unit measure of agents who are risk neutral and equally productive. Agents can be workers, either employed or unemployed, or entrepreneurs trying to start-up a new company. Each agent discounts the future at rate $r > 0$ and dies at rate $\delta_w > 0$.

[3]See also Bagger and Lentz (2014) and Lentz (2014) for recent models with endogenous search intensity.

δ_w also describes the inflow of new agents into the market, where each new agent begins life either as unemployed or as an entrepreneur. I introduce technological growth with vintage effects. The economy's technology frontier grows exogenously at rate $g > 0$. The flow value of home production at date t is be^{gt} where $b \geq 0$. To ensure bounded payoffs I assume growth rate $g < r + \delta_w$.

Firms are risk neutral and have constant returns to scale in the number of employees, n, with fixed marginal revenue product of labour p. At exogenous rate μ, a new start-up firm enters the market with one employee at date t and has initial productivity p, defined as

$$p = ze^{gt}$$

where z is a random draw from baseline c.d.f. $\Gamma(.)$ with support $[b, \overline{p}]$. Thus, $\overline{p}e^{gt}$ describes the most favourable productivity draw at date t, while be^{gt} describes the worst. Exogenous firm destruction shocks occur at rate $\delta_f > 0$, in which event the firm shuts down and its employees become unemployed. On the other hand, while the firm survives, its productivity p is forever fixed at this initial value. However, as the technological frontier grows, there is a relative decline in p with respect to the market average.

It is useful to transform variables by defining

$$x(p, t) = pe^{-gt}.$$

Here output is defined relative to the initial productivity p. For example, if a firm is born in t_0 its initial productivity will be $p = ze^{gt_0}$. Thus, at date t, its relative quality will be $x = ze^{-g\tau}$ where $\tau = t - t_0$. It is possible to think of τ as the age of the firm. Thus a firm with productivity p at date t is equivalent to a new start-up with quality $z = x(p, t)$.

Differentiation implies a firm's quality x declines over time according to:

$$\dot{x} = -gx.$$

A firm's quality, in general, can take any value $x \in [0, \overline{p}]$.

Let $G(x,t)$ denote the number of unemployed workers plus those workers employed at firms with quality no greater than x at date t. In Coles and Mortensen (2016) the employment distribution is a relevant state variable. As, however, I focus only on balanced growth paths, I only consider stationary equilibria in which the equilibrium employment distribution $G(x)$ is time invariant[4].

Thus at any date t, each firm's state is described by (x, n, t), where the firm's productivity is $p = e^{gt}x$, n is its number of employees, and t is time. t can also be considered as a technology parameter which describes the frontier distribution of productivity draws.

Following Coles and Mortensen (2016) there is asymmetric information: quality x is private information to the firm. Following that approach, I consider Markov Perfect (Bayesian) equilibria where each firm posts a sequence of spot wages using an equilibrium wage strategy $w = w(x, n, t)$. Employees observe the size of the firm n and the current state of technology t and so use the announced wage w to infer the firm's current quality x. I only consider fully revealing equilibria where higher quality firms post strictly higher wages.

As in the CM model, firm hiring is costly. The cost of recruiting new workers at rate H is $pC(H, n)$, where $C(.)$ is increasing in both arguments and has constant returns. If a firm with n employees decides to recruit an additional worker at rate H, then the cost of recruitment is $npc(H/n)$ where H/n is the recruitment effort required per employee and p describes their foregone output. $c(.) = C(\frac{H}{n}, 1)$ is a standard twice continuously differentiable function with $c(0) = c'(0) = 0$ and strictly convex with $c''(.) > 0$.

[4]I simplify notation by omitting reference to G in the equilibrium strategies.

Given random contacts and technology t, let $\lambda(t)$ denote the gross job offer rate by firms and $F(W,t)$ denote the fraction of those job offers which yield value to workers no greater than W. These objects are determined endogenously by aggregating over the wage and recruitment strategies of all firms.

Differently from CM, here the worker's job search effort $k \geq 0$ is endogenous. I suppose employed workers can only search for outside opportunities in their own, rather than the firm's time. Thus the cost of job search is $be^{gt}\phi(k)$, so that search costs reflect foregone leisure opportunities, and $\phi(.)$ is positive, increasing, twice differentiable and convex. I assume $\phi(k) = 0$ for $k \in [0, \underline{k}]$ with $\underline{k} > 0$ so that all workers seek at rate $k \geq \underline{k}$, and $\phi'(\underline{k}) = 0$. If $\overline{K}(t)$ denotes aggregate search effort across all workers at date t, then $k\lambda(t)/\overline{K}(t)$ denotes the rate at which a worker who invests effort k receives a job offer. Note this implies a standard congestion externality: greater search effort by others reduces the chances any given job seeker receives a job offer.

In what follows I identify a quality threshold $x_0 > 0$, such that a firm closes once its quality declines to $x \leqslant x_0$. As the employment distribution does not change over time, in a stationary equilibrium also x_0 is time invariant. In any such equilibrium, let $G(x_0) = U$ denote the number of non-employed workers.

Let $E(t) \leq U$ denote the measure of those unemployed workers who choose to be entrepreneurs at date t. There is perfect crowding out, so that each entrepreneur successfully creates a new start-up at rate $\mu/E(t)$. Once the start-up has been created, the entrepreneur sells it, gains expected profit $\pi_0(t)$, and becomes the firm's first employee. The start-up firm's quality is then revealed, considered as a random draw z from $\Gamma(.)$.

2.2.1 Equilibrium Properties

Following CM, I consider Markov perfect (Bayesian) equilibria in which the set of equilibrium wage strategies $w = w(x, n, t)$ is

(P1) fully revealing; i.e. wage $w(x,.)$ is continuous and strictly increasing in quality x, $\forall x \in (x_0, \overline{p}]$ and,

(P2) firm size invariant; i.e. $w(.) = w(x,t)$ is independent of n.

That wage strategies are continuous and strictly increasing in x is a standard property both in the BM literature and in the first price auction literature with independent private values (McAfee and McMillan, 1987). Firm size invariance (P2) occurs as there are constant returns to production and in recruitment costs.

As there is asymmetric information, each employee's belief on the firm's quality x depends on (w', t). Thus, for any announced wage $w' \in [w(x_0,t), w(\overline{p},t)]$, Bayes rule and property (P1) implies the worker believes the firm's quality is $x = \widehat{x}(w',.)$ where $\widehat{x}$ uniquely solves $w' = w(\widehat{x}, t)$. If the firm instead posts wage $w' < w(x_0,t)$, existence of an equilibrium requires belief $\widehat{x}(w',.) = x_0$. If instead the firm posts wage $w' > w(\overline{p},.)$ let $\widehat{x}(w',.) = \overline{p}$.

I suppose throughout that all endogenous objects to be determined in equilibrium are differentiable functions.

2.3 Optimal Behaviour

In this section I first consider worker optimality, then firm optimality and finally the aggregation problem in a stationary equilibrium.

2.3.1 Worker Optimality

Let $V_u(t)$ denote the value of being unemployed at date t. Now consider an employed worker in firm (x,n,t) which announces wage w'. Properties (P1) and (P2) imply the worker's belief of the firm's quality x, denoted $\widehat{x}(w',t)$, is a singleton. As wages do not depend on firm size, the expected discounted value of employment in this firm, in any stationary equilibrium, must then be of the form $W(x,t)$

with $x = \widehat{x}(w', t)$. Of course given the equilibrium wage strategy $w = w(x, t)$ is fully revealing, this belief $\widehat{x}$, along the firm's equilibrium path, coincides with the firm's actual x.

In what follows firms with quality $x \in (x_0, \overline{p}]$ make strictly positive profit, while firm $x = x_0$ makes no profit and so closes down (as $x < x_0$ in the entire future). As the equilibrium wage $w = w(x, t)$ is fully revealing, strictly positive profit implies $W(x, t) \geq V_u(t)$ for all $x \in (x_0, \overline{p}]$, otherwise all employees quit into unemployment which yields zero profit. Thus while $x > x_0$, employed workers do not quit into unemployment and $W(.)$ is identified recursively by:

$$(r + \delta_w)W(x, t) = \max_{k>0} \left\langle \begin{array}{c} w(x, t) - gx\frac{\partial W}{\partial x} + \frac{\partial W}{\partial t} \\ +\delta_f[V_u(t) - W(x, t)] - be^{gt}\phi(k) \\ +\frac{k}{\overline{K}(t)}\lambda(t)\int \max[W' - W(x, t), 0]dF(W', t) \end{array} \right\rangle \tag{2.1}$$

The flow value of being employed at firm (believed to be) x with market technology t equals flow wage income, plus the capital gains attributed to (i) declining quality of employer x (ii) improving aggregate technology t, (iii) a possible job destruction shock and (iv) optimal job search which yields an outside offer at rate $k\lambda(t)/\overline{K}(t)$ with corresponding value $W' \sim F(.)$. As equilibrium requires the wage paid $w(.)$ must be strictly increasing in x, the value of employment $W(.)$ must also be strictly increasing in x. Thus along the equilibrium path an employee at firm x, who earns wage $w = w(x, t)$, only quits to an outside offer from a higher quality firm $x' > x$ which reveals its type by offering a strictly higher wage $w' = w(x', t) > w$. As firms of quality $x \leq x_0$ immediately close down, I have $W(x, t) = V_u(t)$ for all $x \leq x_0$.

Similarly, the value of being unemployed and choosing home production is given by

$$(r + \delta_w)V_u(t) = \max_{k>0} \left\langle \begin{array}{c} be^{gt} + \frac{dV_u}{dt} - be^{gt}\phi(k) \\ +\frac{k}{\overline{K}(t)}\lambda(t)\int \max[W' - V_u, 0]dF(W', t) \end{array} \right\rangle. \tag{2.2}$$

The flow value of being unemployed at time t equals the flow value of home production, plus the capital gains due to (i) improving aggregate technology t and (ii) optimal job search with an outside offer received at rate $k\lambda(t)/\overline{K}(t)$.

As described above, unemployed workers can decide to become entrepreneurs at date t. Free entry into entrepreneurship implies $V_u(t)$ is also given by

$$(r+\delta_w)V_u(t) = \max_{k>0} \left\langle \begin{array}{c} \frac{dV_u}{dt} - be^{gt}\phi(k) \\ +\frac{k}{\overline{K}(t)}\lambda(t)\int \max[W' - V_u, 0]dF(W', t) \\ +\frac{\mu}{E(t)}\left[\pi_0(t) + \int_b^{\overline{p}}[W(z,t) - V_u(t)]d\Gamma(z)\right] \end{array} \right\rangle \tag{2.3}$$

At rate $\mu/E(t)$the entrepreneur creates a new start-up company, which generates expected profit $\pi_0(t)$. Once the firm is sold, the entrepreneur becomes the firm's first employee and receives value $W(z,t)$. Of course if quality $z \leq x_0$, the worker obtains $W(z,t) = V_u(t)$ as the start-up immediately fails.

I now consider optimal behaviour by firms with $x > x_0$ given the above observation: that an employee at firm (x,n,t) only quits to an outside offer from a higher quality firm which reveals its type by offering a strictly higher wage $w' > w(x,t)$. I can thus define $q = q(x,t)$ as the employee quit rate from firm x at date t. This quit rate depends on the employees' search effort choice $k(x,t)$, the aggregate hiring rates of firms $\lambda(t)$, and the distribution of job values $F(W,t)$. Each of these items are determined endogenously.

2.3.2 Firm Optimality

Let $\Pi(x,n,t)$ denote the expected discounted lifetime profit of firm (x,n,t) using an optimal wage and recruitment strategy, with productivity $p = xe^{gt}$. Suppose $x > x_0$ and the firm posts wage w'. As each employee believes $x = \widehat{x}(w',t)$, this belief generates quit rate $q = q(\widehat{x},t)$. Firm (x,n,t) thus chooses wage w and per employee recruitment effort $h = H/n$ to solve the Bellman equation:

$$(r+\delta_f)\Pi(x,n,t) = \max_{w,h\geq 0} \left\langle \begin{array}{c} n[xe^{gt}-w] - nxe^{gt}c(h) - gx\frac{\partial \Pi}{\partial x} + \frac{\partial \Pi}{\partial t} \\ +nh\left[\Pi(x,n+1,t) - \Pi(x,n,t)\right] \\ +n[\delta_w + q(\widehat{x},t)]\left[\Pi(x,n-1,t) - \Pi(x,n,t)\right] \end{array} \right\rangle .$$

The flow value of the firm equals its flow profit less recruiting costs plus the capital gains associated with (i) declining quality, (ii) improving market technology, (iii) a successful hire ($n \to n+1$) (iv) the loss of an employee through a separation ($n \to n-1$).

The constant returns structure implies $\Pi(x,n,t) = nv(x,t)$ solves this Bellman equation, where $v(x,t)$ is the value of each employee in firm (x,n,t) and satisfies

$$(r+\delta_f+\delta_w)v(x,t) = \max_{w,h\geq 0} \left\langle \begin{array}{c} xe^{gt} - w - q(\widehat{x},t)v(x,t) + hv(x,t) - xe^{gt}c(h) \\ -gx\frac{\partial v(x,t)}{\partial x} + \frac{\partial v(x,t)}{\partial t} \end{array} \right\rangle . \tag{2.4}$$

As the firm closes down when $x = x_0$, this yields boundary value $v(x_0,t) = 0$ where $x_0 \in [0,\overline{p}]$ is to be determined. I now consider the simplifications yielded by restricting attention to stationary equilibria.

2.3.3 Stationary Equilibrium

I restrict attention to stationary growth paths. Analogous to a steady state condition, **a stationary equilibrium** is defined as a Markov perfect (Bayesian) equilibrium where strategies satisfy (P1), (P2) and the employment distribution $G(x)$ does not change over time.

The distribution of employment across firms $G(x)$ can only be stationary if on-the-job search effort $k(x,t)$ and firm recruitment effort $h(x,t)$ are also stationary. Inspection of the Bellman equations (2.1) and (2.4) establishes this occurs only if the value functions are time separable with form:

$$W(x,t) = e^{gt}W^*(x), V_u(t) = e^{gt}V_u^*, v(x,t) = e^{gt}v^*(x).$$

(2.1) further implies that the wage strategy of firms $w(.)$ must also be time separable with form $w(.) = e^{gt}w^*(x)$. I now denote the optimal time-invariant recruitment strategy as $h(x,t) = h^*(x)$ and search effort strategy $k(x,t) = k^*(x)$.

Let $K(x)$ denote total search effort by unemployed workers and those employed at firms with quality no greater than x in a stationary environment. For $x \geq x_0$, a stationary equilibrium implies

$$K(x) = G(x_0)k^*(x_0) + \int_{x_0}^{x} k^*(z)G'(z)dz, \tag{2.5}$$

as the unemployed enjoy value $V_u^* = W^*(x_0)$ and so choose effort $k^*(x_0)$, and $G(x_0)$ describes the number of unemployed workers. $K(\overline{p})$ determines aggregate search effort $\overline{K}$.

By aggregating over the firm hiring strategies $h^*(.)$, I now compute λ, the aggregate job offer rate. As contacts are random, then each job offer by firm x is accepted with probability $K(x)/\overline{K}$. Thus an expected hiring rate of $H = nh^*(x)$ at firm (x,n,t) requires the firm makes job offers at rate $H/[K(x)/\overline{K}]$. Aggregating across all firms implies the aggregate flow of job offers is

$$\lambda = \int_{x_0}^{\overline{p}} \frac{\overline{K}}{K(x)} h^*(x)G'(x)dx,$$

where $G'(x)$ describes the measure of workers employed at type x firms. Note that λ is constant over time in a stationary equilibrium.

To determine the composition of those job offers, define $F^*(x)$ as the fraction of job offers made by firms with type no greater than x in a stationary equilibrium.

The same aggregation argument implies

$$\lambda[1 - F^*(x)] = \int_x^{\overline{p}} \frac{\overline{K}}{K(z)} h^*(z) G'(z) dz \tag{2.6}$$

where the right hand side is the aggregated flow of job offers by firms with type greater than x. Random job search now implies expected surplus from job search

$$\lambda \int_{W(x,t)}^{\overline{W}} \max[W' - W(x,t), 0] dF(W', t) = \lambda \int_x^{\overline{p}} e^{gt} [W^*(z) - W^*(x)] dF^*(z),$$

as $\lambda dF^*(z)$ describes the job offer rate from firms z, where such offers yield payoffs $e^{gt} W^*(z)$. Furthermore the worker search effort and firm recruitment strategies yield quit rate

$$q(x) = \frac{k^*(x)}{\overline{K}} \lambda[1 - F^*(x)] = k^*(x) \int_x^{\overline{p}} \frac{h^*(z) G'(z)}{K(z)} dz. \tag{2.7}$$

The quit rate of a firm with relative quality x is the product of the relative search effort exerted by the worker employed at that firm and the flow of job offers by firms with quality greater than x. The flow of job offers by higher quality firms depends on firms' hiring strategies. In this environment, firms are making a specific investment into the employment relationship, but, differently from CM, here also workers are making a job search investment into the relationship. The interaction of firms and workers strategies determines in turn the quit rate.

Using these simplifying conditions in equations (2.1)-(2.4), and cancelling out the e^{gt} terms, yields the following Bellman equations in a stationary environment for $W^*(x)$, V_u^*, and $v^*(x)$.

Lemma 1. For $x > x_0$, a stationary equilibrium implies $v^*(x) > 0$ and $W^*(x) > V_u^*$ given by the Bellman equations:

$$(r+\delta_w+\delta_f-g)W^*(x)=\max_{k>0}\left\langle \begin{array}{c} w^*(x)-gx\frac{dW^*}{dx}+\delta_f V_u^* \\ +\frac{k\lambda}{\overline{K}}\int_x^{\overline{p}}[W^*(z)-W^*(x)]dF^*(z)-b\phi(k) \end{array} \right\rangle, \tag{2.8}$$

$$(r+\delta_w-g)V_u^*=\max_{k>0}\left\langle b+\frac{k\lambda}{\overline{K}}\int_{x_0}^{\overline{p}}[W^*(z)-V_u^*]dF^*(z)-b\phi(k)\right\rangle, \tag{2.9}$$

$$(r+\delta_w+\delta_f-g)v^*(x)=\max_{\omega,h\geq 0}\left\langle x[1-c(h)]-\omega-q(\widehat{x})v^*(x)+hv^*(x)-gx\frac{dv^*}{dx}\right\rangle. \tag{2.10}$$

For $x\leq x_0$, $v^*(x)=0$, $W^*(x)=V_u^*$.

Free entry condition implies that the number of entrepreneurs E is constant over time in a stationary equilibrium:

$$E=\frac{\mu}{b}\left[\pi_0+\int_b^{\overline{p}}\left[W^*(z)-V_u^*(t)\right]d\Gamma(z)\right], \tag{2.11}$$

where expected start-up profit

$$\pi_0=\int_{x_0}^{\overline{p}}v^*(z)d\Gamma(z). \tag{2.12}$$

Equation (2.11) is simply the result of equating the value of being unemployed with the value of being an entrepreneur in a stationary environment.

I denote the normalised wage offered in (2.10) by ω, noting the actual wage paid is $w=\omega e^{gt}$. Equation (2.10) implies the optimal recruitment rate of firm x is

$$h^*(x)=\arg\max_{h\geq 0}\left[hv^*(x)-xc(h)\right]. \tag{2.13}$$

The optimal hiring rate per worker maximises the difference between per-employee total return and hiring cost.

Similarly the optimal search effort choice of an employed worker at firm x is:

$$k^*(x) = \arg\max_{k>0} \left[\frac{k}{\overline{K}} \int_x^{\overline{p}} [W^*(z) - W^*(x)] \lambda dF^*(z) - b\phi(k) \right].$$

The optimal search effort of a worker employed at firm with quality x maximises the difference between the expected surplus from job search and the associated search cost. As $W^*(x)$ is a strictly increasing function of x, it follows that $k^*(x)$ is a strictly decreasing function and $k^*(\overline{p}) = \underline{k}$.

2.3.4 The Equilibrium Wage Equation

Given equilibrium wage strategy $w^*(.)$, then should firm (x, n, t) post any wage $w' = \omega e^{gt}$ with $\omega \in [w^*(x_0), w^*(\overline{p})]$, its employees infer it has quality $\widehat{x}(\omega)$ given by the implicit function $\omega = w^*(\widehat{x})$. Given that belief, each employee then searches with effort $k = k^*(\widehat{x})$ and the firm's quit rate $q(\widehat{x})$ is given by (2.7). Given this quit response, the Bellman equation (2.10) implies the optimal wage strategy solves

$$w^*(x) = \arg\min_{\omega} [\omega + v^*(x) q(\widehat{x})] \tag{2.14}$$

with belief $\widehat{x}(\omega)$ as described above. This equation captures the 'efficiency wage' structure of the model, as in CM: each firm faces a trade off between minimising the wage bill but at the same time maximising its retention rate. Thus, the optimal wage choice minimises the wage paid ω and the loss associated with a quit $v^*(x)q(\widehat{x})$.

By assuming $q(.)$ is differentiable, the optimal choice of ω is given by the necessary condition:

$$1 = -v^*(x) q'(\widehat{x}(\omega)) \frac{d\widehat{x}}{d\omega}. \tag{2.15}$$

As $\widehat{x}(\omega)$ is given by the implicit function $\omega = w^*(\widehat{x})$, (2.15) implies (2.16) in Proposition 1 below. The proof of Proposition 1 now establishes (2.16) is also sufficient and identifies the equilibrium boundary condition for $w^*(.)$.

Proposition 1. The equilibrium wage strategy $w^*(.)$ solves the initial value problem:

$$\frac{dw^*(x)}{dx} = -v^*(x)q'(x) \tag{2.16}$$

subject to $w^*(x_0) = x_0$.

Proof. See Appendix.

As in CM, the wage equation (2.16) describes an efficiency wage outcome where each firm trades-off paying marginally higher wages against a marginally lower quit rate, where $v^*(x)$ describes the loss in profit when an employee quits. Proposition 1 also describes the initial wage: at closure, firm x_0 pays marginal product. In essence x_0 describes the lowest wage paid in the market and so firms with lower quality $x < x_0$ are driven out of business. As $v^*(x_0) = 0$, the wage profile $w^*(.)$ has a zero slope at $x = x_0^+$. As this implies $dW^*/dx = 0$ at $x = x_0^+$, then putting $x = x_0$ in (2.8) and (2.9), the condition $W^*(x_0) = V_U^*$ implies

$$x_0 = b. \tag{2.17}$$

The firm closure margin equals normalized home productivity b. For firms with quality $x > b$, which pay wages $w^*(x) > x_0$, the worker prefers to remain employed. Firms with quality $x < b$ close down.

2.4 Equilibrium

Proposition 1 determines equilibrium wages which depend on the marginal quit propensities of workers. The marginal quit rate is an equilibrium object which, differently from CM, depends not only on the recruitment rates of competing firms, but also on the job search efforts of current employees. Thus, the optimal recruitment strategies of firms and the optimal search effort strategies of workers jointly determine the quit function

$$q(x) = k^*(x) \int_x^{\overline{p}} \frac{h^*(z)G'(z)}{K(z)} dz. \tag{2.18}$$

A stationary equilibrium is therefore an equilibrium wage function w^*, a set of firm-side functions $\{v^*, h^*\}$, worker-side functions $\{k^*, W^*, K\}$ and equilibrium objects $\{q, G\}$ over domain $[b, \overline{p}]$ where wages are consistent with Proposition 1, strategies are consistent with optimality (equations (2.8), (2.9) and (2.10)), $\{q, G\}$ are consistent with firm and worker turnover rates and $x_0 = b$. The following characterises these equilibrium functions as a system of ordinary differential equations: Lemma 2 determines the firm-side objects $\{v^*, h^*\}$, Lemma 3 determines the worker side objects $\{k^*, W^*, K\}$ and, using standard steady state arguments, Lemma 4 identifies $\{q, G\}$, which thus completes the equilibrium conditions.

Lemma 2. In a stationary equilibrium for $x \in [b, \overline{p}]$, $v^*(.)$ satisfies

$$gx\frac{d^2v^*}{dx^2} + (r + \delta_w + \delta_f + q(x) - h^*(x))\frac{dv^*}{dx} = 1 - c(h^*) \tag{2.19}$$

with initial values $v^* = dv^*/dx = 0$ at $x = b$, and h^* given by

$$c'(h^*(x)) = \frac{v^*(x)}{x} \tag{2.20}$$

Proof: See Appendix.

Now consider the worker-side. Lemma 3 determines the equilibrium k^*, $\frac{dW^*}{dx}$ and K. I define the marginal value of a worker $MV(x) \equiv \frac{dW^*}{dx}$.

Lemma 3. In a stationary equilibrium for $x \in [b, \overline{p}]$:

(i) $k^*(.)$ is the solution to the first order differential equation

$$b\phi''(k^*(x))\frac{dk^*}{dx}k^*(x) = -q(x)MV(x). \tag{2.21}$$

with boundary value $k^*(\overline{p}) = \underline{k}$;

(ii) $MV(x)$ is the solution to the first order differential equation

$$gx\frac{dMV(x)}{dx} + [r + \delta_w + \delta_f + q(x)]\, MV(x) = \frac{dw^*}{dx}, \tag{2.22}$$

with initial value $MV(x) = 0$ at $x = b$,

(iii) K is the solution to the first order differential equation

$$\frac{dK}{dx} = k^*(x)\frac{dG}{dx} \tag{2.23}$$

with initial value $K(b) = k^*(b)G(b)$.

Proof. See Appendix.

Now Lemma 4 determines q and $G(.)$. Standard turnover arguments for any $x \in [b, \overline{p}]$ imply:

$$gxG'(x) + (\delta_w + \delta_f)[1 - G(x)] = \frac{K(x)}{\overline{K}}\lambda[1 - F^*(x)] + \mu[1 - \Gamma(x)] \tag{2.24}$$

The left hand side describes the flow out of workers employed at firms with quality greater than x: the first term is the outflow of workers due to quality decline, while the second term is the outflow of workers due to firm or worker death. The right hand side describes the inflow of workers from unemployment and employment at firms below x, and through the creation of new start-ups. Using (2.7) to substitute out $\lambda[1 - F^*(x)]/\overline{K}$ now yields Lemma 4.

Lemma 4. In a stationary equilibrium for $x \in [b, \overline{p}]$:

(i) $G(.)$ solves the first order differential equation

$$gx\frac{dG}{dx} = \frac{q(x)K(x)}{k^*(x)} + \mu[1-\Gamma(x)] - (\delta_w + \delta_f)[1-G(x)] \tag{2.25}$$

with boundary value $G(\overline{p}) = 1$;

(ii) $q(.)$ solves the first order differential equation

$$\frac{dq}{dx} = \frac{q(x)}{k^*(x)}\frac{dk^*}{dx} - \frac{h^*(x)k^*(x)}{K(x)}\frac{dG}{dx} \tag{2.26}$$

with boundary value $q(\overline{p}) = 0$.

I thus obtain the following characterisation of a stationary equilibrium:

A **stationary equilibrium** is a set $\{w^*, v^*, h^*, k^*, MV(x), K, q, G\}$ such that for all $x \in [b, \overline{p}]$:

(i) the equilibrium wage $w^*(x)$ satisfies Proposition 1;

(ii) employee value $v^*(x)$ and hire strategy $h^*(x)$ satisfy Lemma 2;

(iii) employee and aggregate search efforts $k^*(x)$ and $K(x)$, and worker value W^* satisfy Lemma 3;

(iv) quit function $q(x)$ and employment distribution $G(x)$ satisfy Lemma 4.

As the model is too complex to be solved analytically, I solve it using numerical methods. In order for a numerical solution to exist, I need to ensure that an upper bound for $v^*(x)$ exists. From equation (2.10) I assume $x = \overline{p}$, so that $q(\overline{p}) = 0$. Given $g\overline{p}\frac{dv^*}{dx} > 0$,

$$(r + \delta_w + \delta_f - g)v^*(\overline{p}) \leqslant \max_{h \geq 0} \langle \overline{p}[1 - c(h)] - b + hv^*(\overline{p}) \rangle \,,$$

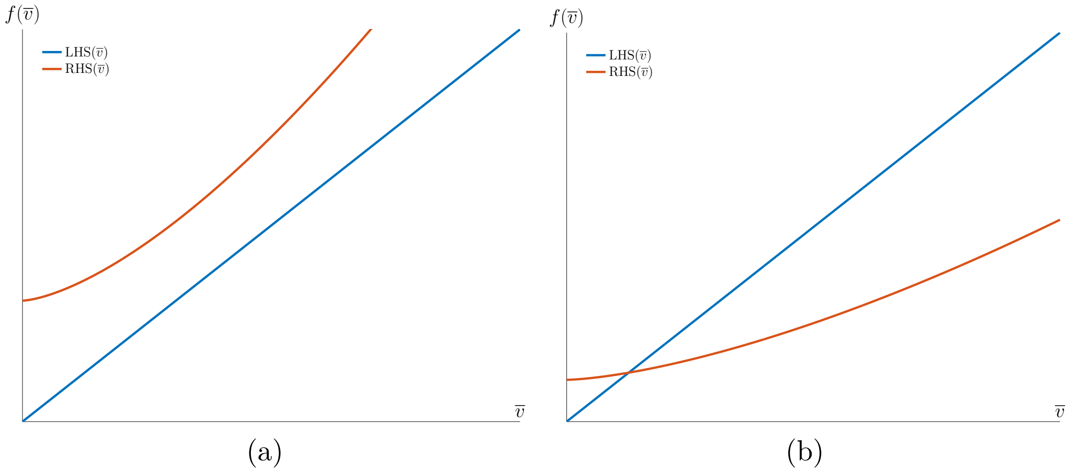
where $\omega = b$ is the firm's profit maximising value.

Thus, I define the maximal value of a worker to a firm $\overline{v}$:

$$\overline{v} = \max_{h \geq 0} \left\langle \frac{\overline{p}[1 - c(h)] - b + h\overline{v})}{(r + \delta_w + \delta_f - g)} \right\rangle. \tag{2.27}$$

A solution for the fixed point of the mapping $\overline{v} = T\overline{v}$ ensures an upper bound for $v^*(x)$.

Figure 2.4.1: Condition for the existence of an upper bound for $v^*(x)$



Note: Graphs obtained using the parameters of Table (2.5.1), but with $r = 0.01/12$ in (a) and $r = 0.05/12$ in (b) for illustrative purposes.

I now show that $r + \delta_w + \delta_f - g$ must be sufficiently large such that a finite solution to (2.27) exists. By the Envelope Theorem, the RHS of equation (2.27) is an increasing function of $\overline{v}$ with slope $h^*(\overline{v})/(r+\delta_w+\delta_f-g)$. As $h^*(.)$ increases with $\overline{v}$, the RHS is convex. If $\overline{v} = 0$, the RHS is positive. Thus, a solution to (2.27) requires $h^*(\overline{v}) < (r + \delta_w + \delta_f - g)$. Figures (2.4.1(a)) and (2.4.1(b)) illustrate the problem. There is no solution when the RHS of equation (2.27) does not intersect the 45-degree line, as in Figure (2.4.1(a)): when $\overline{v} = 0$, the intercept is $(\overline{p} - b)/(r + \delta_w + \delta_f - g)$, which is too high for a solution to exist. On the other hand, when $r + \delta_w + \delta_f - g$ is sufficiently high as in Figure (2.4.1(b)), the intercept is smaller and the curve is flat enough for the existence of a fixed point.

Next section illustrates how to compute the equilibrium numerically.

2.5 Numerical Solution

This section illustrates how to identify a solution to the above differential equation system. Before describing the choice of the parameters, I briefly outline the algorithm implemented in order to solve the boundary value problem identified by Proposition 1 and Lemmas 2-4. I use a finite difference method, which consists in replacing the derivatives in the differential equations by finite difference approximations.

Along with the initial values $w(b) = b, v^*(b) = 0, \frac{dv^*(b)}{dx} = 0, MV(b) = 0$, I have established the following boundary conditions:

$$G(\overline{p}) = 1, k^*(\overline{p}) = \underline{k}, q(\overline{p}) = 0.$$

As I do not know the initial values for unemployment $G(b)$, search effort by unemployed workers $k^*(b)$, and unemployed worker job finding rate $q(b)$, I cannot solve the system by a standard initial value method. Thus, I implement an alternating sweeping strategy (Judd, 1998), iterating forward and backward the above differential equation system for $x \in [b, \overline{p}]$, until convergence. Any such solution, if it exists, identifies a stationary equilibrium.

Initialisation. Discretise the interval $[b, \overline{p}]$ into partitions of equal length. Make an initial guess for w^0, v^0, MV^0 and K^0; choose tolerance level $\epsilon > 0$.

Step 1. Using boundary values $G(\overline{p}) = 1, k^*(\overline{p}) = \underline{k}, q(\overline{p}) = 0$, obtain $G(b), k^*(b), q(b)$ by iterating backward over $x \in [b, \overline{p}]$, where the interval is partitioned into a linearly spaced grid, starting from $x = \overline{p}$ and given the current values w^0, v^0, MV^0 and K^0. Set $G(b) = G^0, k^*(b) = k^0, q(b) = q^0$.

Step 2. Using the initial values $w^*(b) = b, v^*(b) = 0, MV(b) = 0$ and condition $K(b) = k^*(b)G(b)$, obtain $w^*(\overline{p}), v^*(\overline{p}), MV^*(\overline{p}), K(\overline{p})$ by iterating forward over $x \in [b, \overline{p}]$, given the stored values G^0, k^0, q^0.

Step 3. Check for convergence. If the difference between the initial guess and the values of the variables in last iteration are negligibly small, stop. Otherwise, update $w^*(\overline{p}) = w^0, v^*(\overline{p}) = v^0, MV^*(\overline{p}) = MV^0, K(\overline{p}) = K^0$ and return to Step 1.

2.5.1 Parameter choice

I use a month as the reference unit of time and set $r = 0.0033$ that corresponds to a standard annual interest rate of 4%. I set $\delta_w = 0.02/12$, so that the expected working lifetime of a labour market entrant is 50 years. As in Hornstein et al. (2007), I set the monthly growth rate of the economy $g = 0.02/12$, to match the observed US average output growth rate of 2% per annum[5].

I normalise $b = 1$ and I assume a new start-up with the highest possible draw $z = \overline{p}$ can expect to be profitable for 40 years. Therefore, $pe^{-40g} = 1$ which gives $\overline{p} = 2.22$ for a choice of $g = 0.02$.

As in Moscarini and Postel-Vinay (2016), I set the job destruction rate $\delta_f = 0.0114$, to match the monthly separation rate from employment into unemployment.

Recruitment costs $c(h)$ are cubic, as estimated in Merz and Yashiv (2007). The unconventional choice of the scaling factor c_0 is required for the model to converge. As shown in Section 4, a solution to (2.27) implies $h^*(\overline{v}) < (r+\delta_w+\delta_f-g)$. With $c(h) = c_0 h^\alpha/\alpha$ and $\alpha > 1$, a high scaling factor c_0 is required for convergence. As α increases, c_0 must increase as well in order for $\overline{v}$ to exist[6].

I assume the following specification for the worker search cost: $\phi(k) = \phi_0 k^{\phi_1}/\phi_1$,

[5]While here the choice of parameters comes mainly from external sources, Chapter 3 calibrates the parameters to minimise the sum of squared differences between the model's prediction and data moments (simulated minimum distance).

[6]Moscarini and Postel Vinay (2016) estimate $c(h) = (43.47 \times h)^{100}/100$. In their case, the reason for the non-standard choice of the curvature of the hiring cost is that it matches the observed volatility of the job finding rate. The scaling factor instead is chosen to normalise the aggregate measure of job adverts.

with $\phi_1 = 2$ as estimated in Christensen et al. (2005). I normalise $\phi_0 = 1$. In the model, $\underline{k} = k(\bar{p}) > 0$, i.e. some job offers come for free. I set $\underline{k} = 0.1$ to match an average unemployment rate $U = G(b) = 6.91\%$.

Coles and Moghaddasi (2018) find that there are around three million new jobs created by start-up companies every year. Assuming a working population of 150 million, this requires monthly start-up rate $\mu = 3/(150 \times 12) = 0.0017$.

$\Gamma(z)$, which is the baseline productivity c.d.f., is assumed to have a linear density of the form

$$\Gamma'(z) = a_0 + a_1 z,$$

where a_1 determines the skewness of the distribution. As probabilities must add up to one, substituting out a_0 implies

$$\Gamma'(z) = \frac{1}{\overline{p} - b} - \frac{1}{2} a_1 [b + \overline{p}] + a_1 z,$$

and ensuring the density is always positive requires $a_1 \in [-\frac{2}{[\overline{p}-b]^2}, \frac{2}{[\overline{p}-b]^2}]$

Integrating I obtain:

$$\Gamma(z) = (z - b)\Big[\frac{1}{\overline{p} - b} + \frac{1}{2} a_1 (z - \overline{p})\Big].$$

In what follows, I fix $a_1 = -0.1$, which implies Γ slightly skewed towards $x = b$, and solve the model with the proposed parameter choice. The parameter values are summarised in Table 2.5.1.

2.5.2 Results and discussion

Figure 2.5.1(a) shows that the value of a worker to a firm increases with quality x. As the optimal hire strategy of firm x depends on $v^*(x)$ (equation 2.13), the hiring rate increases with quality (Figure 2.5.1(b)). As looking for a worker becomes

Table 2.5.1: Parameter values

Parameter	Value	Description
r	0.0033	Monthly interest rate
b	1	Productivity, lower threshold
$\bar{p}$	2.32	Productivity, upper threshold
δ_w	0.0017	Worker death rate
g	0.0017	Technology growth rate
α	3	Convexity of hiring cost
c_0	60,000	Scale parameter of hiring cost
ϕ_0	1	Scale parameter of search effort
$\underline{k}$	0.1	Costless search
δ_f	0.0114	Destruction shock
μ	0.0017	Start-up rate
a_1	-0.1	Skewness of start-up productivity c.d.f.

expensive for a high quality firm, it will pay a higher wage (Figure 2.5.1(c)).

Equilibrium wages have an efficiency wage structure of the form $w(x, n, t) = e^{gt}w^*(x)$. $w^*(.)$ describes the cross section distribution of wages paid by firms with quality $x \geqslant b$. Equations (2.16) and (2.26) imply:

$$\frac{dw^*(x)}{dx} = v^*(x)\left[\frac{h^*(x)k^*(x)}{K(x)}\frac{dG}{dx} - \frac{q(x)}{k^*(x)}\frac{dk^*}{dx}\right]. \tag{2.28}$$

Wages unambiguously increase with firm quality x for two reasons: first, by raising its wage, a higher quality firm x reduces the probability that a worker, on receiving an outside offer, prefers that outside offer and quits. This effect is captured by the first term on the right-hand side of (2.28). Specifically, $h^*(x)G'(x)$ describes the aggregate hiring rate of competing firms with the same quality x. Thus an employee at firm x is offered a job from a competing firm at rate $k^*(x)h^*(x)G'(x)/K(x)$. The incumbent employer ensures the worker does not quit when receiving such an offer by paying a slightly higher wage, retaining continuation profit v^* (2.5.1(b)). Second, by raising its wage, the employee has a lower return to job search. Since the worker has less to gain, she chooses a lower search intensity $k^*(x)$, as reflected by the second term of the equation and observed in

Figure 2.5.1(d).

The framework has a first price auction structure, where each firm x is effectively competing against local x-neighbours for the retention of its employees, as hiring replacement workers is a costly process. Let's now consider the two endpoints of Figure 2.5.1(c). At the closure level $x = b$, $v(b) = 0$ implies $dw^*/dx = 0$. Firms at $x = b^+$ are struggling to survive and pay wages close to marginal product. Similarly, $q(\overline{p}) = 0$ implies $\mathrm{G}'(\overline{p}) = 0$ by (2.25), and so the wage profile $w^*(.)$ also has a zero slope at $\overline{p}$. There is little local wage competition at $x = \overline{p}$ as almost all firms are born with $z < \overline{p}$ and firm quality strictly falls over time. This explains the s-shape of wages in Figure 2.5.1(c).

Figure 2.5.1(e) shows the employment c.d.f., i.e. the proportion of workers employed at firms with quality no greater than x. At the threshold value $x = b$, $G(b)$ represents the proportion of unemployed individuals, which, in the numerical example, is 6.91%. From equation (2.5), aggregate search effort (Figure 2.5.1(f)) follows closely the behaviour of $G(x)$. $K(\bar{p})$ determines total search effort exerted by employed individuals.

Figure 2.5.2 illustrates the size of numerically simulated search cost $\phi(k)$ relative to quality x and individual search effort k. As expected, search costs increase with k, thus they are low at high quality firms. When unemployed, the search cost for an individual is about 1.5% of the flow value of home production, b.

2.5.3 Comparative statics

I now conduct a series of counterfactual exercises, by comparing the equilibrium results with those obtained with different parameter choices. Figures 2.5.3 and 2.5.4 show the effect of changing the start-up rate μ on the equilibrium variables. A higher entry rate implies less unemployment, as there are simply more firms in the market (notice in Figure 2.5.3(d) that the job finding rate of an unemployed worker, $q(b)$, increases with μ). As there is more competition, firms enjoy smaller profits and recruit less. In addition, they need to offer a higher wage in order to keep their workers, as both job-to-job quits and search effort increase faster when quality x falls.

A lower skewness parameter a_1 (Figures 2.5.5 and 2.5.6) implies that there are more firms born with a low quality draw. Firms cannot grow, thus the hiring rate is low and the unemployment level is high. There are few firms with high quality x, so they do not need to compete to retain a worker and post lower wages, enjoying greater profit. Thus, $q(x)$ and $k^*(x)$ are lower at those firms.

Figures 2.5.7 and 2.5.8 show that a high degree of convexity of the hiring cost is necessary in order to generate the right volatility of the hiring rate and of job-to-job quits. The higher unemployment rate implies that firms are less likely to 'poach' workers from other firms, as they hire mainly from the pool of the unemployed individuals. Thus, the hiring rate does not respond much to an increase in x, job-to-job quits and search effort experience a very small change, and firms do not need to offer high wages to retain workers, as there are plenty of unemployed workers to hire.

The effect of a fall in α is similar to the effect of an increase in c_0: a higher scale parameter of the hiring cost increases the unemployment rate, as now it is more costly for all firms to hire. The hiring rate falls down, together with the job-to-job quits (Figures 2.5.7 and 2.5.8).

An increase in g (Figures 2.5.11 and 2.5.12) determines a higher unemployment rate in equilibrium. As there is more turnover, incumbent firms quickly die and soon leave way to new, more productive start-ups. As the frontier grows quickly, there are only few firms who maintain a high level of productivity, and they can hire more, offer low wages and enjoy high profit. An increase in g does not have a large impact on worker search effort: workers still move from low-ranked to high-ranked x.

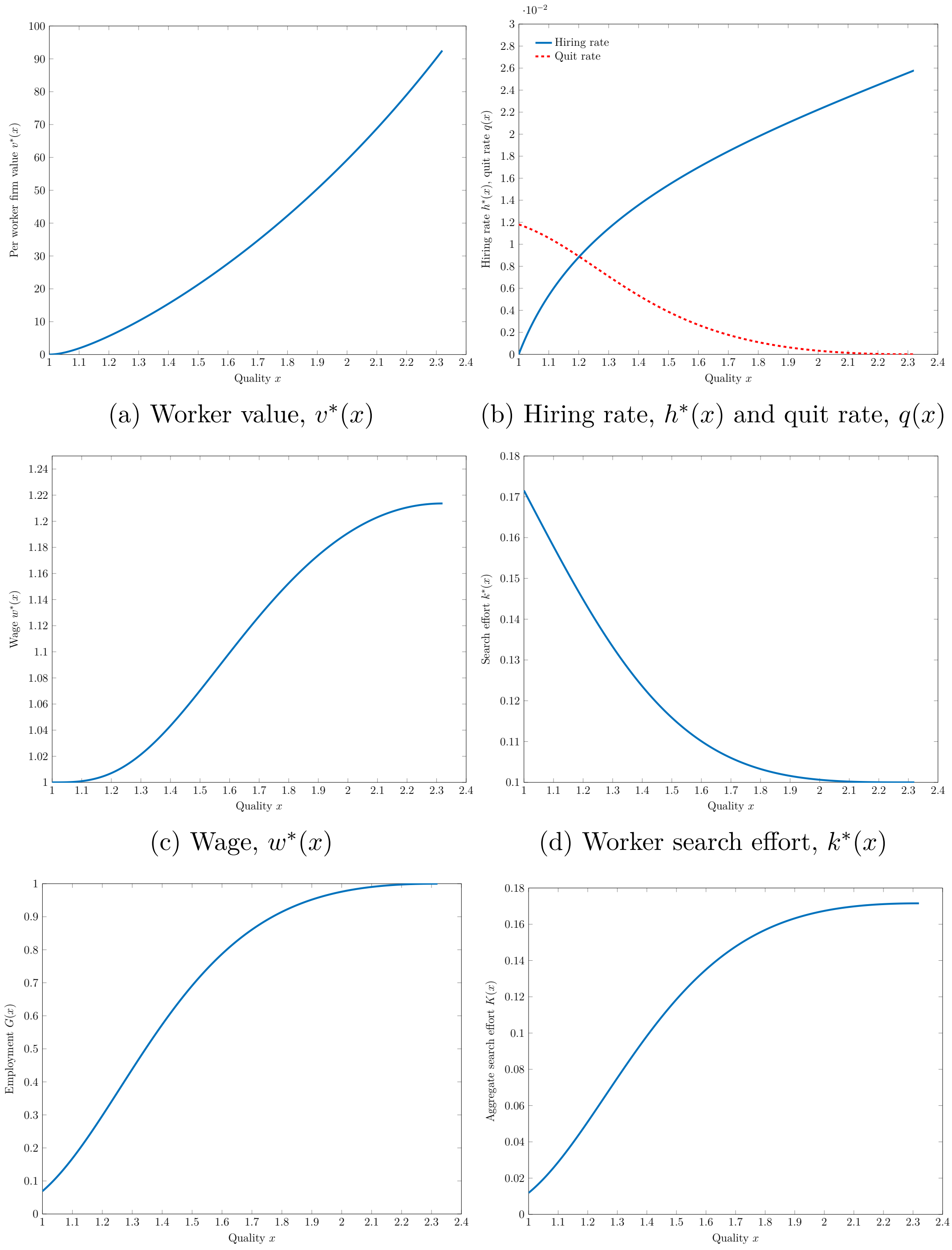
In the model, there is costless search: workers at high quality firms $\bar{p}$ still search while on the job at rate $\underline{k}$ at no additional cost. As Figures 2.5.13 and 2.5.14 illustrate, changing the level of $\underline{k}$ affects mainly wages and job-to-job transitions: a higher $\underline{k}$, by increasing the effort exerted by workers at all firms, induces firms to offer a higher wage to prevent workers from leaving. The effect of $\underline{k}$ is akin to an increase in ϕ (Figures 2.5.15 and 2.5.16).

2.6 Conclusions

This paper analyses equilibrium in a stationary growth economy with firm turnover and labour reallocation. Firms post wages and choose their hiring margin, while workers choose their intensity of searching. The paper, assuming constant return to scale in recruitment costs, implies size-independent firm strategies in equilibrium, as in Coles and Mortensen (2016). It also relies on the CM result that wage offers are fully revealing. However, differently from the stochastic CM framework, the paper introduces a deterministic technological progress with vintage effects. This simplification allows to investigate the role of firm age and its implications for worker turnover. In addition, the introduction of endogenous search effort preserves a 'well-behaved' wage dispersion without the need to impose a higher arrival rate of job offers (i.e. a better search technology) for the unemployed.

The equilibrium, numerically computed, suggests that there is a strong relationship between firm growth, turnover and labour reallocation. Firms with higher productivity offer higher wages and manage to attract more workers, increasing their size. Therefore, the model can capture interesting firm dynamics: start-ups have a high risk of failure, but conditional on survival, they can be highly productive, offer high wages and grow large over time.

Figure 2.5.1: Endogenous variables, numerical solution



(a) Worker value, $v^*(x)$

(b) Hiring rate, $h^*(x)$ and quit rate, $q(x)$

(c) Wage, $w^*(x)$

(d) Worker search effort, $k^*(x)$

(e) Employment, $G(x)$

(f) Aggregate search effort, $K(x)$

Figure 2.5.2: Search cost and effort, numerical solution

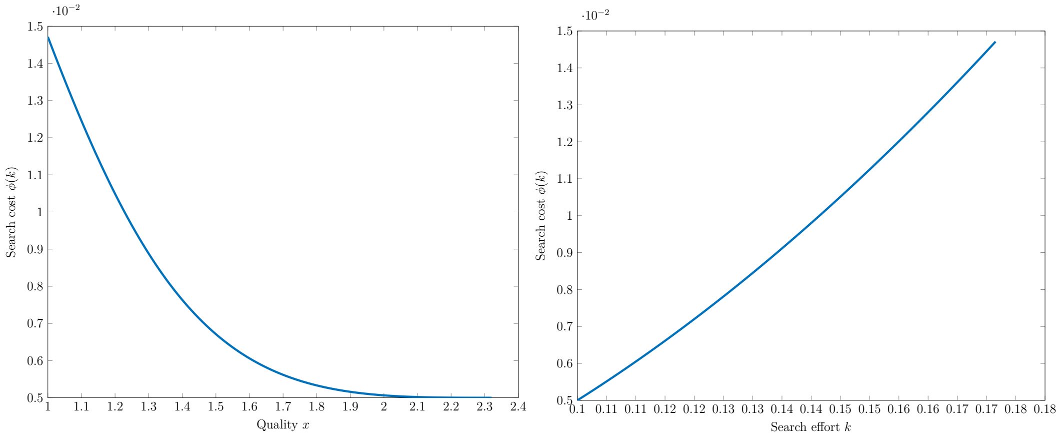
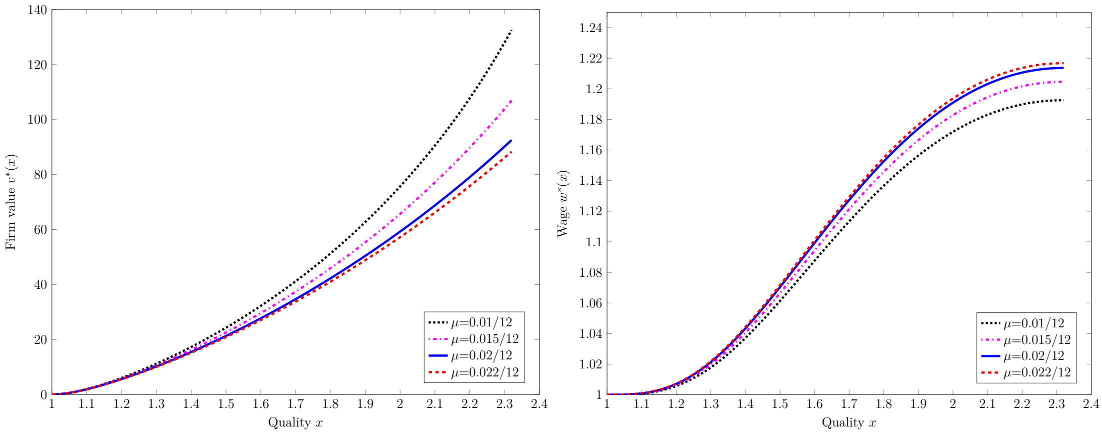
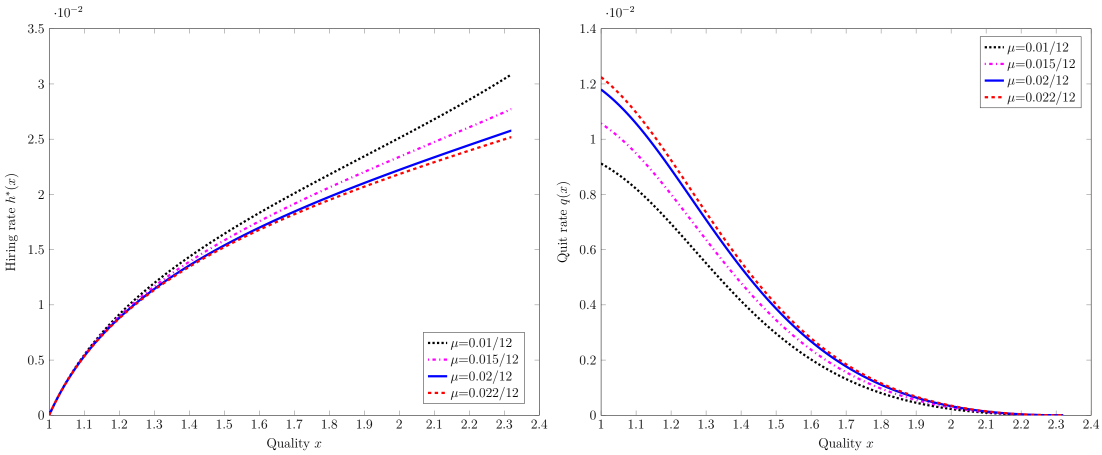


Figure 2.5.3: Effect of a change in μ on equilibrium

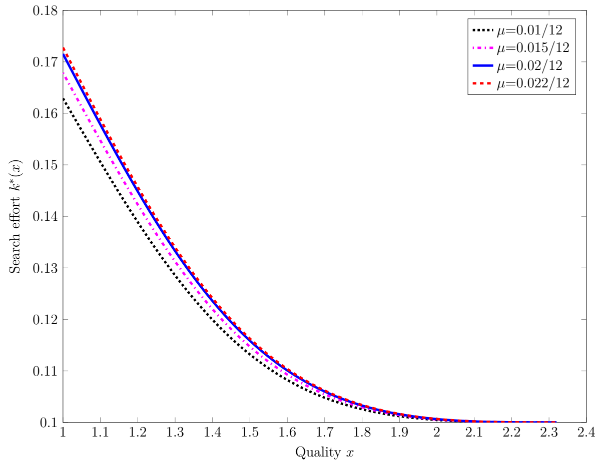


(a) Worker value, $v^*(x)$ (b) Wage, $w^*(x)$

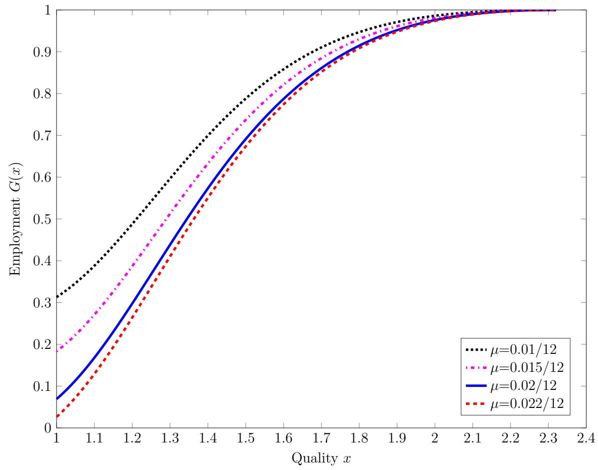


(c) Hiring rate, $h^*(x)$ (d) Quit rate, $q(x)$

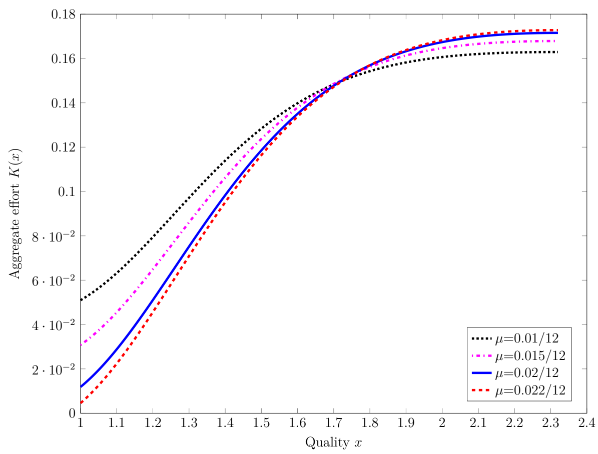
Figure 2.5.4: Effect of a change in μ on equilibrium (2)



(a) Worker search effort, $k^*(x)$

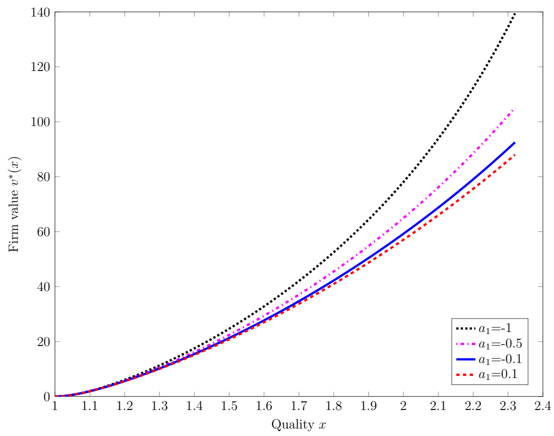


(b) Employment, $G(x)$

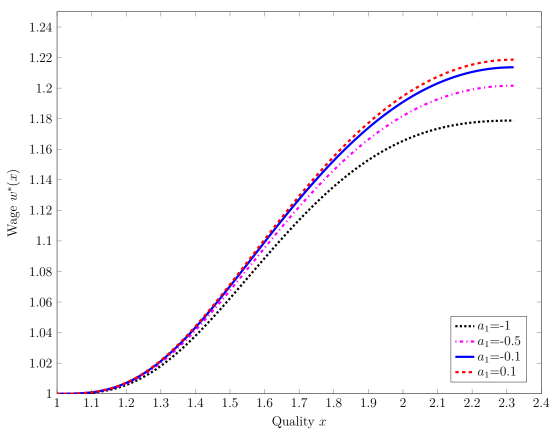


(c) Aggregate search effort, $K(x)$

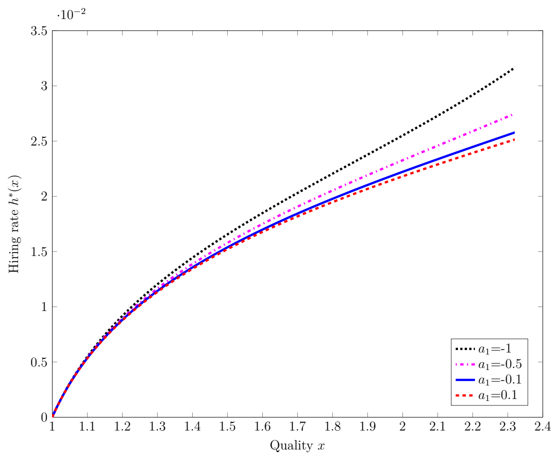
Figure 2.5.5: Effect of a change in a_1 on equilibrium



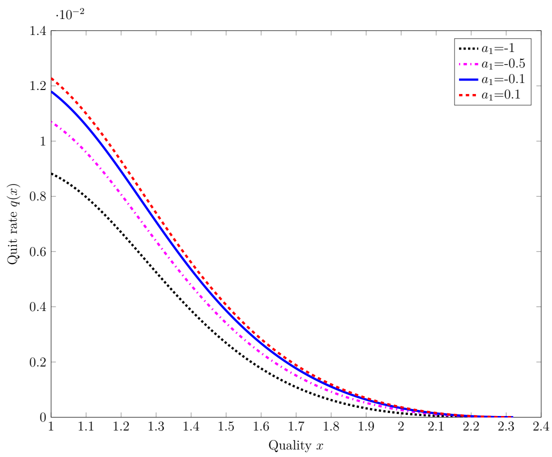
(a) Worker value, $v^*(x)$



(b) Wage, $w^*(x)$

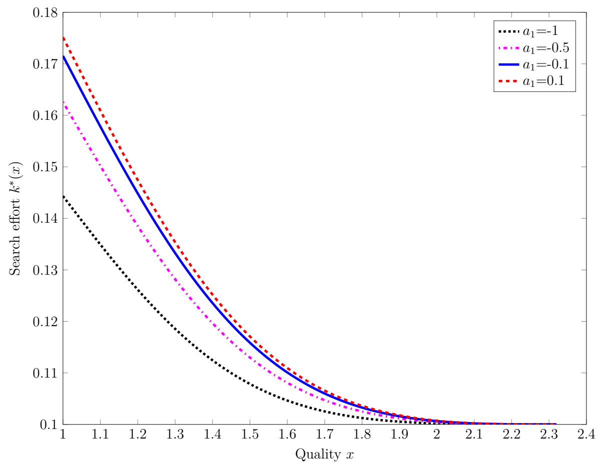


(c) Hiring rate, $h^*(x)$

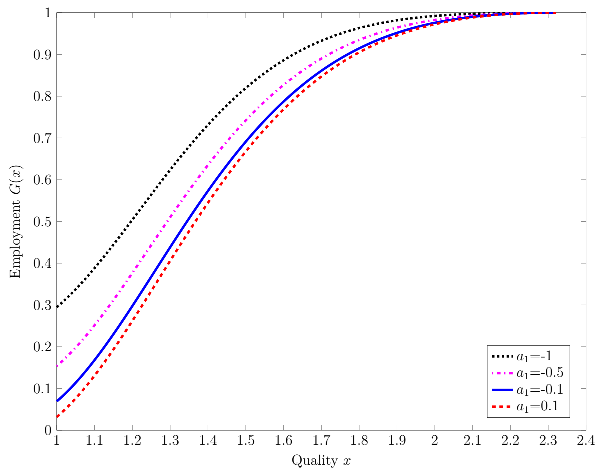


(d) Quit rate, $q(x)$

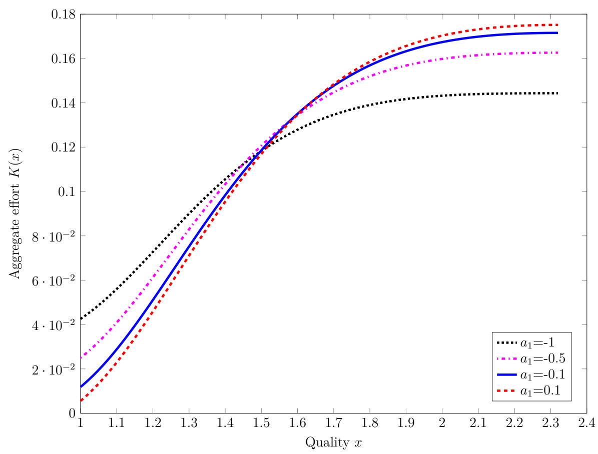
Figure 2.5.6: Effect of a change in a_1 on equilibrium (2)



(a) Worker search effort, $k^*(x)$

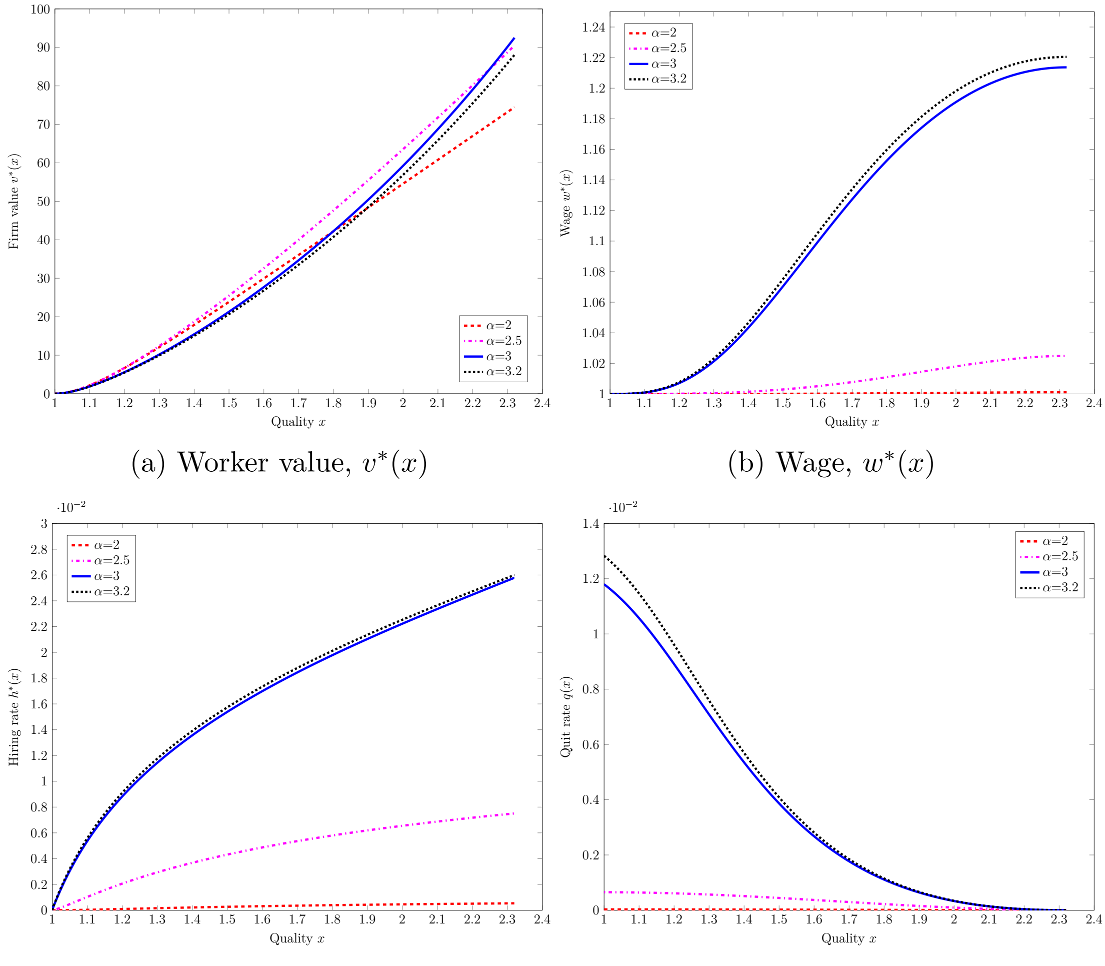


(b) Employment, $G(x)$



(c) Aggregate search effort, $K(x)$

Figure 2.5.7: Effect of a change in α on equilibrium



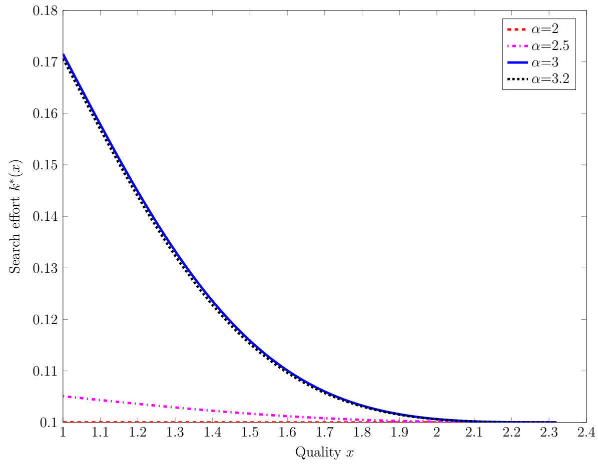
(a) Worker value, $v^*(x)$

(b) Wage, $w^*(x)$

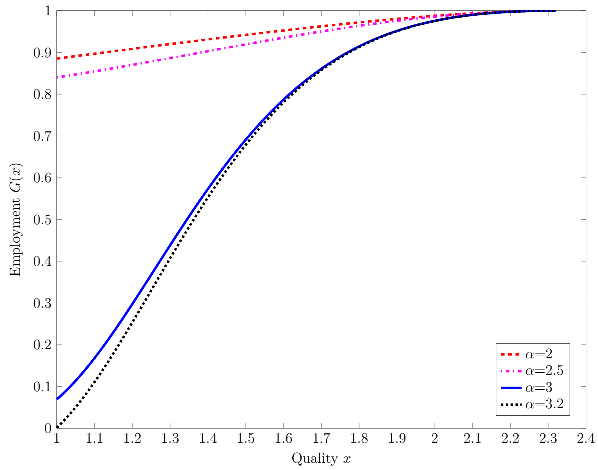
(c) Hiring rate, $h^*(x)$

(d) Quit rate, $q(x)$

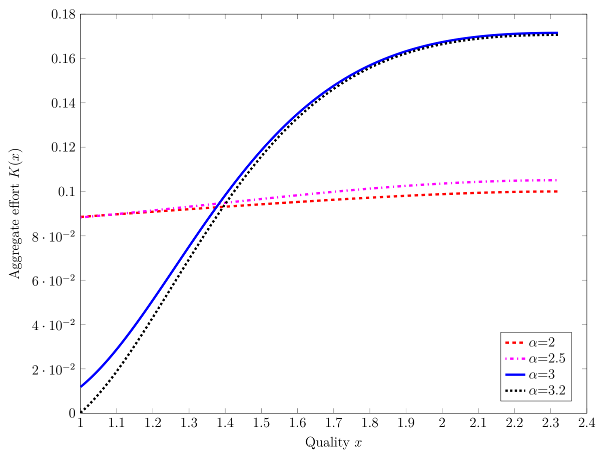
Figure 2.5.8: Effect of a change in α on equilibrium (2)



(a) Worker search effort, $k^*(x)$

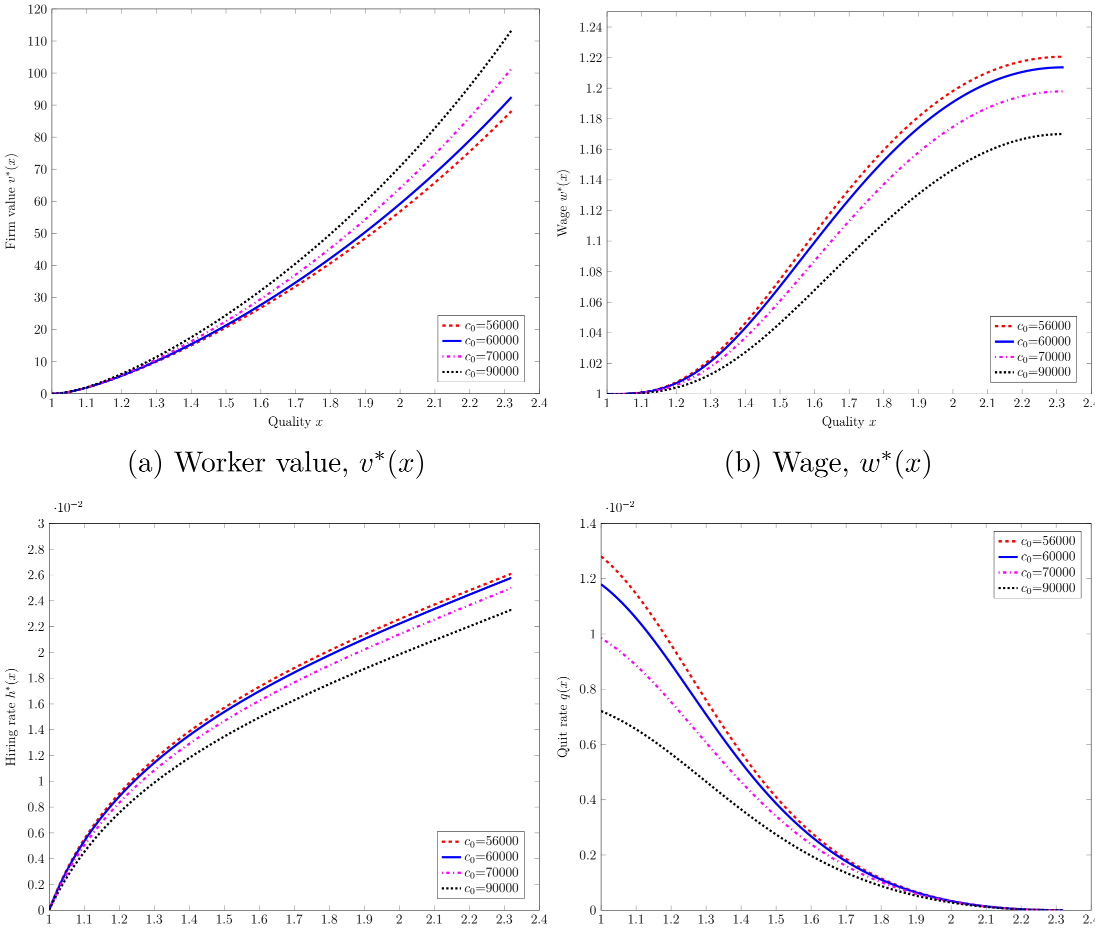


(b) Employment, $G(x)$



(c) Aggregate search effort, $K(x)$

Figure 2.5.9: Effect of a change in c_0 on equilibrium



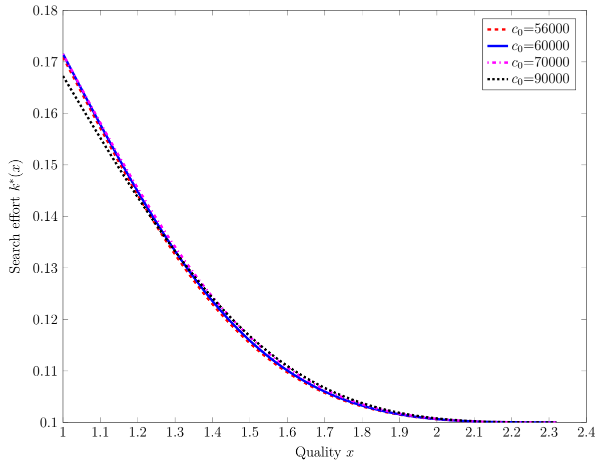
(a) Worker value, $v^*(x)$

(b) Wage, $w^*(x)$

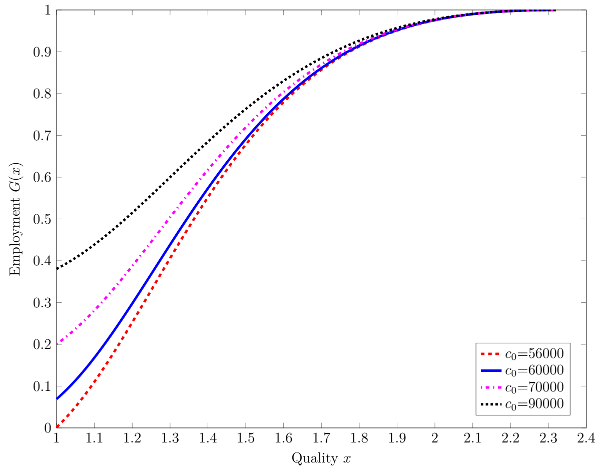
(c) Hiring rate, $h^*(x)$

(d) Quit rate, $q(x)$

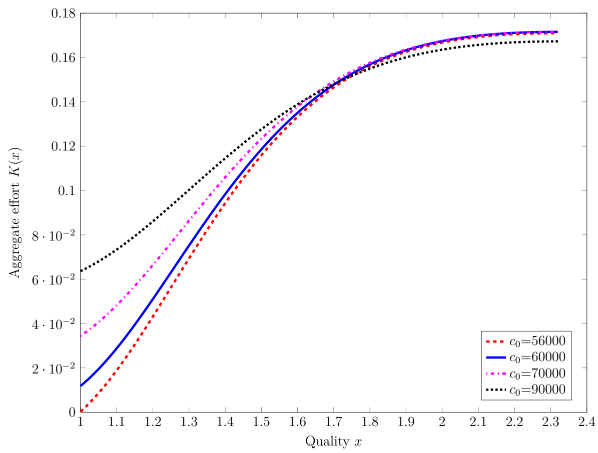
Figure 2.5.10: Effect of a change in c_0 on equilibrium (2)



(a) Worker search effort, $k^*(x)$

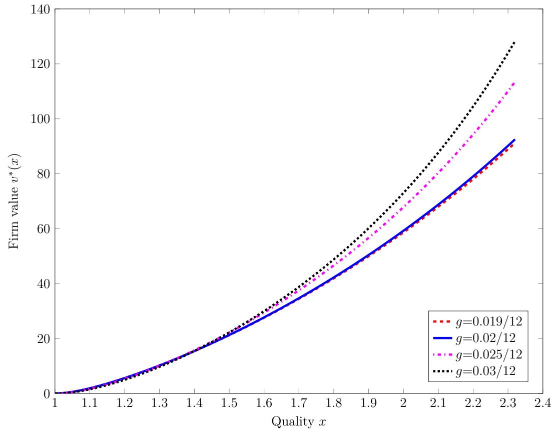


(b) Employment, $G(x)$

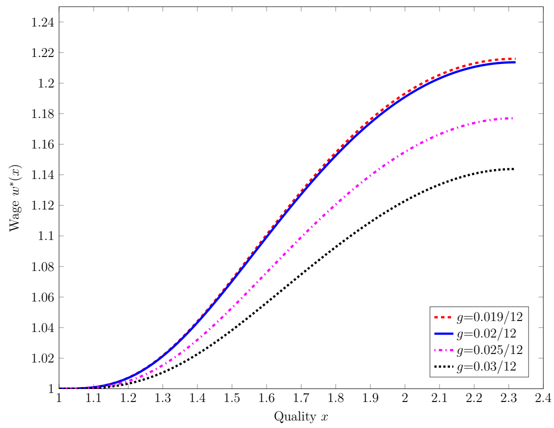


(c) Aggregate search effort, $K(x)$

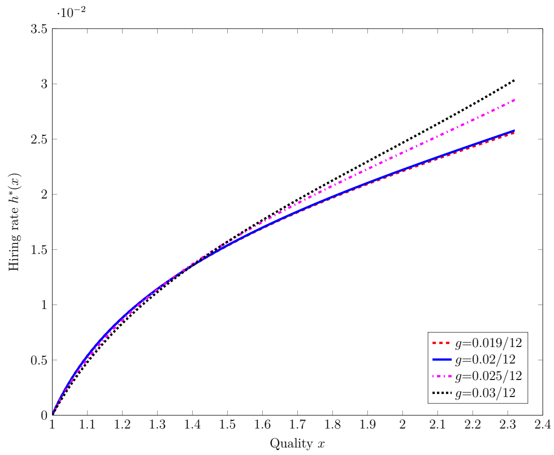
Figure 2.5.11: Effect of a change in g on equilibrium



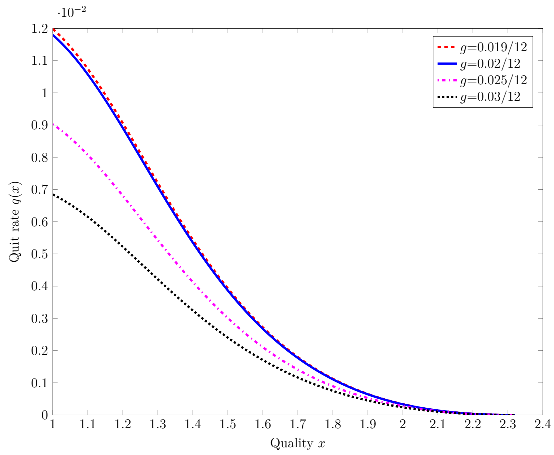
(a) Worker value, $v^*(x)$



(b) Wage, $w^*(x)$

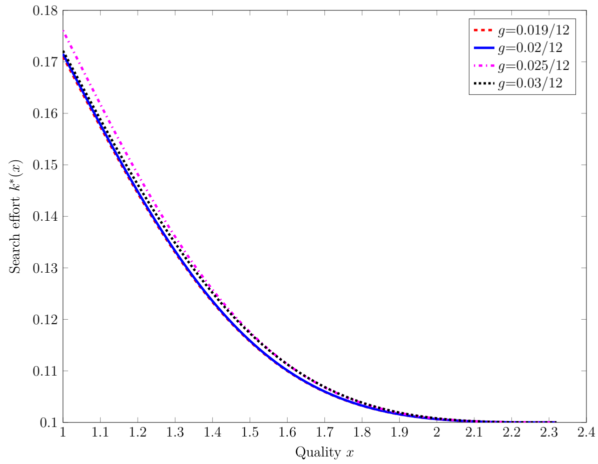


(c) Hiring rate, $h^*(x)$

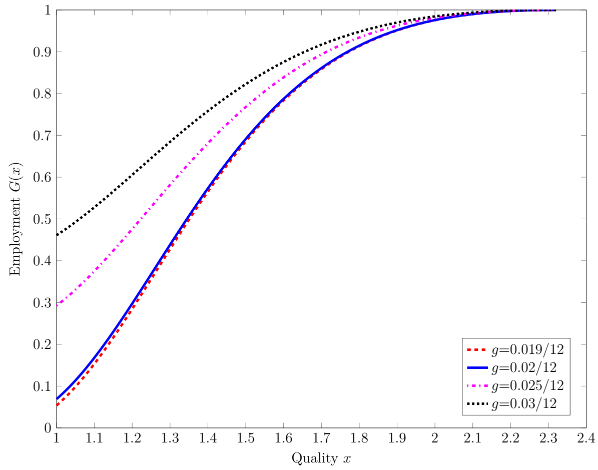


(d) Quit rate, $q(x)$

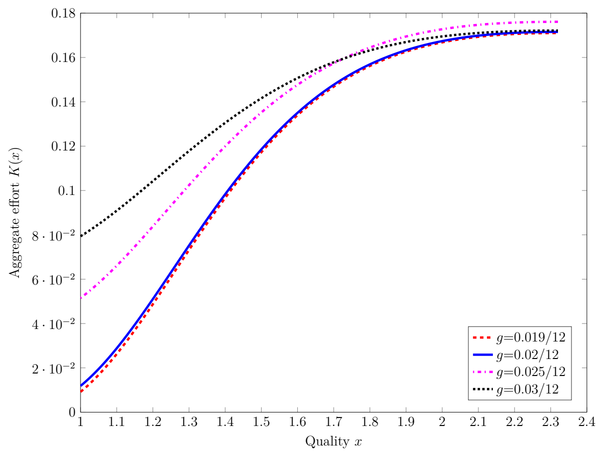
Figure 2.5.12: EFFECT OF A CHANGE IN g ON EQUILIBRIUM (2)



(a) Worker search effort, $k^*(x)$

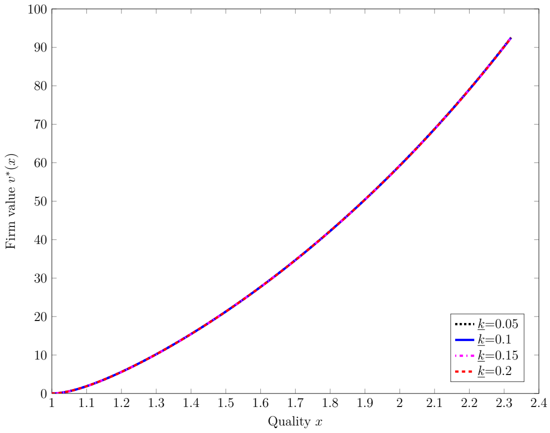


(b) Employment, $G(x)$

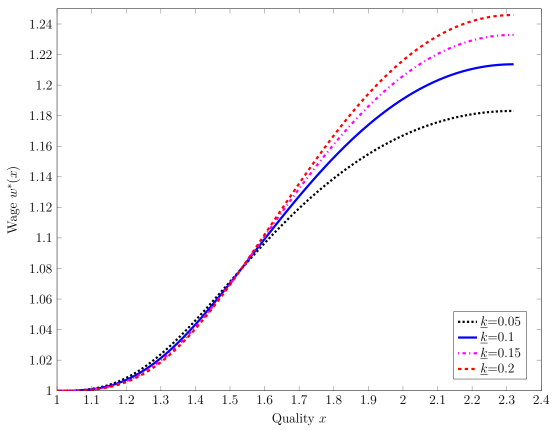


(c) Aggregate search effort, $K(x)$

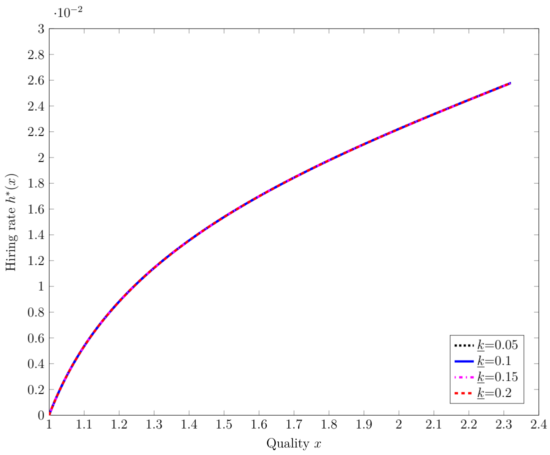
Figure 2.5.13: Effect of a change in $\underline{k}$ on equilibrium



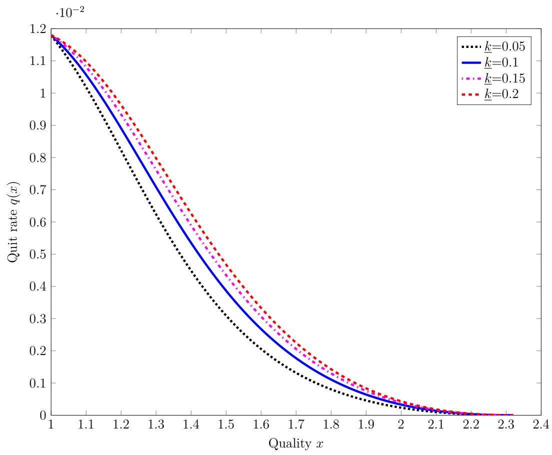
(a) Worker value, $v^*(x)$



(b) Wage, $w^*(x)$

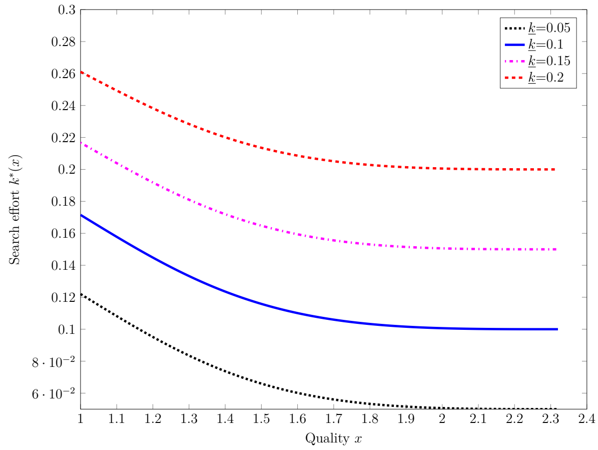


(c) Hiring rate, $h^*(x)$

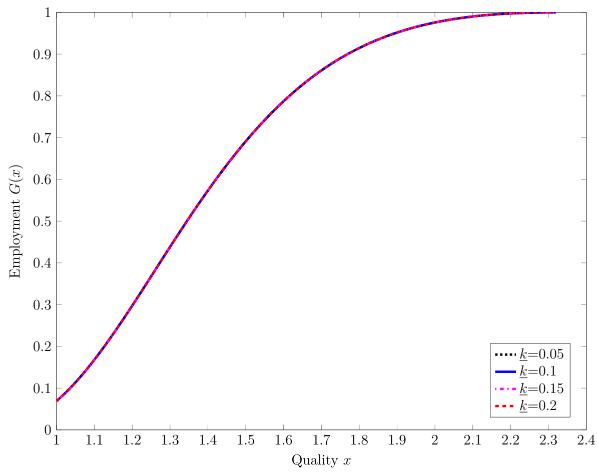


(d) Quit rate, $q(x)$

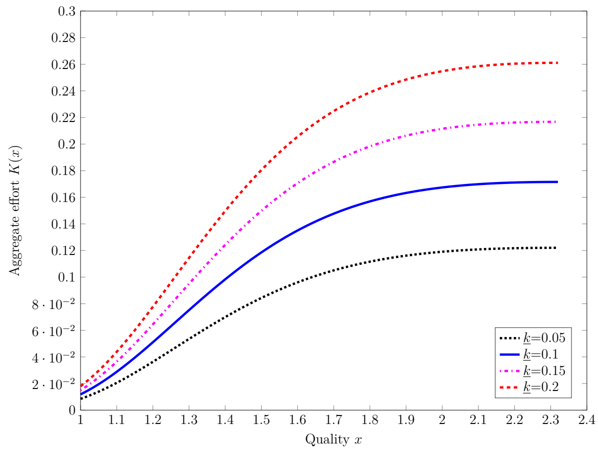
Figure 2.5.14: Effect of a change in $\underline{k}$ on equilibrium (2)



(a) Worker search effort, $k^*(x)$

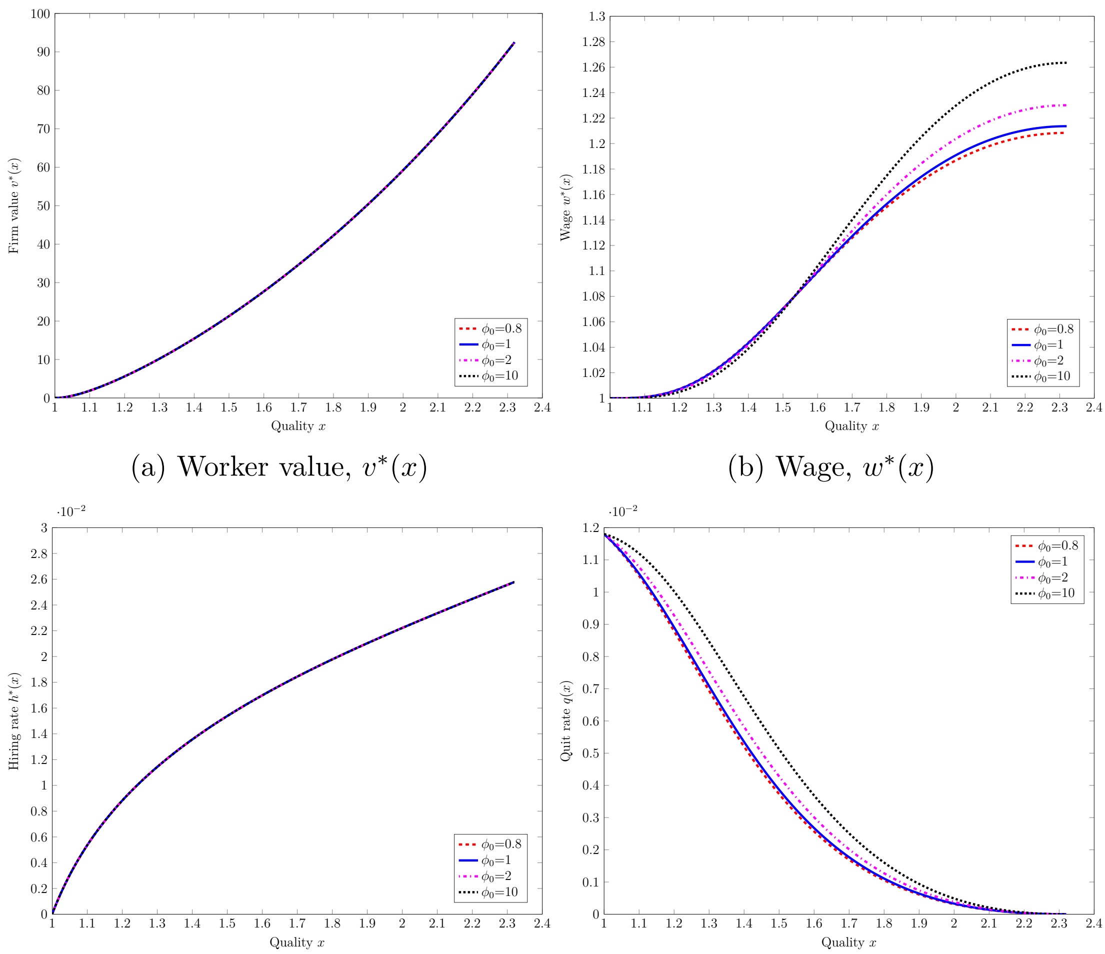


(b) Employment, $G(x)$



(c) Aggregate search effort, $K(x)$

Figure 2.5.15: EFFECT OF A CHANGE IN ϕ_0 ON EQUILIBRIUM



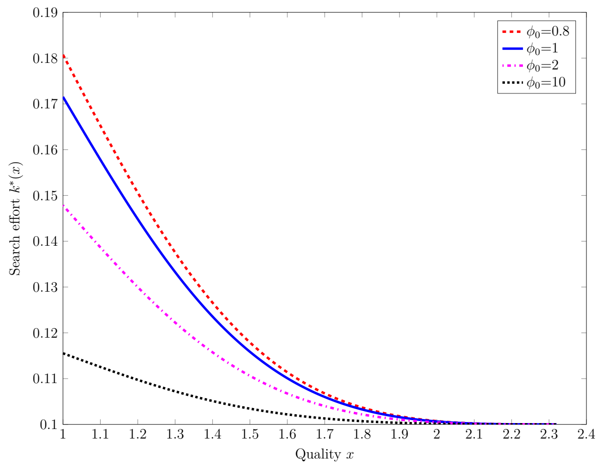
(a) Worker value, $v^*(x)$

(b) Wage, $w^*(x)$

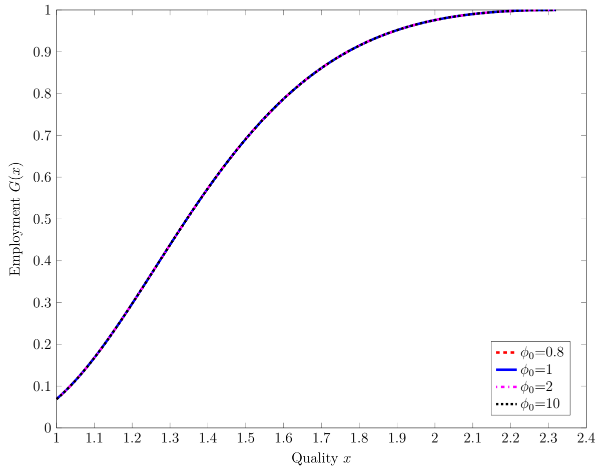
(c) Hiring rate, $h^*(x)$

(d) Quit rate, $q(x)$

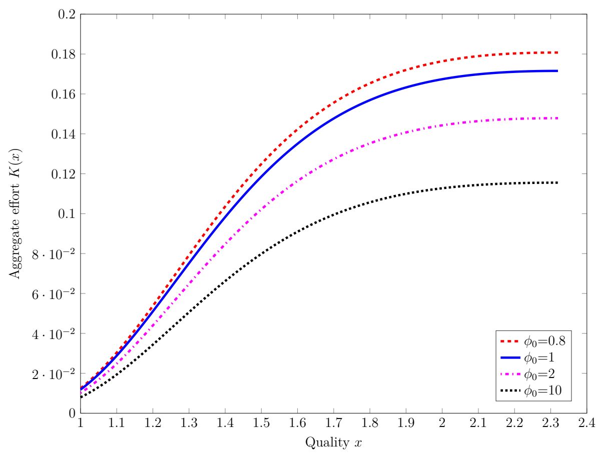
Figure 2.5.16: Effect of a change in ϕ_0 on equilibrium (2)



(a) Worker search effort, $k^*(x)$



(b) Employment, $G(x)$



(c) Aggregate search effort, $K(x)$

Appendix

2.A Proofs

2.A.1 Proof of Proposition 1

A simple contradiction argument implies $w^*(x_0) = x_0$.[7] Given (2.16) is a necessary condition for optimality, (2.14) describes its solution given initial value $w^*(x_0) = x_0$.

To establish sufficiency, consider firm x objective function

$$C(\omega, x) = \omega + v^*(x)q(\widehat{x})$$

where given any wage offer $\omega \in [x_0, w^*(\overline{p})]$, each employee infers quality $\widehat{x}$ where

$$\omega = x_0 + \int_{x_0}^{\widehat{x}} [q(z) - q(\widehat{x})] \frac{dv^*(z)}{dz} dz.$$

To establish wage $\omega = w^*(x)$ is optimal, suppose the firm deviates to any offer $\omega = w^*(x')$ with $x' \in [x_0, x)$. As employees update belief $\widehat{x}(w) = x'$, this deviation yields payoff:

$$C = w^*(x') + v^*(x)q(x').$$

[7] if $w^*(x_0) < x_0$ then $W^*(x_0) < V_u$, while $w^*(x_0) > x_0$ implies negative profit.

Differentiating with respect to x', implies

$$\begin{aligned}\frac{\partial C}{\partial x'} &= \frac{dw^*(x')}{dx} + v^*(x)q'(x') \\ &= [v^*(x) - v^*(x')]\, q'(x') < 0\end{aligned}$$

as $q'(.) < 0$. Hence increasing wage $\omega = w^*(x')$ is cost decreasing while $w^*(x') < w^*(x)$. The converse argument holds for $w^*(x') > w^*(x)$. Hence announcing wage $\omega = w^*(x)$ minimizes $C(.)$ relative to announcing any other wage $w^*(x')$ with $x' \in [x_0, \bar{p}]$. Furthermore announcing $\omega < w^*(x_0)$ implies all workers quit into unemployment (which yields zero profit for the firm). Conversely announcing wage $\omega > w^*(\bar{p})$ yields even lower profit relative to announcing $w = w^*(\bar{p})$ (turnover is the same and wages are strictly higher). Hence announcing wage $\omega = w^*(x)$ is optimal for all $x \in [x_0, \bar{p}]$. This completes the proof of Proposition 1.

2.A.2 Proof of Lemma 2

Equilibrium wage strategy $w^*(.)$ given by Proposition 1 and (2.10) imply the Bellman equation

$$(r + \delta_w + \delta_f - g + q(x))v^*(x) = x - w^*(x) + \max_h [hv^*(x) - xc(h)] - gx\frac{dv^*}{dx}. \quad (2.29)$$

As $v^*(b) = 0$, $w^*(b) = b$, this implies $\frac{dv^*}{dx} = 0$ at $x = b$. Differentiating (2.29) w.r.t. x, the Envelope Theorem and Proposition 1 yield (2.19). Equation (2.20) follows from (2.13).

2.A.3 Proof of Lemma 3

Consider (2.8) which describes $W^*(.)$. As $\phi(.)$ is strictly convex, privately optimal job search effort $k^*(x)$ is given by

$$b\phi'(k^*(x)) = \frac{\lambda}{\overline{K}} \int_x^{\overline{p}} [W^*(z) - W^*(x)] dF^*(z).$$

Differentiating with respect to x implies equilibrium $k^*(.)$ satisfies the differential equation:

$$b\phi''(k^*(x))\frac{dk^*}{dx} = -\frac{dW^*}{dx}\frac{\lambda}{\overline{K}}[1 - F^*(x)].$$

Using (2.7) to substitute out $\lambda[1 - F^*(x)]/\overline{K}$ gives (2.21). Differentiating (2.8) w.r.t x, the Envelope Theorem and substituting out $\lambda[1-F^*(x)]$ using (2.7) yields (2.22). Finally, from (2.5) follows (2.23).

Chapter 3

Firm growth and worker reallocation: a quantitative assessment

3.1 Introduction

The theoretical literature of on-the-job search predicts that job-to-job flows reallocate workers from small and less productive, to large and highly productive firms (Burdett and Mortensen, 1998). Recent empirical evidence, however, highlights that the direction of worker flows across firm characteristics is not so straightforward. Haltiwanger, Hyatt, Kahn and McEntarfer (2018), using U.S. matched employer-employee data, find that workers tend to move from low-wage to high-wage firms, but they find no evidence of worker reallocation by firm size. Chapter 1 explores worker reallocation across establishment size and wage using German matched employer-employee data. As in Haltiwanger et al. (2018), while there is evidence of a net job-to-job movement from low to high-wage establishments, the relationship with size is not straightforward. When I consider the role of establishment age, I document net flows from mature establishments to their younger counterparts. Haltiwanger, Jarmin and Miranda (2013) show that many small firms are not young; in addition, young and small firms have a high risk of going out of business, but, conditional on survival, they grow faster. Indeed, small establishments can be young and fast-growing, hence net attractors in terms of employee turnover. At the same time, small establishments can also be mature, declining, and net losers. Chapter 1 compares hiring and separation flow rates of small, young establishments with those of small, and mature ones, finding that small and young establishments have positive worker net flows, while mature establishments, regardless of their size, tend to lose workers on net, both to non-employment and towards other employers. Therefore, a theoretical model that aims at analysing worker turnover across firms cannot neglect the role of firm age. Moscarini and Postel-Vinay (2013) develop a stochastic version of the Burdett and Mortensen (1998) model aimed at studying the cyclicality of employment dynamics. However, the model imposes the wage strategy to be dependent on size: as only large firms can offer high wages, it cannot describe start-up firms that are born small but can quickly grow large by offering higher wages. Chapter 2 builds a theoretical model that draws on Coles and Mortensen (2016), which allows for these richer firm dynamics. This chapter provides a quantitative exploration of the theoretical model presented in Chapter 2. In particular, it estimates the parameters of the model by simulated minimum distance, using the LIAB matched employer-employee data. Then, it evaluates the performance of the model in replicating the main features of the data, in particular the establishment size distribution and worker reallocation. The rest of the Chapter proceeds as follows. Section 3.2 lays out the main equations of the model presented in Chapter 2; Section 3.3 describes the simulation and the parameters to estimate.;Section 3.4 shows the results of the calibration and the model's fit to the data; Section 3.5 performs some counterfactual exercises to further highlight the properties of the model; Section 3.6 concludes.

3.2 Model and equilibrium

This section briefly outlines the main equations of the model that is illustrated in Chapter 2, on which the quantitative exploration is based[1].

The framework draws on Coles and Mortensen (2016) efficiency wage model of quit turnover. The labour market is populated by homogeneous workers and heterogeneous firms with initial productivity p, where $p = ze^{gt}$, with z drawn from a given distribution with c.d.f. $\Gamma(z)$ and support $[b, \bar{p}]$. Productivity declines relative to the market average, thus each firm is characterised by its quality $x(p,t) = pe^{-gt}$, where $x \in [0, \overline{p}]$. As in Coles and Mortensen (2016), firm quality x is not observed by workers. The model considers Markov (Bayesian) equilibria where each firm signals its quality using an equilibrium wage strategy $w = w(x, n, t)$. Wage is strictly increasing in the firm quality x. As established in Chapter 2, it is possible to normalise all the variables by dividing by e^{gt}.

Hiring new workers is costly, and in a stationary equilibrium more productive firms pay higher wages to minimise workers' quit rate. Moreover, I introduce endogenous search effort: employed workers who receive a higher wage have less to gain from searching for another employer, hence they search less. As wages strictly increase in firm's quality x, workers employed at a high quality firm will exert low search effort in equilibrium. By simulating firms' lives I am able to observe their growth over time. All new start-ups are initially small (they have only one worker). Depending on their initial productivity, they can either grow and become large, or they can quickly die and be replaced by new, more productive young firms. Before illustrating the simulation and the implications in terms of firm's size, I briefly outline the equilibrium.

A stationary equilibrium is an equilibrium wage function w^*, firm value and hiring functions $\{v^*, h^*\}$, worker functions $\{k^*, MV^*, K\}$ and equilibrium quit rate and

[1]For a detailed description of the theoretical model, refer directly to Chapter 2.

employment $\{q, G\}$ such that for all $x \in [b, \overline{p}]$:

(i) the equilibrium wage $w^*(x)$ satisfies

$$\frac{dw^*(x)}{dx} = -v^*(x)q'(x) \tag{3.1}$$

subject to $w^*(b) = b$;

(ii) employee value $v^*(x)$ and hire strategy $h^*(x)$ are the solutions to

$$gx\frac{d^2v^*}{dx^2} + (r + \delta_w + \delta_f + q(x) - h^*(x))\frac{dv^*}{dx} = 1 - c(h^*), \tag{3.2}$$

$$c'(h^*(x)) = \frac{v^*(x)}{x}, \tag{3.3}$$

with initial values $v^* = dv^*/dx = 0$ at $x = b$;

(iii) employee and aggregate search efforts $k^*(x)$ and $K(x)$, and marginal worker value $MV^*(x)$ solve

$$b\phi''(k^*(x))\frac{dk^*}{dx}k^*(x) = -q(x)MV^*(x), \tag{3.4}$$

with boundary value $k^*(\overline{p}) = \underline{k}$,

$$\frac{dK}{dx} = k^*(x)\frac{dG}{dx}, \tag{3.5}$$

with initial value $K(b) = k^*(b)G(b)$,

$$gx\frac{d\left[MV^*(x)\right]}{dx} + \left[r + \delta_w + \delta_f + q(x)\right]MV^*(x) = \frac{dw^*}{dx}, \tag{3.6}$$

with initial value $MV^*(x) = 0$ at $x = b$;

(iv) quit function $q(x)$ and employment distribution $G(x)$ are given by

$$\frac{dq}{dx} = \frac{q(x)}{k^*(x)}\frac{dk^*}{dx} - \frac{h^*(x)k^*(x)}{K(x)}\frac{dG}{dx}, \tag{3.7}$$

with boundary value $q(\overline{p}) = 0$,

$$gx\frac{dG}{dx} = \frac{q(x)K(x)}{k^*(x)} + \mu[1 - \Gamma(x)] - (\delta_w + \delta_f)[1 - G(x)], \tag{3.8}$$

with boundary value $G(\overline{p}) = 1$.

Chapter 2 provides a numerical solution of the model using fixed parameters, mainly retrieved from the literature. The aim of this Chapter is to illustrate how well the model can reproduce the overall features of the data, in particular the size distribution of firms and the behaviour of worker movements observed empirically[2].

3.3 Calibration

I estimate the parameters of the model using simulated method of moments. This method consists in minimising the distance between a set of empirical moments and the same moments recovered from a simulation of the model. Thus, I solve $\min_\Psi \sum_{i=1}^{m}[\frac{M_i^S - M_i^D}{M_i^D}]^2$, where M_i^S is the moment i obtained from the simulation, while M_i^D is the same moment retrieved from the data. As solving for the equilibrium is computationally intensive, I don't estimates all the parameters of the model: after fixing some of them, I am left with $m = 6$ parameters to calibrate, $\Psi = \{\delta_f, \mu, \phi_0, c_0, \underline{k}, a_1\}$. Table 3.3.1 describes both the predefined and the calibrated parameters. For the empirical moments, I use the LIAB longitudinal matched employer-employee data, which is described in Chapter 1[3]. However, as the LIAB comes in spell format, I choose to convert it into a monthly panel to

[2] I follow an approach similar to Trapeznikova (2017).

[3] This study uses the Linked-Employer-Employee Data longitudinal model 1993-2010 (LIAB LM 9310) from the IAB. Data access was provided via on-site use at the Research Data Centre (FDZ) of the German Federal Employment Agency (BA) at the Institute for Employment Research (IAB) and subsequently remote data access.

calculate the moments. The simulation will mimic the monthly frequency of the data.

I define the following analysis a 'calibration', and not an 'estimation' exercise. Indeed, while the former involves choosing model parameters in order to match certain features (i.e. moments) of the data, the latter, on the other hand, makes use of standard errors and yields goodness-of-fit measures in order to assess the empirical performance of the model. Formal model estimations, which are beyond the scope of this Chapter, are, for example, indirect inference and maximum likelihood[4].

3.3.1 Simulation

After having numerically solved for the equilibrium of the model[5], I simulate the employment histories of 25,000 establishments for 4,500 months. As establishments' births and deaths happen randomly at Poisson rates μ and δ_f, I can first simulate the establishments life paths as a birth-death process, where the waiting time until the occurrence of an event is an exponentially distributed random variable with parameter equal to the Poisson rate. For example, the duration until an establishment will exogenously close is $T = -log(1 - r_1)/\delta_f$, where $r_1 \in [0, 1]$ is a random number drawn from a uniform distribution. Similarly, I obtain the time the establishment is born and thus I determine its life span. Thus, both old and young establishments coexist at any given month. At start-up, the establishment productivity is drawn from a c.d.f. given by

$$\Gamma(z) = (z - b)\Big[\frac{1}{\overline{p} - b} + \frac{1}{2}a_1(z - \overline{p})\Big].$$

Then, quality declines exponentially at rate g. Thus, an establishment's life may

[4]The interested reader should refer to Dejong and Dave (2011) for a thorough discussion on those advanced methods.

[5]Chapter 2 explains the algorithm to solve the model for a given set of parameters.

Table 3.3.1: PARAMETERS

Parameter	Value	Description
A. Fixed Parameters		
r	0.0033	Monthly interest rate
b	1	Productivity, lower threshold
$\bar{p}$	2.32	Productivity, upper threshold
δ_w	0.0017	Monthly worker death rate
g	0.011/12	Output growth rate
α	3	Convexity of hiring cost
B. Calibrated Parameters		
c_0	48,601	Scale parameter of hiring cost
ϕ_0	51,418	Scale parameter of search effort
$\underline{k}$	0.0052	Costless search
δ_f	0.0150	Destruction shock
μ	0.0010	Start-up rate
a_1	0.3981	Skewness of start-up productivity

end not only because of a destruction shock, but also because quality reaches its threshold value $x_0 = b$. The model assumes that on its immediate start-up, the establishment has one employee. Conditional on surviving, its employment evolves according to the equilibrium hiring and quit identified in equations (3.3) and (3.7). The expected hiring flow of firm (x, n, t) is $nh^*(x)$ while its separation flow is $(q^*(x) + \delta_w)n$. The expected growth rate of firm (x, n, t) is therefore

$$\frac{\dot{n}(x, n, t)}{n} = h^*(x) - q(x) - \delta_w.$$

Starting with one employee and given quality x in every period, I determine the employment dynamics at each firm. In the simulation, an establishment's life ends if its size falls below one, even if it has not reached the threshold level $x_0 = b$. This implies that young establishments with low initial draw z will die with a high probability. I then discard the first 1,000 months to allow for convergence to the ergodic distribution. The simulation generates a joint distribution of firm quality, age, and size. From this population of simulated firms I calculate the moments of interest.

3.3.2 Parameter choice

Some parameter values are fixed in order to save computational time. They are summarised in the top panel of Table 3.3.1. The monthly discount rate is set at $r = 0.33\%$, which corresponds to a 4% yearly rate. I fix $\delta_w = 0.02/12$, so that the expected working lifetime of a labour market entrant is 50 years. The monthly growth rate of the economy $g = 0.011/12$ matches the average output growth rate in Germany for the years 2001-2009, which is the time period of the LIAB data I use for the calibration. In order to obtain the growth rate, I regress the log of per-capita GDP[6] on a linear trend. I normalise the threshold quality $x_0 = b = 1$ and set $\overline{p} = 2.32$. As $x(p,t) = \overline{p}e^{-gt}$, a new start-up with the highest initial draw $z = \overline{p}$ can expect to be profitable for at most 76 years.

Recruitment costs have the following specification: $c(h) = c_0 h^\alpha/\alpha$. Following Merz and Yashiv (2007), I assume $\alpha = 3$. While I use the cubic specification for the benchmark calibration, the comparative statics section compares the benchmark results with those for $\alpha = 2.5$. The cost of search $\phi(k) = \phi_0 k^{\phi_1}/\phi_1$ is quadratic in effort as estimated in Christensen et al. (2005), thus $\phi_1 = 2$.

This leaves to a set of six parameters $\Psi = \{\delta_f, \mu, \phi_0, c_0, \underline{k}, a_1\}$ to estimate.

3.3.3 Calibrated parameters

I target six data moments that relate to the employment distribution and worker reallocation, which I want the model to reproduce. The bottom panel of Table 3.3.1 describes the parameters that I estimate simultaneously. As $G(x)$ is the proportion of workers employed at establishments with quality no greater than x, $G(b)$ denotes the unemployment rate. Thus, the destruction shock δ_f is calibrated to be consistent with 9% monthly average unemployment rate in Germany for the

[6]Data source: World Development Indicators of the World Bank.

period 2001-2009[7]. The remaining parameters are chosen to fit moments retrieved from the LIAB dataset for the period 2001-2009 (Table 3.3.2). I choose to match the empirical average hiring rate in order to identify the scale parameter of the hiring cost, c_0. As illustrated in Chapter 2, the slope and scaling factor of the cost function are linked, so that a higher convexity requires a higher scaling parameter for the model to converge[8]. In order to fit the worker reallocation observed in the data, I choose ϕ_0, the scale parameter of the worker search effort, to match the observed average quit rate, i.e. the employer-to-employer transition rate. In the model, some job offers come for free: the costless search $\underline{k}$, which is the relative search effort of workers employed at the most productive establishments, targets the empirical average job creation rate. The job creation is the sum of all new jobs created, and the relative rate it is calculated as in Davis, Haltiwanger and Schuh (1996):

$$JC_t = \sum_{e \in E^+} \frac{H_{et} - S_{et}}{0.5(N_{et} + N_{et-1})}.$$

H_{et} is the total hires, S_{et} the total separation, and N_{et} the total employment of establishment e in month t and the superscript $+$ indicates the subset of establishments that expand. The job destruction, on the other hand, considers only negative job reallocations.

The parameter a_1 affects the skewness of the start-up productivity. The smaller a_1, the more $\Gamma(z)$ is skewed towards $z = b$. The majority of establishments in the data has small size, so the employment distribution of establishments is skewed to the right and presents a long right tail. In order to match these features, I calibrate a_1 and the start up rate μ to match the dispersion and the skewness of the employment found in the data.

[7]Data source: Eurostat database, seasonally adjusted monthly unemployment rate.

[8]Hiring and quit rates are calculated as in Chapter 1, with the only difference that now they are monthly, and not yearly, rates.

Table 3.3.2: Targeted Moments

Moment	Model	Data
Hiring rate	0.0189	0.0181
Quit rate	0.0047	0.0053
Unemployment rate	0.0890	0.0890
Job creation	0.0124	0.0127
Standard deviation of employment	27.969	27.363
Skewness of employment	14.890	15.213

Note: Monthly LIAB, 2001-2009, sample weights are used. Establishments with more than 1,000 employees are excluded from the sample.

Table 3.4.1: Moments of the employment distribution

	Model	Data
Mean	6.92	7.26
Median	2	2
Standard deviation	27.97	27.36
Skewness	14.89	15.21

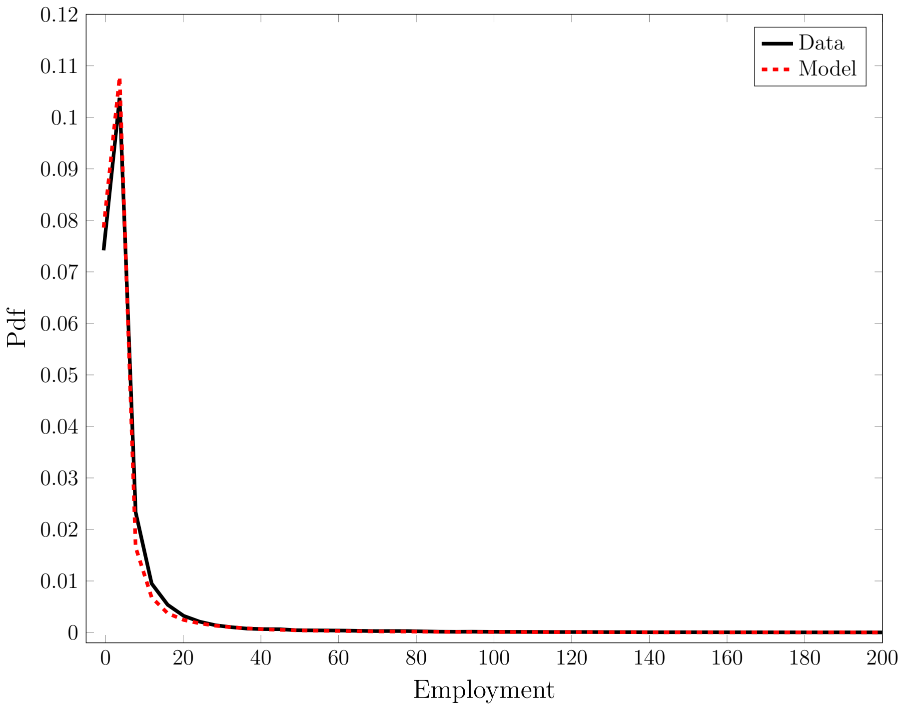
Note: Monthly LIAB, 2001-2009, employment has been weighted using sample weights. Establishments with more than 1,000 employees are excluded from the sample.

3.4 Empirical Implications

In the model, quality is an exogenous process, whose initial value z is a random draw from Γ and declines exponentially at rate g until closure. Establishment size, however, is an endogenous process. Besides matching the calibration targets, the model is also able to generate a size distribution which is close to the one observed in the data, as illustrated in Figure 3.4.1. As shown in Table 3.4.1, the model is able to capture the main empirical moments of the employment distribution.

The model is also able to fit reasonably well the data with respect to the employment share by firm size and age classes, which are illustrated respectively in Tables 3.4.2 and 3.4.3. In particular, the model is able to replicate the fact that there are many small establishments that, overall, employ a large share of workers, and also that most workers are employed in mature establishments.

Figure 3.4.1: Model fit: Employment distribution



Note: Gaussian kernel, bandwidth = 1.5. Data: LIAB, 2001-2009, employment has been weighted using sample weights. Establishments with more than 1,000 employees are excluded from the sample.

Table 3.4.2: Share of employment by establishment size

	Model	Data
Small	0.4418	0.4899
Medium	0.2666	0.2286
Large	0.2917	0.2815

Note: Monthly LIAB, 2001-2009.'Small' indicates <20 employees; 'Medium' indicates ⩾20 and <100 employees; 'Large' indicates ⩾100 employees. Establishments with more than 1,000 employees are excluded from the sample.

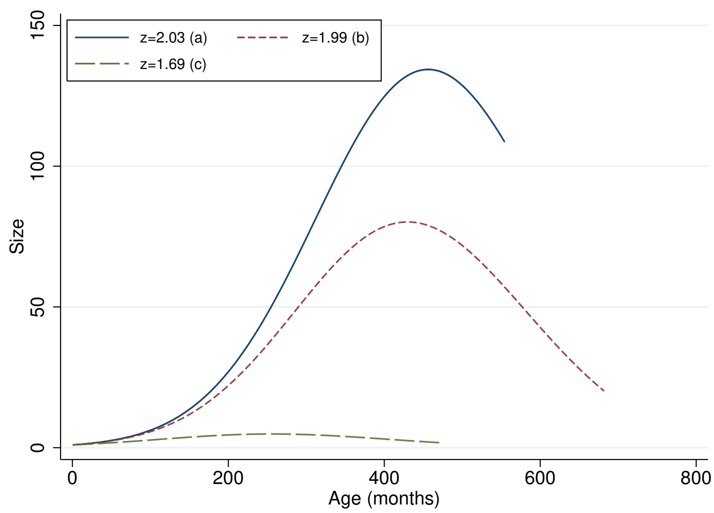
Table 3.4.3: Share of employment by establishment age

	Model	Data
Start-up	0.1458	0.1185
Young	0.1546	0.0923
Mature	0.6996	0.7892

Note: Monthly LIAB, 2001-2009.'Start-up' indicates the establishment is <5 years old; 'Young' indicates the establishment is ⩾5 and ⩽10 years old; 'Mature' indicates it is >10 years old. Establishments with more than 1,000 employees are excluded from the sample.

The simulation produces a life path for each new establishment. Figure 3.4.2 shows different life-cycle trajectories for establishments with different initial quality z-draws. In order to become large and mature, an establishment must have a favourable initial draw: establishment (a) has a very high initial productivity, which allows it to grow over time and reach its maximum size after about 40 years. After that, it starts to shrink, as its quality is declining relative to the technological frontier. If it were not hit by a destruction shock, it would have lived more than establishment (b). Option (c), on the other hand, shows an establishment born with low initial productivity. It stays small and dies before the others. Thus, there may be establishments with the same age that have very different size, as a small difference in the initial level of productivity generates very different size trajectories. As in every period new start-ups are born at rate μ, and each start-up has a different initial z-draw, at any given month old and large establishments coexist with young establishments which are very productive and have a high growth rate, and young establishments with low initial productivity, struggling to survive.

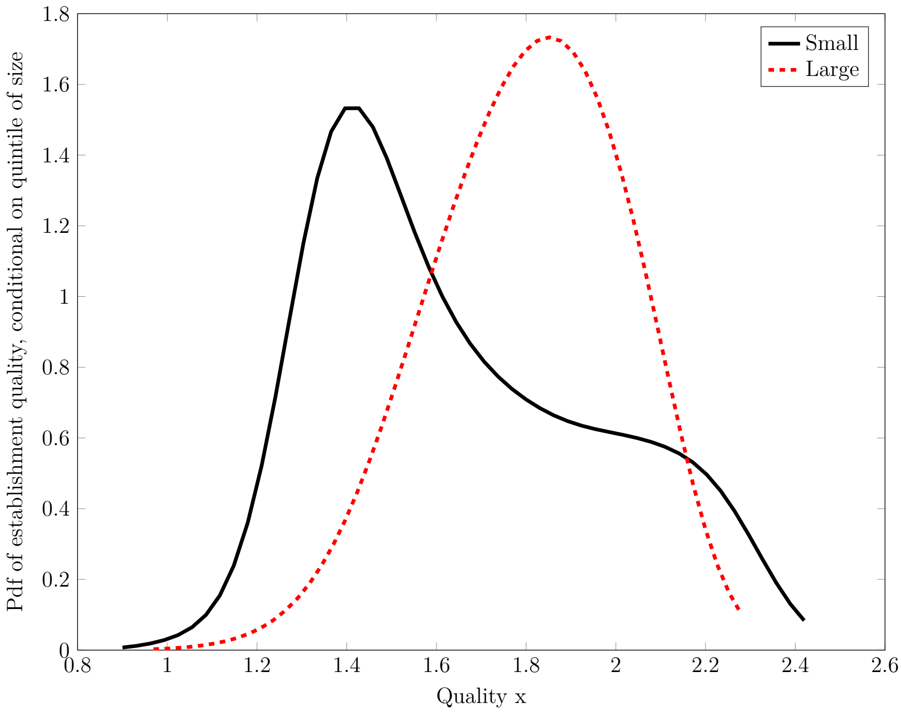
Figure 3.4.2: Simulated establishment size trajectories



Note: Evolution of establishment size depending on different levels of initial productivity.

Figure 3.4.3 plots the distribution of establishment quality x conditional on the upper and lower quintile of employment. Large establishments have, on average,

Figure 3.4.3: QUALITY DISTRIBUTION CONDITIONAL ON SIZE

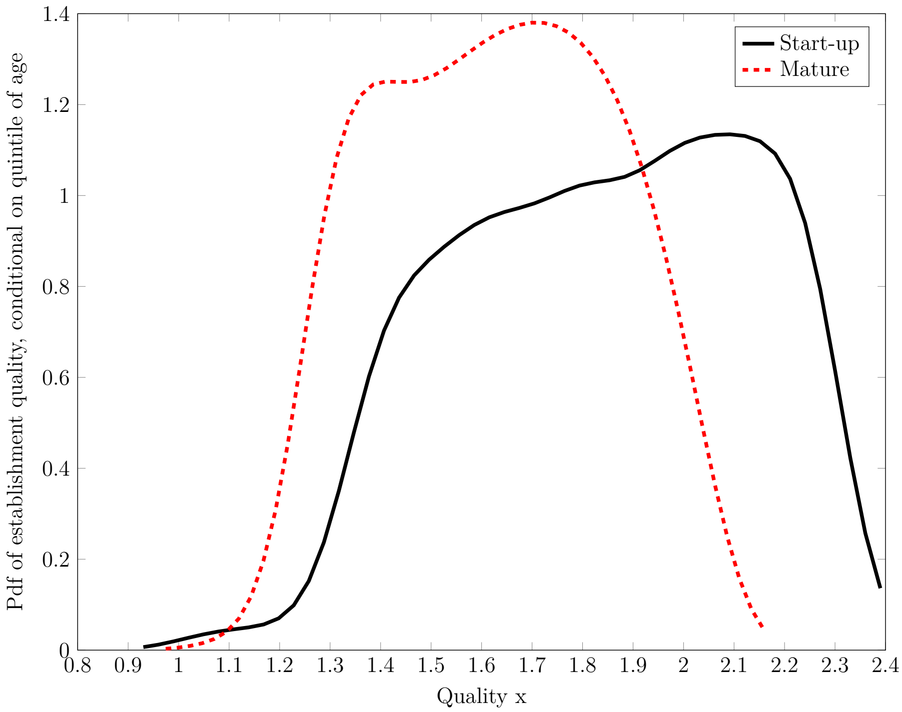


Note: Pdf of establishment quality x, conditional on quintile of size. 'Small' corresponds to the 1st quintile, 'Large' to the 5th quintile.

higher quality than small establishments. A currently large firm must have enjoyed a favourable z-draw on start-up, as shown in Figure 3.4.2. Conditional on survival, establishments born with a higher initial productivity become larger. As destruction rates δ_f are the same for all establishments, higher productivity establishments are, on average, larger. However, the conditional density of small establishments is more spread out: in order to become large, an establishment has declined relative to the technology frontier and has given way to the new fast growing start-ups, which, by construction, are born small. Therefore, large establishments cannot have the top quality level.

Figure 3.4.4 allows to observe the same quality distribution, conditional on establishment age. Younger firms will have, on average, higher quality than their more mature counterparts. However, their quality distribution is more spread out, as new establishments have heterogenous initial productivities. Some may be born with a very high quality, while others may have a very low z and quickly die. In

Figure 3.4.4: Quality distribution conditional on age

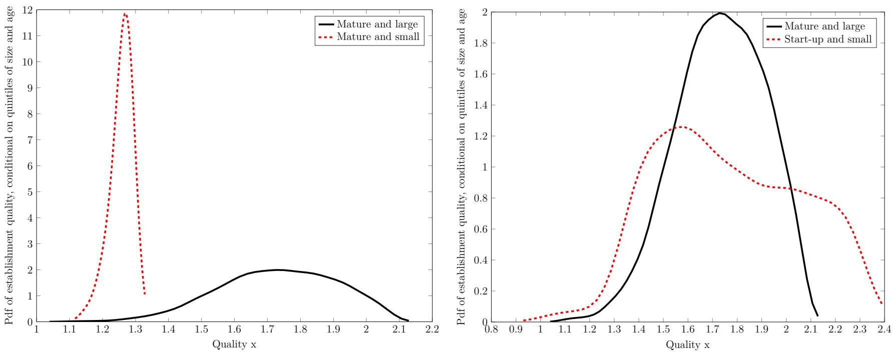


Note: Pdf of establishment quality x, conditional on quintile of age. 'Start-up' corresponds to the 1st quintile, 'Mature' to the 5th quintile.

order to become mature, they must have had a high quality in the past, which then declined relative to the market average.

Finally, Figure 3.4.5 compares the productivity distributions conditional on different size-age combinations. On the left panel, the high, narrow distribution and the low average quality indicate that the majority of small and mature establishments are dying, or struggling to survive. On the other hand, mature and large establishments are more heterogeneous, as there are establishments that are still growing (because they were born with a favourable z-draw) or establishments that grew large but are now in their declining phase. The right panel shows that start-up and small establishments have an even more spread out distribution. By construction, start-up are born small and can draw different quality levels from Γ.

Figure 3.4.5: Quality distribution conditional on size and age



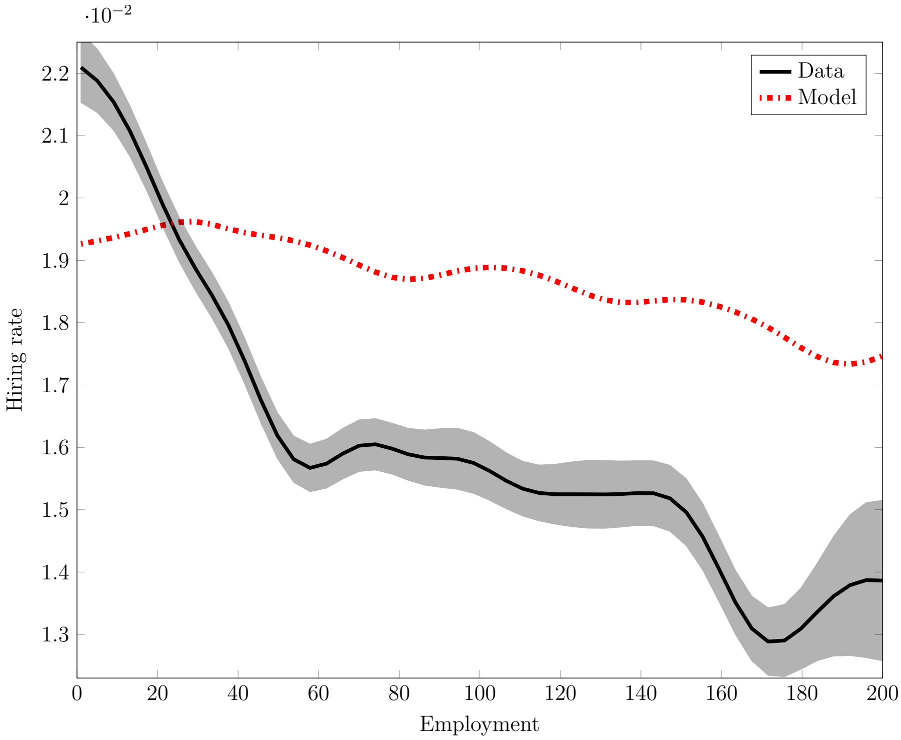
Note: Pdf of establishment quality x, conditional on quintiles of size and age. 'Small' corresponds to the 1st quintile of size, 'Large' to the 5th quintile of size; 'Start-up' corresponds to the 1st quintile of age, 'Mature' to the 5th quintile of age.

3.4.1 Worker Flows

I now illustrate the empirical implications of the model as regards worker flows.

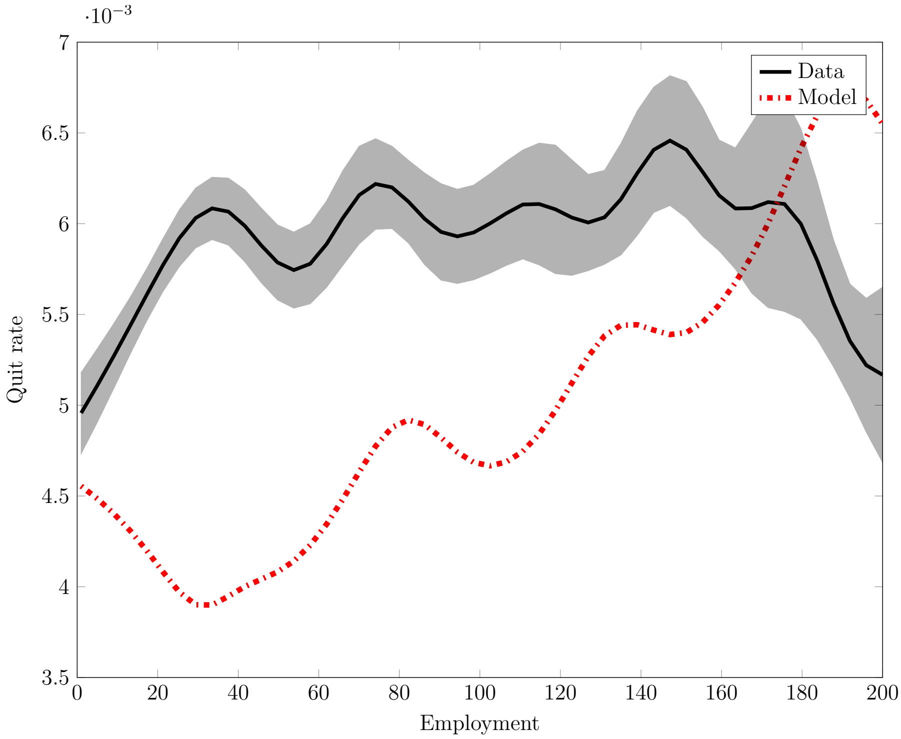
Figure 3.4.6 compares the relationship between establishment hiring rate and size in the model to that in the data. The model predicts a negative relationship between size and hiring rate. More productive firms hire more and grow large. As they grow, they become old and decline relative to the technology frontier. Thus, the hiring rate falls. Albeit the graph shows a less sharper decline of the hiring rate in the model, the model qualitatively captures the negative pattern. On the other hand, as expected, the model does not perform well when illustrating the quit behaviour, as shown in Figure 3.4.7. The model predicts that size and job-to-job quits are initially negatively related. As the establishment grows, its quit decreases. However, the establishment starts to decline relative to the market average, and workers start to leave it for more productive employers. This is why after size reaches about 30 employees, the relationship between size and quit rate is positive. The data, on the other hand, do not suggest the same pattern. Job-to-job quits do not seem to be affected by the size of the employer. In addition, for a small size, the relationship is positive.

Figure 3.4.6: Relationship between hiring rate and employment: model vs. data



Note: Non-parametric regression of hiring rate on employment, in the model and in the data; the shaded area on the left panel shows the 90% confidence intervals (data).

Figure 3.4.7: Relationship between quit rate and employment: model vs. data



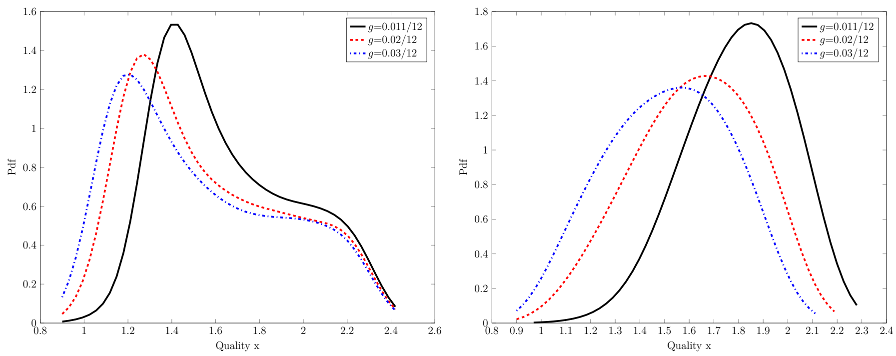
Note: Non-parametric regression of quit rate on employment, in the model and in the data; the shaded area shows the 90% confidence intervals (data).

3.5 Comparative Statics

To further illustrate the properties of the model, I perform some counterfactual exercises in order to examine the effect of changes in the parameters on the outcomes of the model, in particular on the distribution of establishment productivity, conditional on size and age. I first explore the effect of alternative rates of technological growth g, keeping constant the other parameters of the model. The left panel of Figure 3.5.1 shows that in the benchmark calibration, there are few establishments that become mature and small, because they are destroyed in advance by a destruction shock δ_f. This is because in the benchmark calibration g is relatively small, in order to account for the empirical economic growth observed for Germany. On the other hand, a higher g implies more establishment turnover: as the technology frontier moves fast, establishments quickly decay and soon reach a low quality level before being hit by the destruction shock. An increase in g does not affect much the right tail, as all establishments by construction start small, and their start-up productivity depends on the initial draw z. The right panel of Figure 3.5.1 illustrates that an increase in g has a greater impact on large establishments: as the technology frontier moves fast, establishments quickly become obsolete, and they cannot become as large as in the benchmark case.

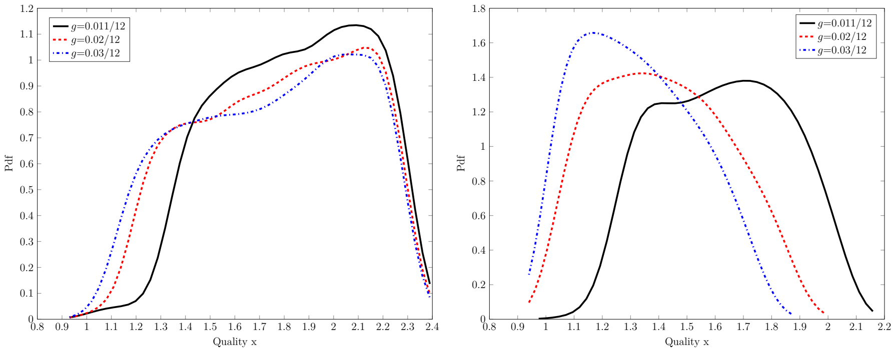
The left panel of Figure 3.5.2 shows that an increase in g shifts the age-conditional

Figure 3.5.1: SMALL VS. LARGE: EFFECT OF A CHANGE IN g



Note: Effect of a change in g on the distribution of quality x, conditional on size.

Figure 3.5.2: Young vs. mature: effect of a change in g



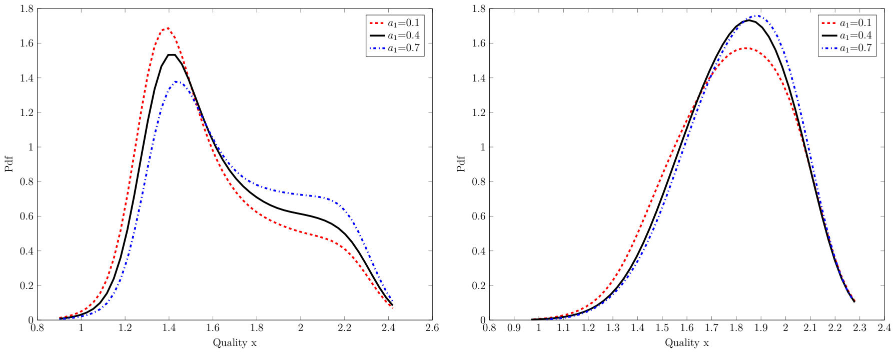
Note: Effect of a change in g on the distribution of quality x, conditional on age.

distribution of establishment productivity to the left. As the technology grows faster, there are more establishments at risk of failure during the first stages of their life. More interesting is what happens to mature establishments, shown in the right panel. There is a large shift to the left associated with an increase in g. On average, a mature establishment is less productive and quickly arrives to its closure threshold before being hit by the destruction shock.

Figure 3.5.3 assesses the effect of a change in a_1, the skewness parameter of the c.d.f. of initial productivity $\Gamma(z)$. A higher a_1 increases the average initial productivity, thus there are more young establishments, born small, that have a higher initial quality level. The shape of the distribution remains almost invariant. In addition, the change in the distribution is more prominent for small establishments than for large ones, as the initial differences in productivity lessen by the time the establishments become large. The effect of a change in a_1 is clearer when observing Figure 3.5.4. An increase in the skewness parameter increases the proportion of start-ups with high productivity (left panel). This has an effect also over time (right panel): surviving establishments are, on average, more productive, as they started with a higher quality and they all face the same rate of technological growth.

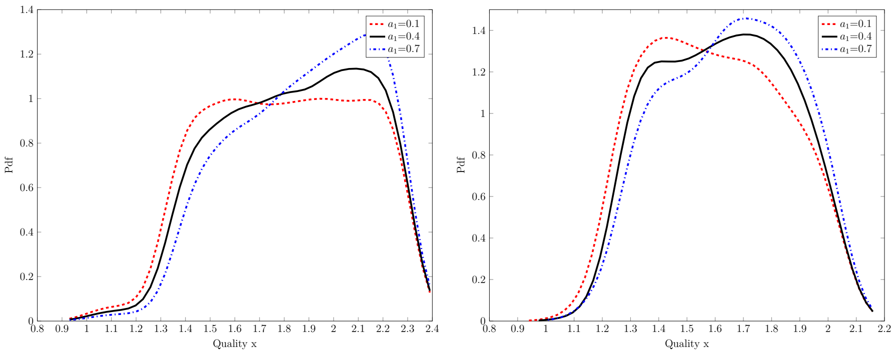
Finally, Figure 3.5.5 shows the effect of a lower α on the quality distributions, conditional on size. As observed in Chapter 2, a higher convexity of the hiring

Figure 3.5.3: Small vs. large: effect of a change in a_1



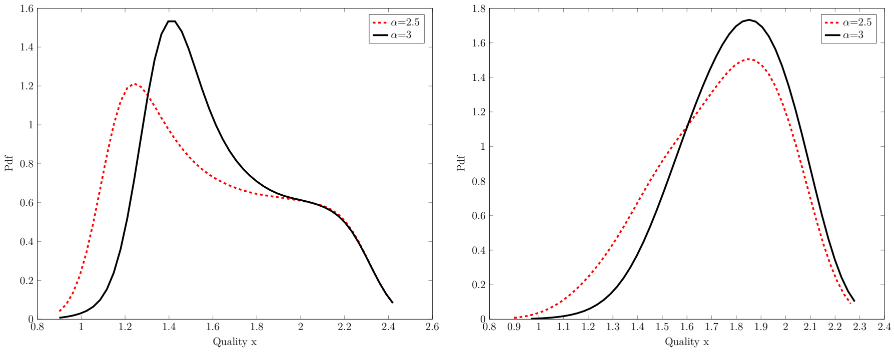
Note: Effect of a change in a_1 on the distribution of quality x, conditional on size.

Figure 3.5.4: Young vs. mature: effect of a change in a_1



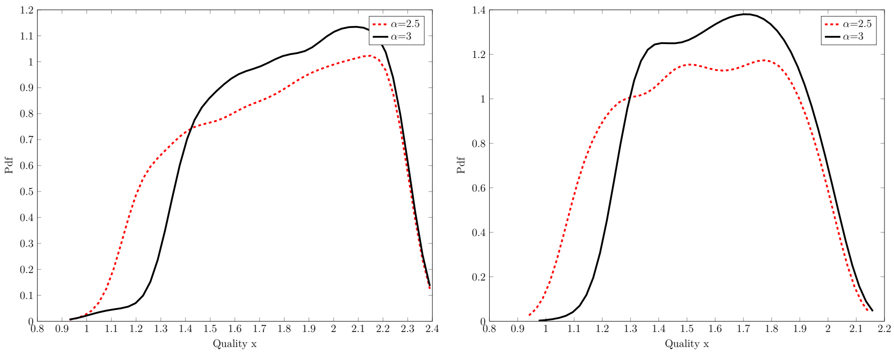
Note: Effect of a change in a_1 on the distribution of quality x, conditional on age.

Figure 3.5.5: SMALL VS. LARGE: EFFECT OF A CHANGE IN α



Note: Effect of a change in α on the distribution of quality x, conditional on size.

Figure 3.5.6: YOUNG VS. MATURE: EFFECT OF A CHANGE IN α



Note: Effect of a change in α on the distribution of quality x, conditional on age.

cost is necessary to generate enough job-to-job quits. When $\alpha = 2.5$, both small and large firms have lower productivity, on average. As the unemployment is high, establishments can hire not only by 'poaching' workers from other employers, but they can also benefit from the larger pool of unemployed individuals. Thus, also less productive firms can hire and become large (right panel). Small, old establishments are those struggling to survive, they cannot hire and grow, and have very low productivity (left panel). This implies that the distributions conditional on age are wider (Figure 3.5.6): young establishments with low quality x can still survive by hiring from the unemployed and other low quality employers (left panel). Moreover, less productive establishments have a higher chance to survive and become old.

3.6 Conclusions

This chapter quantitatively assessed the performance of the theoretical model described in Chapter 2, using the LIAB matched employer-employee data. The model is able to generate interesting firm dynamics: small start-ups have a high risk of exit, but, conditional on having a favourable initial productivity, manage to grow over time. This Chapter shows that the model is able to match the establishment size distribution observed in the data, and does a good job in replicating the relationship between employment and hiring. However, it does not capture the behaviour of job-to-job quits across size. Nevertheless, the quantitative analysis highlights interesting features of the model: establishment size is correlated with productivity, hence wages (*large firm-wage* effect), but establishment size does not have any causal impact on productivity or wages. At the same time small, young establishments, offering high wages, together with large but mature establishments that offer lower wages and decline, can coexist. This is consistent with what observed in Chapter 1: workers do indeed reallocate from low to high wage establishments, but there is no evidence of workers moving from small to large employers.

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