The Careers of Immigrants*

Ana Damas de Matos†

London School of Economics

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Abstract

I use a unique linked employer employee panel covering all wage earners in the private sector in Portugal to shed new light on the careers of immigrants. During the first ten years in the country immigrants close one third of the initial immigrant-native wage gap. I show that one third of this wage catch-up is accounted for by firm heterogeneity: Immigrants remain in the same occupations but get jobs with better paying firms. Over time immigrants move to larger, more productive firms and with a higher share of native workers. These patterns are similar for all the recent immigrants irrespective of their origin and in particular of whether their mother tongue is the host country's language. Motivated by these new stylized facts, I suggest an economic assimilation mechanism which highlights imperfect information about immigrant productivity. I build an employer learning model with firm heterogeneity and complementarities between worker and firm type. The initial uncertainty over immigrants' productivity prevents them from getting access to the best jobs. Over time, productivity is revealed and immigrants obtain better firm matches. I derive predictions on the immigrant wage distributions over time, on their mobility patterns and on the productivity distribution of firms they are matched with. The predictions of the model are in line with the data and are not trivially derived from competing explanations.

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†London School of Economics. E-mail: a.s.matos@lse.ac.uk.

1 Introduction

Over the past thirty years, the literature on the economic assimilation of immigrants has focused on measuring the immigrant-native wage gap and the speed at which the gap closes with time spent in the host country. According to Chiswick (1978) immigrants earnings' would equal and then exceed the natives' after 10 to 15 years of residence. Although this estimate has been shown to be overly optimistic, there is widespread evidence that immigrant wages catch up with the natives over time. Duleep and Dowhan (2002) and Lubotsky (2007) in particular present evidence using longitudinal data for the US.

A number of potential explanations for the wage catch-up have been proposed. Eckstein and Weiss (2004) summarize the channels through which immigrants assimilate as follows: "With the passage of time in the host country, immigrants invest in local human capital and search for better matches with local employers, and employers become less uncertain of the immigrant's potential and realized quality." Similar explanations are mentioned in Chiswick (1978), Borjas (2000) and LaLonde and Topel (1997). This quote refers to three models of the distribution of earnings which may be used to explain immigrant economic assimilation: a human capital, a search and matching and an employer learning model.

Surprisingly no research has focused on studying the relative importance of these channels. In fact, most empirical studies of immigrant wages start from a generic statement of the human capital model[1] and focus mainly on measuring the immigrant catch-up rate. Within the human capital framework, several contributions highlight the importance of different factors, such as speaking the host country language (Chiswick and Miller (1995)), the age at arrival in the host country (Friedberg (1992)) or the country of origin (Chiswick (1978),Borjas (2000)) in explaining the immigrant wage catch-up. However, no systematic attempt has been made to differentiate between immigrant economic assimilation channels.

This paper is a first step to address this gap in the literature. I use a unique linked employer-employee panel to study the early careers of immigrants in Portugal. The contribution of this paper is two-fold. First, exploiting the richness of the data, I document new immigrant assimilation patterns in

[1]Borjas (2000) shows how different assumptions made on the human capital production function may lead to very different predictions in terms of immigrant wage patterns. Few papers take the human capital model seriously to investigate the mechanisms further. An exception is Eckstein and Weiss (2004) who assume an exogenous increase in the returns to immigrants' skills and model the investment in human capital with time spent in the host country.

the first years in the host country. In particular, I show that job mobility and firm heterogeneity play an important role in the assimilation process. Second, motivated by the stylized facts, I build an economic assimilation model based on employer learning with firm heterogeneity and complementarities between worker and firm type. I derive additional predictions from the model and show that they are in line with the patterns in the data and that they can not be trivially explained by a search and matching or human capital model.

I start the empirical analysis by measuring the immigrant wage catch-up rate. I document that upon arrival immigrants earn 34% less than natives of the same age and 16% less than natives of the same age working in the same region, industry and occupation. I show that the gap closes at a rate of 1 percentage point per year spent in the country. As I use a panel which covers virtually all workers in the private sector, selection concerns are reduced. Estimates with and without individual fixed effects are very similar showing that selection is not a major concern in this context. This estimate of the wage catch up is in line with the literature for the US. For instance, Lubotsky (2007), using longitudinal social security data, shows that immigrants' earnings catch up with the natives at a rate of 10 to 15 percentage points in 20 years.

Accounting for immigrant sorting across regions, industries and occupations does not change the estimated catch up rate significantly. Immigrants do not assimilate by changing occupations and moving to different industries. However, this paper shows that they do assimilate by switching firms. In fact, the first years in the country are characterized by a very high job mobility rate and one third of the immigrant wage catch up is linked to moving to better paying firms. This finding relates to a small but growing literature which measures how the sorting of immigrants across firms relates to the wage gap between immigrants and natives. Evidence for Canada[2] indicates that wage differences between firms are more important than differences within firms in explaining the immigrant-native wage gap. I build on this literature and show that moving to better paying firms is an important channel through which immigrants move up the wage distribution.[3]

I then use the rich information in the data to focus more directly on the role of firms in the

[2]See Aydemir and Skuterud (2008) and Pendakur and Woodcock (2009)

[3]Pendakur and Woodcock (2009) find evidence that immigrants who have spent more years in the host country work in less segregated and better paying firms than recent immigrants. However they are unable to rule out that this result may be driven by differences in characteristics of different cohorts of immigrants or by self-selection in out-migration. I estimate the wage regressions with firm *and* worker fixed effects, which allows to separate the effects.

assimilation process. Over time, immigrants move to bigger and more productive firms and get access to longer term contracts. Immigrants tend to start their careers in firms with a high proportion of immigrant workers and over time they move to firms with a higher share of native workers.

Moreover, I show that the wage catch up and firm mobility patterns are very similar for all the recent immigrants irrespective of their origin and in particular of whether their mother tongue is Portuguese. This result is at odds with a human capital accumulation explanation of the wage catch up. One would expect immigrants who speak the language to suffer a lower wage penalty to begin with but also to catch up more slowly.

Motivated by this new set of empirical facts on immigrant careers, I suggest an economic assimilation mechanism which highlights imperfect information about the productivity of immigrants. The model presented is an employer learning model with firm heterogeneity and complementarities between worker and firm type. It builds on the employer learning model by Farber and Gibbons (1996) and Lange (2007). These models assume that firms are homogeneous and that workers are paid their expected marginal productivity, which is independent of the firm they work for. I introduce firm heterogeneity and an assignment mechanism to allocate workers to firms. The mechanism considered is similar to the one in the differential rents model presented in Sattinger (1993). Each firm hires one worker and workers are assigned to firms according to their expected productivity given the information available at the time. As there are complementarities between worker and firm productivity, workers with higher expected productivity are assigned to more productive firms.[4]

The focus of the model is on the uncertainty: I assume that the only difference between immigrants and natives entering the labour market is that there is more uncertainty about immigrants' productivity than about natives'. I consider this to be a reasonable assumption: Typically it is easier for employers to judge the skills of a native than those of an immigrant. For instance, the evaluation of prior experience and education is less straightforward in the case of immigrants.

In the model, firms produce subject to decreasing returns to skill and thus value certainty over worker productivity. This prevents immigrants from getting access to the more productive firms in the first years in the host country. With time spent in the labour market, the uncertainty over worker

[4]Two papers who combine complementarities in the production function and employer learning are Gibbons et al. (2005) and Groes et al. (2010). The complementarity I am assuming is between worker and firm type, whereas in these papers they refer to industry and worker type and occupation and worker type.

productivity decreases and workers get matched on average to more productive firms.

The predictions of the model on the mean wages and the job mobility patterns are in line with the stylized facts. The learning model also has strong predictions on the evolution of the distribution of immigrant wages over time, and in particular on the variance of wages. I take these predictions to the data and study the variance of wages of immigrants and natives entering the market in the same year over time. The variance of the log wages is higher for natives than for immigrants and increasing for both groups over time. I show that firm heterogeneity accounts for a significant part of the increase in the variance of log wages. These results are in line with the predictions of the model.

Finally, I show that the results are not trivially derived from a competing search and matching or human capital explanation.

Section 2 of the paper describes the data and presents some descriptive statistics on the immigrant population. Section 3 documents immigrant assimilation patterns. In section 4, I present an employer learning model with firm and worker heterogeneity and derive predictions on the distribution of immigrant wages. Section 5 compares the distribution of wages for immigrants over time against the predictions from the model and section 6 discusses other possible assimilation mechanisms and how they compare to the patterns in the data. Concluding remarks are presented in section 7.

2 Data and Descriptive Statistics

2.1 Data, Context and Sample Selection

Every year in November, firms registered in Portugal must hand in a detailed questionnaire ('Quadros de Pessoal') to the Portuguese Ministry of Labour. This process is mandatory for all firms in the private sector employing at least one wage earner. With the exception of the public service and domestic workers, virtually all wage earners in the Portuguese economy are covered by the survey. The questionnaire contains detailed information about the firm (the location, the volume of sales, the industry, etc.), the establishment (the location, the number of workers, the collective bargaining agreement, the industry, etc.) and the worker (age, gender, education, nationality, etc.). All workers, firms and establishments have a unique identifier which allows to track them over the years.

When a worker is not in the panel in a given year, it is impossible to distinguish whether he is unemployed, working in the public sector or in the informal sector. In the case of immigrants, in particular, when a worker drops out of the panel, it is impossible to know whether he has migrated to the home country (or to a third country).

Portugal, like Italy, Spain or Greece, has been an emigration country for most of the last century and this trend has only been reversed in the last 10 years. These traditional emigration countries are now experiencing large inflows of immigration. Net migration numbers between 2000 and 2007 are striking: there are an additional 4.6m legal immigrants in Spain, 2.6m in Italy and close to half a million in Portugal and Greece.[5] In order to deal with the large inflow of undocumented immigrants, the Portuguese government organized an "extraordinary regularization" in 2001. The foreign legal population in Portugal increased by 69% in that year. Approximately 183,000 individuals got a permit to live in the country for a year. The permits were renewable up to four times. After five years, immigrants could apply for a long-term residence permit. Having a work contract in Portugal was the main condition to obtain and renew a short-term residence permit. In 2003, bilateral agreements were signed with Brazil which allowed Brazilian immigrants residing in Portugal before July 2003 to obtain a long-term residence permit. Although there has been no major regularization programme since 2003, immigrants may apply for a residence permit if they are in the country, have a work contract and are

[5]These numbers represent respectively 10.5%, 4.2%, 3.7% and 2.7% of the countries' total populations in 2007, according to Eurostat.

registered with the social security.

I restrict the analysis to immigrants from the new immigration wave, that is immigrants who enter the labour market after 2001. In 2000, only 0.5% of workers in the data are immigrants, in 2002 immigrants represent 4% of workers. The data set covers only workers in the formal sector. As there is no direct information on the years immigrants have spent in the country, I build a proxy which indicates the first year the immigrant appears in the data, that is the first year the immigrant has a job in the formal sector. In all the analysis, the variable "years since migration", YSM, refers to years in formal employment, and the "cohort" the immigrant belongs to is the first year he is tracked in the data.

Figure 1 shows the mean hourly wages for the different cohorts of immigrants over time. The trend in mean wages is similar for all cohorts. The 2002 cohort captures a high proportion of the immigrants who took advantage of the 2001 regularization. These immigrants may have been working informally in the country in the previous years.[6] One may thus be concerned that this cohort is unusual. The trend in mean wages of the 2002 cohort is nevertheless similar to the other cohorts which eases this concern.

I use the information in the data on the workers' nationality to define immigrants as foreigners. In the short run naturalization is not an issue, since immigrants need at least six years of legal residence to be able to apply for Portuguese citizenship.[7]

I restrict the analysis to immigrant men. Women represent less than 30% of immigrant observations in the data and would need a separate analysis. Immigrant women in Portugal often get jobs as domestic workers and are hence not covered in the data. I restrict the sample used to native and immigrant men. In the 2002-2009 period, I follow the early careers of close to 120,000 immigrant men.

2.2 Descriptive Statistics

The immigrants considered in the data are divided into three main origin groups, representing more than 90% of the total number of immigrant observations: Immigrants from Eastern and South Eastern Europe (Eastern Europeans, in the text), Brazil, and the former Portuguese African colonies (Africa)[8].

[6] Detailed information on the construction of the panel and the variables is in the appendix.

[7] Also, if an individual is foreign for five years and then becomes Portuguese, he is considered to be an immigrant for the analysis. More details on the construction of the panel are presented in the appendix.

[8] The exact definitions of the groups are in the appendix. Immigrants from the EU15 represent 4.5% of immigrant observations and are excluded from the analysis.

Graphics 2 and 3 illustrate the number of immigrants in the data each year; and the number of immigrants who belong to each cohort, from 2002 until 2009. After the large increase of foreign legal residents in Portugal in 2001, the number of immigrants continued to increase. With worsening labour market conditions, the inflow of immigrants slowed down after 2005 and the stock of foreigners in the data actually decreased in 2006 and 2009. The representation of the main origin groups has also changed over the years. Immigrants from Eastern Europe are the group which took greatest advantage of the 2001 regularization (101,000 permits), in particular citizens from the Ukraine (65,000 permits) and Moldova. The number of immigrants from Eastern Europe entering the country declined sharply over the years and, as figure 2 shows, even the stock of Eastern European immigrants is in decline. Brazilians started migrating later to Portugal, and by 2009 are the biggest of the three groups in terms of new migrants. Since 2007 Brazil is the most common citizenship of immigrants residing legally in Portugal. Immigrants from Africa are the oldest immigrant community in Portugal. Although this group also benefited from the 2001 regularization, there has been immigration from Africa, mainly from Cape Verde, since the 1980s. Until 2007 Cape Verdeans were the largest foreign community in Portugal. The assimilation patterns of this group turn out to be slightly different from those of the immigrants from the recent immigration wave.

Selected descriptive statistics of the data used are presented in table 1. Immigrants are younger than the native population, and they have worked in Portugal on average just a little more than 3 years. Immigrant men are very concentrated in a small number of industries: construction by itself accounts for more than 42% of the immigrant observations. Immigrants from different origin groups select into different industries: 46% percent of the observations for men from Eastern Europe and 56% from Africa are jobs in construction, whereas for Brazilians the proportion is only 34%. Brazilian immigrants are more likely to work in hotels and restaurants. Furthermore, immigrants from Eastern Europe are more evenly spread in the different regions of the country, whereas immigrants from Africa are very concentrated in the Lisbon metropolitan area where the traditional community has settled since the 1980s.

3 The Economic Assimilation of Immigrants

3.1 Measuring the Wage Catch-up

The main question in the immigrant assimilation literature is whether the gap in wages immigrants experience upon arrival decreases with time spent in the host country. Following the literature, I estimate equation (1) below by ordinary least squares. The log hourly wage of worker i in job j in year t is given by:

$$ln(HW)_{ijt} = \alpha FG_i + \gamma YSM_{it} + X_{ijt}\beta + \eta_i + \epsilon_{ijt} \tag{1}$$

The dependent variable is the worker's log hourly wage, FG is a dummy that indicates whether the individual is an immigrant and YSM are the years since migration. YSM is set to 0 for natives. The coefficient α measures the immigrant-native wage gap and γ the rate at which the gap decreases with years since migration[9]. I measure the wage gap and the wage catch-up controlling first only for a quartic in age, and then progressively controlling for region, industry and occupation. This specification is restrictive since it assumes that the returns to characteristics are the same for immigrants and natives but nevertheless represents a useful benchmark.

The results for the different specifications are presented in table 2. The mean hourly wage gap is 34.4% in the first year and decreases by 0.9 percentage points with each year spent in the country.[10] Adjusting by differences in sorting across regions and industries reduces the initial gap to 24.5% and accounting for occupational differences reduces the gap still further to 14.6%. More than half of the wage gap between natives and immigrants is due to differences in immigrant sorting into different regions, industries and occupations. The wage catch-up rate γ however is very stable across specifications. This result shows that the immigrant wage catch-up occurs within narrowly defined regions, industries and occupations. In the first years in the country, immigrants have higher wage growth than natives of the same age. The catch-up is not correlated to immigrants moving to different industries or occupations over time.

Cross-sectional calculations of the catch-up rate tend to over-estimate immigrant assimilation if

[9]Introducing higher order polynomials in YSM does not change the results. The effect of years in the country is close to linear in the first ten years in the country.

[10]The variable YSM is set to 1 in the first year an immigrant is in the country so the initial gap is $-0.353 + 0.009 = -0.344$

more successful immigrants have a higher probability of remaining in the host country and less successful ones return to their home countries. I estimate all the specifications with individual fixed effects in order to address the selection concern. The results are presented in the last three columns of table 2. Controlling for individual fixed effects also does not change the γ significantly which indicates that the bias due to self-selection in out-migration is not a major concern in this context. Changing regions, industries and occupations is part of the assimilation process. I therefore choose the specification controlling only for a quartic in age and individual fixed effects as my preferred specification. The immigrant wage catch-up is set at 1 percentage point per year. This estimate is similar to the estimates for the US using panel data. Lubotsky (2007) evaluates the closing of the wage gap in the US at 10 to 15 percentage points in 20 years.

Next, I run the regressions separately for different origin groups. Table 3 presents the preferred specification, which controls only for a quartic in age, with and without individual fixed effects, for the 3 main origin groups. The wage gap is similar for all origin groups. It is 6 percentage points lower for Brazilians than for immigrants from Eastern Europe. The gap for immigrants from Africa lies in between. After accounting for individual fixed effects, the wage catch-up rate is slightly higher than 1 percentage point for Brazilians and Eastern Europeans but immigrants from Africa lag substantially behind. These results show that speaking the host country language may not be as important as one might have imagined for immigrant assimilation. Eastern Europeans are the only immigrants whose mother tongue is not Portuguese, yet their wage growth is comparable to the one experienced by Brazilians. The descriptive statistics show that immigrants from Brazil self-select into different sectors and occupations than Eastern Europeans, but after this initial sorting the assimilation patterns are very similar.

3.2 A Distributional Approach

The previous results establish that there is immigrant wage catch-up as measured by the mean hourly wages. Comparing the whole distribution of log hourly wages of immigrants and natives shows that the distribution of wages of immigrants is becoming more similar to that of the natives with time spent in Portugal. Figure 4 illustrates this point. The graphic shows the representation of immigrant wages in the distribution of native wages by years since migration, and more specifically in the entry year, after 5 years and 9 years in the country. For example, in the first year in the country on average 33% of immigrants earn less than the lowest decile of the native distribution. After 5 years in the host country, less than 5% of immigrants do so. With years spent in the country, the distribution of wages of immigrants widens and comes closer to the native wage distribution.

The calculations in this section use all cohorts and all years pooled together. One might worry that the results are confounded by cohort effects and selection. To address this concern, I do the same calculations for each cohort separately, for the whole cohort and for "stayers" only. I consider "stayers" immigrants who can be tracked in the data each year. The graphics in figure 5 show the results for the 2003 cohort. Immigrants move up the wage distribution also when considering only "stayers" of the same cohort. The results for all other cohorts and origin groups are similar and presented in the web appendix.

These results show that over time immigrants move up the wage distribution. In the next sections, I focus on a specific mechanism through which the catch up occurs: job mobility. I first estimate a linear probability model of job mobility; I then show that the wage catch up is linked to immigrants moving to better firms; and finally I present descriptives on the firms that immigrants work for over time.

3.3 Immigrant Job Mobility

A very strong empirical regularity in the data is that the immigrant job mobility is very high. Table 4 presents results on a linear probability model of changing employers. The dependent variable is a dummy that equals 1 if the worker-firm match will end in the next period, 0 if the worker is still working for the same firm in the next period. Only workers who are in the data in two consecutive years are considered in the analysis. On average 7% of native workers change employers in a given year. The rate is much higher for immigrants : after the first year in the host country, 26% of immigrants change employers[11]. The probability of changing firms for immigrants decreases by approximately 2.1 percentage points per year. In specifications (3) to (5) of table 4, I introduce other variables in the model. In line with the literature on job mobility, eg. Farber (1999), I control for a cubic in tenure and the current hourly wage in column (3), and account for differences in sorting across regions and industries (column (4)) and occupations (column (5)). Immigrants have on average lower tenure, lower

[11] The variable YSM is set to 1 in the first year an immigrant is in the country so the initial gap is $0.211 - 0.021 = 0.191$

wages and work in different industries and occupations than natives. These differences account partly for the differences in job mobility rates: there is nevertheless a remaining unexplained gap between immigrants and natives.

3.4 The Role of Firms in Immigrant Assimilation

3.4.1 Introducing Firm Heterogeneity in the Wage Catch-up Estimations

Recent evidence from Canada[12] indicates that the immigrant native wage gap is associated to immigrant sorting across firms. Immigrants are not paid less than natives working in the same firm, but are systematically concentrated in firms that pay less, holding worker and job characteristics fixed. In this section, I look at whether with time spent in the host country immigrants move to firms that pay better, and if so, how much of the wage catch-up does this upward mobility account for.

I introduce firm heterogeneity in the wage equation estimated in the previous section in order to investigate whether the immigrant wage catch-up is related to immigrants moving to better paying firms over time. This estimation is a wage decomposition with individual and firm fixed effects following Abowd et al. (1999). This paper is the first to present the AKM decomposition in the context of immigrant assimilation. I thus augment equation (1) as follows[13]:

$$ln(HW)_{ijt} = \alpha FG_i + \gamma YSM_{it} + X_{ijt}\beta + \eta_i + \mu_j + \epsilon_{ijt} \tag{2}$$

The estimation results are presented in table 5. Columns (1) to (3) reproduce the results from table 2 controlling for individual fixed effects. Columns (4) and (5) add firm fixed effects. Column (4) controls only for a quartic in age, whereas column (5) controls also for occupation. Comparing the estimates for the main coefficient of interest, the wage catch-up rate γ, with and without firm fixed effects, gives us an idea of the role of firm heterogeneity in immigrant assimilation. Controlling for firm fixed effects, in addition to region and industry, decreases the estimated catch-up rate from 1 to 0.6 percentage points. In the estimations controlling also for occupations, the rate decreases similarly from 0.9 to 0.6 percentage points. When analyzing the importance of sorting across firms in the immigrant wage gap, Pendakur and Woodcock (2009) show evidence that immigrants who have been in Canada

[12]The main papers are Aydemir and Skuterud (2008) and Pendakur and Woodcock (2009).

[13]I estimate this wage regression with two high dimensional fixed effects using the algorithm presented in Guimaraes and Portugal (2009) implemented in Stata through the command reg2hdfe.

for 10 years or more work in higher fixed effect firms than more recent immigrants. However, they can not exclude that this result may be due entirely to selection. The estimations with firm and individual fixed effects indicate that moving to higher paying firms is indeed an important channel through which immigrant wages catch up.

Table 6 shows the estimations for immigrants from the main origin groups. Comparing the estimates with and without firm fixed effects, the wage catch-up decreases from 1.3 to 0.9 percentage points for Eastern Europeans, 1.1 to 0.8 percentage points for Brazilians and from 0.3 to -0.1 percentage points for immigrants from Africa. Changing firms accounts for approximately one third of the wage catch-up for Eastern Europeans and Brazilians. For immigrants from Africa, all of the observed catch-up occurs by changing firms.

3.4.2 Immigrants Climb up the 'Firm Quality Ladder' with Time Spent in the Host Country

Not much is known about firms that hire immigrants and how immigrants progress in the firm "quality ladder" with time spent in the host country. The previous section shows that immigrants sort into low-wage firms and part of the assimilation process goes through switching to better paying firms. In this section, I take a closer look at firms where immigrants work and at immigrant careers in the first years in the country from a firm perspective.

Figure 6 shows firm descriptives for firms where immigrants work over time. With years spent in the host country, a higher proportion of immigrants gains access to long-term contracts. Immigrants also become more integrated in the labour market: They start off their careers in firms with a very large share of immigrant workers[14], but are exposed to more native co-workers as time goes by. They also move to larger firms.

Firm fixed effects measure the firm wage premium, i.e., how firms in narrowly defined regions and sectors reward individuals working in the same occupation differently. The firm fixed effects are often thought of as a measure of firm productivity. Another more direct measure of firm productivity is the firm's volume of sales per worker. The firm fixed effects estimated in the previous section are net of the individual fixed effect. As a robustness check, I also estimate firm fixed effects using the

[14]For papers that analyze immigrant segregation in the workplace using linked employer-employee data see Andersson et al. (2010) and Dustmann et al. (2011).

same specification than in equation 2 but without individual fixed effects. All measures of productivity (volume of sales per worker and firm fixed effects estimated with or without individual fixed effects) show similar patterns: over time, immigrants move to firms which are on average more productive.

The results for all immigrant groups are similar and are presented in the web appendix.

One worry about these descriptive statistics is that they pool together all cohorts and do not deal with selective out-migration. For instance, if only immigrants who start off their careers in more productive firms remain in the country, the results would be driven exclusively by selection and would not tell us much about the assimilation process. To address this concern, I do the same calculations for all cohorts separately distinguishing between all the immigrants from a cohort and "stayers". The means are first calculated each year for all immigrants belonging to a certain cohort and then only for immigrants who can be tracked in the data each year. The graphics for the 2003 cohort are presented in figure 7. The graphics for all other cohorts are similar and are presented in the web appendix. There is no initial difference in the proportion of immigrants who hold long-term contracts comparing immigrants who remain in the panel all the years and all the immigrants in the cohort. However, as immigrants get long-term contracts, they become more likely to remain in formal employment in Portugal, which explains the divergent trends between the two groups. All the other graphics suggest a common analysis. Immigrants who stay in formal employment each year are the ones who start off in larger, more productive and more integrated firms. In terms of assimilation, the important aspect is that although the means are higher in levels for "stayers", the trends are in most cases parallel.

The detailed calculations allowing for cohort effects and selection confirm the overall interpretation of the plots in figure 6. One of the channels of immigrant assimilation goes through moving to larger, more integrated and more productive firms.

The descriptives presented above show that immigrants move up the wage distribution with years spent in the host country labour market. A third of this upward mobility is linked to moving to firms that are more productive and that pay higher wages. In the next section, I build a model of immigrant economic assimilation based on firm heterogeneity and employer learning. When immigrants enter the labour market, little is known about their true productivity. There are complementarities between worker and firm type and firms value certainty over a worker's productivity. With high uncertainty about their types, immigrants begin their careers at the bottom of the firm productivity distribution.

Over time, worker productivity is revealed and, on average, immigrants get better matches. I simulate the model and show in the subsequent section that it can account for many qualitative features of the data.

4 A Learning Model with Firm and Worker Heterogeneity

4.1 The Workers and the Firms

Each worker has a productivity η_i. This productivity is composed of three additive terms:

$$\eta_i = q_i + a_i + s_i$$

The term q is observed for all workers as, for example, skills easily observed at a job interview. The component a is unobserved for all workers and captures "true" ability or IQ. Finally, the term s is observed for natives but not for immigrants as, for example the quality of a worker's education. All three terms are independently drawn from normal distributions with means μ_a, μ_q and μ_s and standard deviations σ_a, σ_q and σ_s. The independence of a with respect to q and s is a strong assumption but common in the employer learning literature. The productivity η hence follows a normal distribution with mean $\mu_\eta = \mu_a + \mu_q + \mu_s$ and standard deviation $\sigma_\eta = (\sigma_a^2 + \sigma_q^2 + \sigma_s^2)^{\frac{1}{2}}$. In line with the employer learning literature[15], I assume the different components of worker productivity to remain unchanged over time.

The productivity of firms in the economy is assumed to follow a log normal distribution with mean μ_c and standard deviation σ_c.[16] The distribution of firms is taken as given in the model and is fixed over time. The productivity of each firm is known by all agents in the market and is constant over time. Each firm hires only one worker and takes the wage schedule as given. The worker i - firm j match at time t produces output:

$$y_{ijt} = c_j \left[K - (\exp(-(\eta_i + \epsilon_{it})))\right]$$

where K is a large positive constant and $\epsilon_{it} \sim N(0, \sigma_\epsilon)$ is a random error to production.[17] For a given firm j, output is concave in the worker's ability η_i. The shape of the production function captures the idea that the quality of the machine (the firm productivity) limits the productivity of the worker. This production function ensures that the firm's expected output depends negatively on the uncertainty on

[15] Farber and Gibbons (1996) or Lange (2007)

[16] For evidence on the skewness of the firm productivity distribution in the US, see Bartelsman and Doms (2000)

[17] Since η follows a normal distribution, there are workers who produce negative output. I choose m_η and K large enough such that this fraction of workers is negligible.

the worker's productivity which will be a key element in the allocation of workers to firms in the model.

4.2 The Learning Process

Each period, all employers observe a noisy measure of the worker's productivity, $\eta_i + \epsilon_{it}$, and update their beliefs. There is symmetric learning: the current employer does not have more information about the worker's productivity than other potential employers. What is learnt about worker i at time t is also independent of the worker-firm match. Agents observe y_{ijt} and make their update on

$$\xi_{it} \equiv -\log\left(K - \frac{y_{ijt}}{c_j}\right) = \eta_i + \epsilon_{it}$$

The noise is assumed to be independent of all other variables in the model and is the same for immigrants and natives.

The normality assumptions make the learning process easily tractable. After a worker has spent x years in the labour market, the posterior distribution of worker i's type is a normal distribution with mean $\mu_{x,k,i}$ and standard deviation $\sigma_{x,k}$, where k is an index for immigrant fg or native nat. The expected productivity of an immigrant worker is:

$$\mu_{x,fg,i} = \frac{\sigma_\epsilon^2}{x(\sigma_a^2 + \sigma_s^2) + \sigma_\epsilon^2}(q_i + \mu_a + \mu_s) + \frac{\sigma_a^2 + \sigma_s^2}{x(\sigma_a^2 + \sigma_s^2) + \sigma_\epsilon^2}\sum_{l=0}^{x-1}\xi_{il}$$

and its variance is:

$$\sigma_{x,fg}^2 = \frac{\sigma_\epsilon^2(\sigma_a^2 + \sigma_s^2)}{x(\sigma_a^2 + \sigma_s^2) + \sigma_\epsilon^2}$$

For a native worker:

$$\mu_{x,nat,i} = \frac{\sigma_\epsilon^2}{x\sigma_a^2 + \sigma_\epsilon^2}(q_i + \mu_a + s_i) + \frac{\sigma_a^2}{x\sigma_a^2 + \sigma_\epsilon^2}\sum_{l=0}^{x-1}\xi_{il}$$

and

$$\sigma^2_{x,nat} = \frac{\sigma^2_\epsilon \sigma^2_a}{x\sigma^2_a + \sigma^2_\epsilon}$$

The expected worker productivity is a weighted average of the initial prior and the observed performance on the labour market. Initially, the weight on the prior is higher for natives as the prior is more precise. Over time the worker's expected productivity converges to the true productivity. The variance of the posterior is higher for immigrant workers as there is more uncertainty about them. Over time, the difference between the two groups decreases and in the limit the variance of the posterior tends to zero for every worker.

After x years in the labour market, the cross-sectional distribution of expected productivity for all immigrant workers of the same cohort is a Normal distribution with expected value

$$E\left(\mu_{x,fg}|I_x\right) = \mu_\eta$$

and variance[18]

$$V\left(\mu_{x,fg}|I_x\right) = \sigma^2_q + \frac{x^2(\sigma^2_a + \sigma^2_s)^3}{(x(\sigma^2_a + \sigma^2_s) + \sigma^2_\epsilon)^2} + \frac{x\sigma^2_\epsilon(\sigma^2_a + \sigma^2_s)^2}{(x(\sigma^2_a + \sigma^2_s) + \sigma^2_\epsilon)^2}$$

Similarly for natives, expected productivity for all native workers of the same cohort, $\mu_{x,nat}$, follows a Normal distribution with expected value

$$E(\mu_{x,nat}|I_x) = \mu_\eta$$

and variance

$$V(\mu_{x,nat}|I_x) = \sigma^2_q + \sigma^2_s + \frac{x^2(\sigma^2_a)^3}{(x\sigma^2_a + \sigma^2_\epsilon)^2} + \frac{x\sigma^2_\epsilon(\sigma^2_a)^2}{(x\sigma^2_a + \sigma^2_\epsilon)^2}$$

Over time, the distribution of expected productivity becomes wider for both groups, while the mean always stays the same. Due to the initial information asymmetry between natives and immigrants, the distribution of expected productivity is always wider for natives. Over time, the two distributions converge.

[18]The calculation is in the appendix.

4.3 The Assignment Mechanism

The expected production of a firm j that hires worker i conditioned on all information available about the worker after x periods in the labour market is:[19]

$$E\left(y_{ijt}\right) = c_j \left[K - \exp\left(-\mu_{x,k,i} + \frac{1}{2}(\sigma^2_{x,k} + \sigma^2_{\epsilon})\right)\right]$$

Firms prefer to hire workers with a higher risk-adjusted expected productivity $\mu_{x,k,i} - \frac{1}{2}\sigma^2_{x,k}$. Within a group and cohort, firms prefer workers with a higher expected productivity $\mu_{x,k,i}$. The term $\sigma_{x,k}$ introduces a distortion across groups and cohorts: For a given expected productivity, firms prefer workers for whom expected productivity is more certain. This introduces an advantage for older cohorts and natives in the labour market.

For each cohort of natives or immigrants at each level of experience in the labour market, $\mu_{x,k} - \frac{1}{2}\sigma^2_{x,k}$ follows a normal distribution with expected value

$$M_{x,k} = E\left(\mu_{x,k} - \frac{1}{2}\sigma^2_{x,k}|I_x\right) = \mu_\eta - \frac{1}{2}\sigma^2_{x,k}$$

and variance

$$V_{x,k} = V\left(\mu_{x,k} - \frac{1}{2}\sigma^2_{x,k}|I_x\right) = V(\mu_{x,k})$$

The distribution of $\mu_{x,k} - \frac{1}{2}\sigma^2_{x,k}$ for *all* workers, immigrants and natives, of a given cohort after x years in the market is hence a mixture of two normal distributions. The C.D.F. of this distribution is:

$$F(t) = p\Phi\left(\frac{t - M_{x,fg}}{V^{\frac{1}{2}}_{x,fg}}\right) + (1-p)\Phi\left(\frac{t - M_{x,nat}}{V^{\frac{1}{2}}_{x,nat}}\right)$$

where Φ is the C.D.F of the standard normal distribution and p is the proportion of immigrants in the cohort.

Assuming that each worker remains in the labour market for T periods, that all cohorts are similar and that the proportion of immigrants is constant across years, the C.D.F. of the distribution of

[19] This expression comes from the fact that $\exp(-(\eta_i + \epsilon_{i,t}))$ follows a log normal distribution with mean $\exp(-\mu_{x,k,i} + \frac{1}{2}(\sigma^2_{x,k} + \sigma^2_{\epsilon}))$

$\mu_{x,k} - \frac{1}{2}\sigma^2_{x,k}$ for *all* workers in the market in a given year is:

$$F(t) = \sum_{x=1}^{T} \frac{p}{T} \Phi \left(\frac{t - M_{x,fg}}{V_{x,fg}^{\frac{1}{2}}} \right) + \frac{1-p}{T} \Phi \left(\frac{t - M_{x,nat}}{V_{x,nat}^{\frac{1}{2}}} \right)$$

An efficient equilibrium at time t consists of an assignment of workers to firms and a wage schedule that maximize expected aggregate output. In such an assignment, each period workers are matched to firms according to the worker's risk-adjusted expected productivity and the firm's productivity. Worker i is assigned to firm j with productivity $c_j^* \left(\mu_{x,k,i} - \frac{1}{2}\sigma^2_{x,k} \right)$, such that

$$G\left(c_j^* \left(\mu_{x,k,i} - \frac{1}{2}\sigma^2_{x,k} \right) \right) = F\left(\mu_{x,k,i} - \frac{1}{2}\sigma^2_{x,k} \right)$$

where G is the C.D.F. of firm productivity. This assignment means that workers and firms are matched by their relative position in the probability distributions. In a discrete setup, this would mean that the nth worker, in order of decreasing expected worker productivity, will be employed by the nth firm, in order of decreasing firm productivity. This has to hold in an efficient equilibrium and follows from the firm-worker complementarity.

In this setup there is no need to solve a dynamic problem as every period the distributions of firms and workers' expected productivity are the same and there are no moving costs. Each period there is a new equilibrium based on all available information. Facing a wage schedule $w(z)$, where z is risk adjusted worker productivity, firm j maximizes expected profits:

$$\max_{z} \left\{ c_j \left[K - \exp\left(-z + \frac{1}{2}\sigma^2_{\epsilon} \right) \right] - w(z) \right\}$$

The first order condition implies that the expected marginal product must equal the marginal increase of the wage.[20] In equilibrium, this is only true for the proposed assignment, so I can write:

$$w'(z) = b\, c^*(z) \exp(-z)$$

where $b = \exp\left(\frac{1}{2}\sigma^2_{\epsilon}\right)$ is a constant. The wage schedule in the economy can be found by integrating this

[20]The second order condition holds, since the cross-derivative of expected production is positive. See Sattinger (1993).

expression:

$$w(x) = b \int_A^x c^*(z) \exp(-z) dz$$

where A is the minimum worker productivity. Since there exists no closed-form solution for the optimal firm match $c^*(z)$, no explicit solution for the wage can be found. In the following subsection, the model's predictions on the moments of the wage distribution will thus be derived by simulation.

The shape of the wage schedule is governed by decreasing returns to skill, captured by $\exp(-z)$, and the match function $c^*(z)$. Decreasing returns alone would make the wage schedule concave. This is counteracted by the equilibrium assignment, according to which better workers work at better firms. Depending on the rate at which the optimal match function increases, the wage schedule can be locally convex or concave, but is in all cases increasing in worker productivity. The graphics in figure 8 plot the optimal firm match $c^*(z)$ and the wage $w(z)$ as a function of worker risk-adjusted productivity $z = \mu_{x,k,i} - \frac{1}{2}\sigma^2_{x,k}$. For the parameters chosen, the firm match function is strictly convex. In general, its exact shape depends on the parameters of the underlying skill and productivity distributions of workers and firms. In particular, the convexity of $c^*(x)$ is related to the skewness of the firm productivity distribution. If the firm productivity distribution is heavily right-skewed, then a marginal improvement in worker skill is associated with an increasingly better firm match, thus making the optimal match function convex.

5 Comparing the Predictions of the Model to the Data

In this section, I derive predictions from the model presented in the previous section on the distribution of wages and on job mobility patterns. I first show that the predictions on the immigrant mean wage, mean firm productivity and job mobility over time are in line with the stylized facts of section 3. I then take the additional prediction of the model on the variance of wages to the data.

The model does not have a closed form solution for the optimal worker firm match as c^* is the inverse of the C.D.F. of a log normal distribution. I therefore simulate the model. There are 600,000 workers who each spend 30 periods in the labour market and immigrants represent 10% of workers in each cohort.

5.1 The Predictions of the Model and the Stylized Facts

In the empirical analysis in section 3, I highlighted three main stylized facts about the immigrant wage catch-up:

1. Immigrant wages catch up to the wages of natives of the same age group
2. In the first years in the country, immigrants exhibit high job mobility rates which decrease over time
3. Part of the immigrant wage catch-up is explained by immigrants moving to better paying and more productive firms

In this first section, I show how the model accounts for these stylized facts.

5.1.1 The Mean Firm Productivity and the Mean Wage over Time

In the model, the distribution of the risk-adjusted expected productivity for a cohort of immigrants moves to the right and becomes wider over time: the right-shift in the distribution is due to less uncertainty about immigrant true productivity: σ^2_{xk} decreases. The widening of the distribution comes from employer learning about each worker's true productivity.

Mean Firm Match: As firms reward certainty over the worker's productivity, new entrants on the market are matched to less productive firms on average. Among new entrants, immigrants have a higher uncertainty than natives and hence occupy on average the bottom of the firm productivity distribution. Over time, uncertainty decreases and workers gain access to better firms. This effect shifts the distribution of their firm matches to the right and hence increases the mean firm productivity over time. This effect is stronger for immigrants than for natives of the same cohort as there is more to learn about immigrants.[21]

Mean Wage: The reduced uncertainty about productivity also improves immigrants' wages through two main effects. First, as described above, they gain access to better firms, thus increasing their marginal product. Second, their expected marginal product increases due to reduced uncertainty: $\exp(-\mu_{xki} + \frac{1}{2}\sigma_{xk}^2)$ declines. Job mobility thus accounts for only a part of the total wage gains in the model.[22]

The model also predicts an increase in the mean of the log firm match and the mean of the log wage for an entering cohort of workers. The same mechanisms that increase the mean wage and the mean firm match also lead to increases in the log of these variables.[23]

The graphics of figure 9 show the mean log firm productivity and the mean log wage for an entry cohort of immigrants over time. The left hand side graphics compare an entry cohort of immigrants to natives of the same cohort, and the right hand side graphics compare an entry cohort of immigrants to the whole native labour force. The mean log wage of immigrants is increasing and part of the increase is due to firm heterogeneity. Comparing immigrants and natives of the same cohort, the mean log wage is initially higher for natives as they start their careers in better firms. Over time, the mean log wage for both groups increases, more so for immigrants as there is initially more uncertainty about their productivity.

The model thus generates predictions that are consistent with the first and third stylized fact of the data: On average, immigrants catch up to natives of the same age group, and part of this catch up is accounted for by moving to better firms. To sensibly derive predictions on job mobility, a variant of the model is discussed in the next subsection.

[21] If the match function $c^*(x)$ is convex, as in the present simulation, there is another effect on the mean firm match: as true worker productivity is revealed, and the variance of the expected productivity distribution of a cohort rises, the mean match increases. However, as explained earlier, the local convexity of $c^*(x)$ depends on the exact parameter values chosen. This effect is second-order relative to the shift of the worker productivity distribution.

[22] Again, the local curvature of the wage function together with the increasing variance of the expected productivity distribution exerts a second order effect on mean wages.

[23] Since the log wage function is concave the second order effect of an increasing variance of expected productivity now depresses the mean log wage.

5.1.2 Job Mobility

The assignment model presented above has very strong continuity assumptions and a restrictive one to one match. This way of modeling allows to solve explicitly for the optimal worker-firm match and hence to simulate the patterns of the firm productivity distribution over time. In this continuous version of the model, all workers move jobs every period as information is revealed. In order to make the predictions on job mobility more realistic, I make a small change to the model above and assume that there is a finite number of firms, and that each has a fixed number of jobs. Firms are ordered by their productivity level: $0 < c_1 < c_2 < .. < c_m$. All the other ingredients of the model remain the same.

As before, an equilibrium is defined by an assignment of workers to firms and a wage schedule. I can define $m-1$ worker risk-adjusted expected productivity thresholds, l_j, so that workers with risk-adjusted expected productivity $\mu_{x,k} - \frac{1}{2}\sigma_{x,k}^2 \in [l_j, l_{j+1}]$ are assigned to the firm of productivity c_j. The wages are derived in the same way as in the model above. I assume that there are no moving costs. Workers switch firms when their risk-adjusted expected productivity is revealed to be much higher or much lower than expected - that is, when their expected productivity crosses a threshold l_j.[24]

Comparing immigrant and native workers, the model yields a main prediction: Immigrant workers switch firms more often than natives do, but the difference in job mobility between the two groups decreases over time. There is initially more uncertainty about immigrant productivity and more updating for immigrants each period. The difference between the two groups decreases over time as extra information each period represents a smaller and smaller part of all information available about the worker. This prediction is in line with the stylized fact on immigrant job mobility from section 3. Immigrants move jobs more often than natives but at a decreasing rate.[25]

[24] The distribution of the changes in risk-adjusted expected productivity for a cohort over time is derived in the appendix.

[25] The model considered is silent on the effect of tenure. A possible way to introduce the impact of tenure is to add accumulation of employer specific human capital. This generates moving costs which depend on the firm productivity. Solving for the extended model implies solving for a dynamic equilibrium instead of the stable equilibrium in the previous section.

5.2 Taking an Additional Prediction of the Model to the Data

5.2.1 The Variance of Wages over Time

The model considered is an employer learning model and as such generates clear predictions on the second moment of the wage distribution. In this section, I show that the model predicts an increase in the dispersion of wages for immigrants over time and that this increase arises through switching firms.

Variance of Wages: As worker productivity is revealed, the distribution of expected productivity for a cohort of workers widens over time. This effect increases the variance of wages since workers are paid according to their expected marginal product. In the present model, this effect is magnified by worker assignment to heterogeneous firms. As the distribution of expected productivity widens over time, so does the distribution of firm productivity workers are matched to. If the c^* schedule is convex, then the dispersion of firm productivity will further increase due to a second effect: As new entrants move up the firm-quality ladder, they gain access to increasingly better firms. This is related to the underlying skewness of the firm productivity distribution. The distribution of assigned firm productivity for these workers widens and further contributes to the increase in the variance of wages. According to the model, we should thus see an increasing profile of the variance of log wages[26] for a cohort over time and this increase arises in the model through switching firms. If we consider a model with a finite number of firms, not all of the increase in the variance of wages is related to switching firms: the dispersion of immigrant wages increases even within the same firm as employers learn about worker productivity.

In the next section, I conduct an empirical analysis of the variance of log wages for immigrant and native workers entering the labour market between 2002 and 2009 in order to take this prediction to the data.

5.2.2 The Variance of Wages in the Data

I start by estimating equation (3) below by ordinary least squares:

$$\ln(HW)_{it} = origin_i * cohort_i * year_t + \epsilon_{it} \tag{3}$$

[26] The increase in the variance of wages will also raise the variance of log wages. In the present simulation, this effect dominates the effect coming from the higher mean of wages, which depresses the variance of log wages.

The variable *origin* is a dummy for each origin group: native, Brazilians, Eastern Europeans, Africans and other immigrants; *cohort* is a dummy variable for each entry cohort from 2002 until 2009; and *year* denotes a dummy for calendar year, from 2002 until 2009. This specification is a more general form of the specification used in section 3. The aim is to estimate the dispersion of the wages net of all mean effects. The residual estimated from this regression represents the part of the log wages which is not explained by the evolution of the mean log wages of workers from a given group and cohort over time.

The graphics in figure 11 plot the variance over time of the residuals estimated for natives and immigrants of the 2003 cohort under different specifications. I focus on the 2003 cohort as an example, the same analysis is conducted for all other cohorts in the web appendix. The first plot uses the specification of equation (3), the following plots add controls first for age groups, region and industry; then occupations; and finally firm fixed effects.

The variance of log wages is higher for natives than for immigrants and it is increasing over time for both groups. This stylized fact holds true independent of the exact specification considered. Controlling for region, industry and occupation explains part of the difference in the level of the variance of log wages between natives and immigrants. Immigrants have more undifferentiated log wages because they sort into more similar industries and occupations than natives. However, the increase in the variance profiles over time remains the same. Controlling for firm heterogeneity has a different effect. The increasing variance profile of immigrants and natives is flattened when firm heterogeneity is taken into account. I interpret this effect as evidence that new entrants on the market sort through changing firms. This effect is particularly strong in the first years in the labour market.

Figure 12 presents the same results but restricting the sample to workers from the 2003 cohort who are in employment every year. The patterns are very similar to those in figure 11 which shows that selection out of the labour market does not have an effect in these estimations. The results are similar for all cohorts and origin groups. This is shown in the web appendix.

The stylized facts are in line with the predictions of the model on the variance of log wages. The variance of log wages is higher for natives than for immigrants as initially more is known about native productivity. Natives have a higher variance of expected productivity and gain access to a wider range of firms. The variance of log wages is increasing over time for all new entrants in the market.

As productivity is revealed, workers are sorted and work at more diverse firms. This mechanism is consistent with the stylized fact that firm heterogeneity explains part of the increase in the variance of log wages.

6 Competing Theories of the Distribution of Wages

6.1 The Learning Model with Firm and Worker Heterogeneity

The model of the distribution of wages presented in section 4 is a model in which the type of workers is unknown and as productivity is revealed workers are assigned to more productive firms. The predictions of the model are consistent with the empirical analysis presented in section 5. The mean wages and the variance of wages are increasing over time. Both of these effects are partly explained by switching firms and the probability of switching firm decreases over time.

To model the difference between natives and immigrants, I assumed that there is initially more uncertainty about immigrant productivity than native productivity. Two stylized facts are in line with this assumption: immigrants switch firms more often than natives; and the variance of wages is higher for natives than for immigrants.

An additional prediction from the learning model is that the variance of the changes in expected productivity of workers of the same cohort declines over time. With time spent in the labour market there is progressively less to be learnt about the worker's productivity. This is the mechanism which leads to the decrease in job mobility over time. Initially, as there is more uncertainty about immigrants, the variance of the changes in expected productivity is higher for immigrants than for natives. The variance decreases for both groups over time but faster for immigrants than for natives.[27] In order to investigate this prediction, I first estimate the following equation with ordinary least squares:

$$\Delta \ln(HW)_{it} = origin_i * cohort_i * year_t + \epsilon_{it} \tag{4}$$

This equation is similar to the one used to estimate the variance of log wages in the previous section. I calculate the variance of the residual for immigrants and natives for each cohort, each year. I consider in this calculation only "stayers", that is workers who remain in employment every year. I then estimate the following regression by weighted least squares:

$$Var(\hat{\epsilon}_{lt}) = \alpha FG_l + \beta EXP_l + \gamma FG_l * EXP_l + year_t + \epsilon_{lt} \tag{5}$$

[27] The distribution of the changes in risk-adjusted expected productivity for a cohort over time is derived in the appendix.

l refers to a origin-cohort (for ex. natives belonging to the 2003 cohort), t refers to calendar time. Table 7 presents the estimations. The variance of the wage growth is on average higher for immigrants than for natives and decreases for both groups over time. I interpret the fact that the variance of the wage growth is higher for immigrants than for natives as evidence of the higher uncertainty over immigrant productivity.

In the next sections I consider two competing models of the wage distribution and investigate whether they match the stylized facts on immigrant economic assimilation. Table 8 compares the predictions of the three competing explanations to the stylized facts.

6.2 Search Model

A competing model of the distribution of wages which may be useful in the context of understanding the immigrant wage catch up is a search model. This class of models departs from the perfect competition framework and introduces search frictions. Workers need time to receive wage offers, and as they do, they climb up the wage distribution. I assume the difference between immigrants and natives to be that immigrants have less "search capital" upon arrival in the country and over time they receive wage offers at an increasing frequency.

In order to be more specific, let us consider a simple search model: The distribution of wages is exogenous, workers get wage offers from a wage distribution with C.D.F F. Offers arrive at a rate $\lambda(x)$. If the new wage offer is higher than the current wage the worker switches jobs, if not he remains with the same employer. This model is a simple on the job search model as for instance Burdett (1978). I abstract in this simple model from unemployment. Workers remain in employment all periods. When taking the predictions of the model to the data I consider only "stayers", that is, workers of an entry cohort who are always in employment. The difference between immigrant and native workers in the model is then modeled by a different arrival rate of wage offers. Immigrants are assumed to have initially lower search capital, $\lambda_{fg}(0) < \lambda_{nat}(0)$, but the rate of arrival increases faster for immigrants than for natives $\lambda'_{fg}(x) > \lambda'_{nat}(x)$.

According to this simple model, the mean wages of workers of a cohort increases and the increase is due to switching firms. All workers move up the wage distribution as they receive more wage offers over time. Workers also switch firms at a decreasing rate with time spent in the labour market. As workers move to better firms, the probability of receiving a better offer decreases over time. These two predictions are in line with the patterns in the data for new entrants. However, another prediction of the search model is that the distribution of wages of a cohort over time becomes truncated to the left. Workers who started off in the worse jobs move up over time, faster than the workers who started with a higher relative wage. This mechanism implies that the variance of wages of a cohort decreases over time.[28]

Figure 13 shows a simulation of the mean and variance of the log wages and wage growth of the model above for an entry cohort in the labour market. In this simulation, the probability of receiving a wage offer each period is constant and set equal to 0.1. The mean wage is increasing and the variance of wages is decreasing with time spent on the market. The exact shape of the curves depends on the assumption on the arrival rate $\lambda(x)$ but these two results hold for all cases. A decreasing variance of wages is in contradiction with the patterns in the data for new entrants in the market, immigrants and natives. Independently of the precise assumption on the difference between immigrants and natives entering the labour market, a simple search model is not compatible with the increase in the variance of wages for "stayers" over time, as documented in section 5.

6.3 Human Capital Model

Another competing model is based on human capital accumulation.

Let us consider the following setup: There are complementarities between worker skill and firm productivity, as in the model above. Over time, workers accumulate human capital and become more productive. A possible assumption to model the difference between natives and immigrants is that immigrants have an initial lower level of human capital but that they accumulate human capital in the first years in the host country faster than natives. Let us assume also that the human capital function is concave: there are decreasing returns to investment in human capital.

New entrants in the market start off at the bottom of the firm distribution since they have the lowest levels of human capital. Over time, as their human capital stock increases, they gain access to better firms and the mean wages increase. As the productivity of workers increases at a decreasing

[28] This prediction on the monotonicity of the variance of wages only holds when considering only workers who remain in employment every year. The model is the same than the one in Manning (2000), however he finds that the patterns of the variance of wages are non-monotonic: this is due to the effect of workers who accept a job offer after an unemployment spell.

rate, the job mobility rate decreases over time. The prediction on the immigrant wage catch up and on job mobility are the same than those in the model of section 4.

To derive predictions on the variance of wages, an extra assumption is needed which is that workers accumulate human capital heterogeneously. This implies that as workers accumulate human capital, the wages of a cohort become more dispersed. The variance of the wage growth also decreases over time as there are decreasing returns to human capital accumulation.

As this specific example illustrates, a human capital model can explain any set of stylized facts, if the appropriate assumptions are made. It is therefore not really testable. Distinguishing between heterogeneous accumulation of human capital and learning is an unsolved problem in the literature, and goes beyond the scope of this paper.

7 Conclusion

Although there is widespread evidence that immigrant wages catch-up to the wages of comparable natives with years spent in the host country, the mechanisms through which wages catch-up are not well understood. I use a unique linked employer employee panel for Portugal to study the careers of immigrants in the first years in the host country. The data allows following all workers in the private sector in the country and provides detailed information on the firms.

I show that immigrant wages catch up to the natives of the same age at a rate of 10 percentage points in 10 years. Immigrants exhibit very high job mobility rates and one third of the wage catch-up is associated to moving to better paying firms. Sorting across occupations explains a large part of the immigrant-native wage gap but changing occupations does not contribute to the catch-up. Over time, immigrants move to bigger, better paying and more productive firms. They tend to start their careers in segregated firms but the share of native co-workers increases as time goes by. The proportion of immigrants with a long term contract also increases with years spent in the labour market.

Motivated by these new stylized facts, I suggest a model of immigrant economic assimilation which highlights the role of uncertainty about immigrant productivity. Workers and firms are heterogeneous and firms value certainty over worker productivity. The model predicts that immigrants start their careers in the host country working in low productivity firms. Over time, they get access to more productive firms and move up the wage distribution. I derive additional predictions from the model on the variance of wages. In line with the model, immigrant wages become more dispersed with time spent in the host country and the increase in dispersion is associated with firm heterogeneity.

Finally, I consider two competing explanations of the immigrant wage catch-up: search and human capital accumulation. The predictions on the evolution of the variance of wages of immigrants from a simple search model are not in line with the patterns in the data. A human capital accumulation model with heterogeneous agents may be consistent with the data. Distinguishing between the predictions from a learning model and from a human capital model with heterogeneous agents is an unsolved problem in the literature, which is beyond the scope of this paper.

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Figure 1: Mean Hourly Wages for Immigrants by Cohort

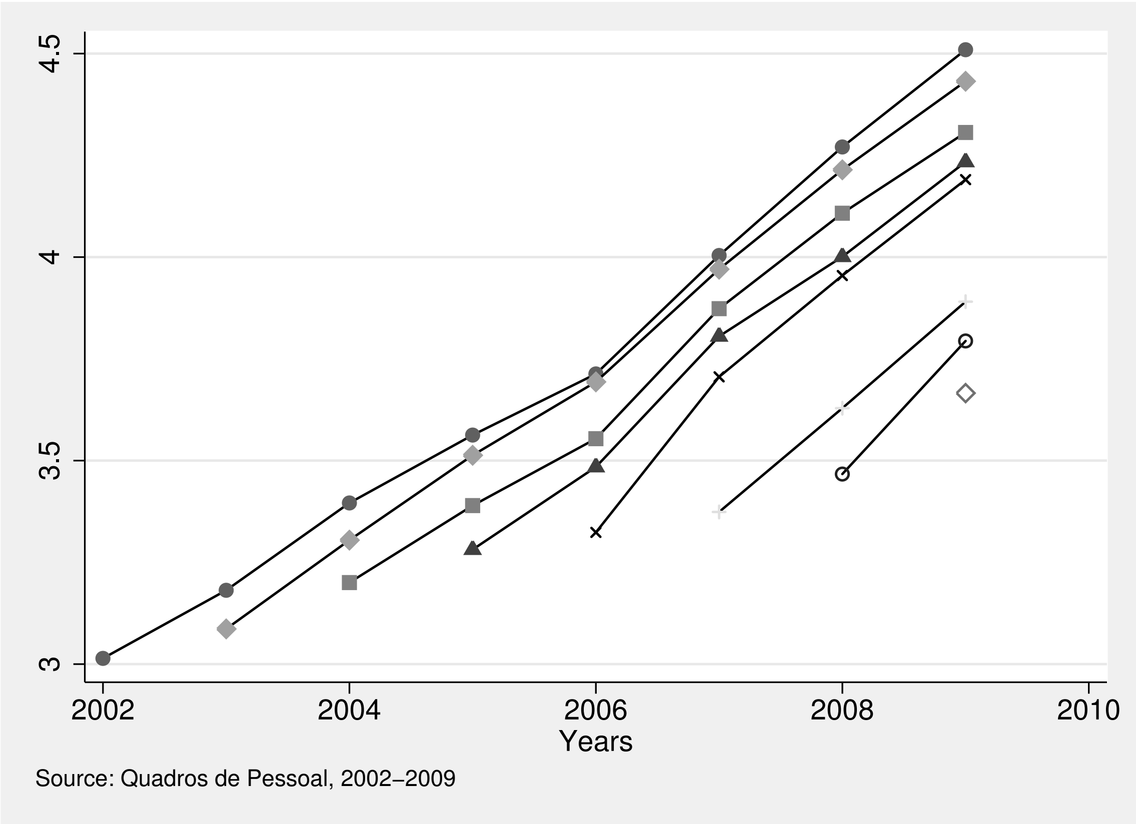


Figure 2: Number of Immigrant Workers in the Data

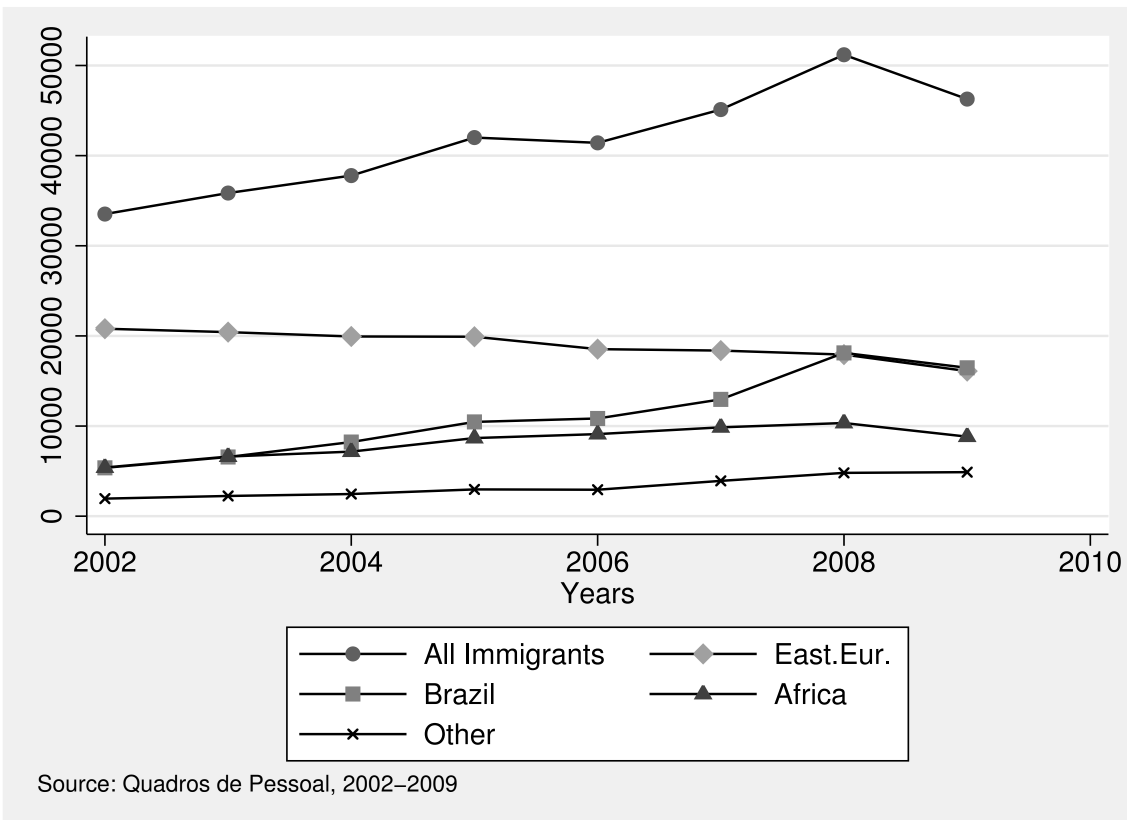


Figure 3: Region of Origin of Immigrants by Cohort

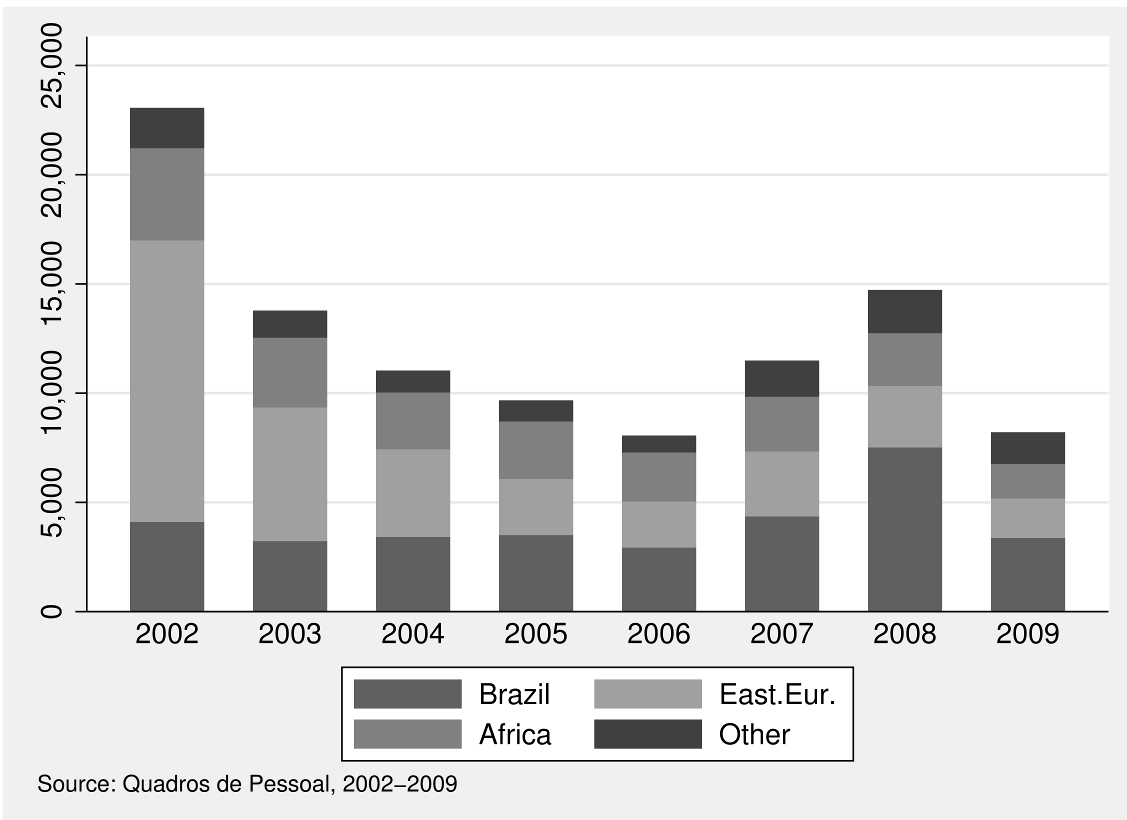
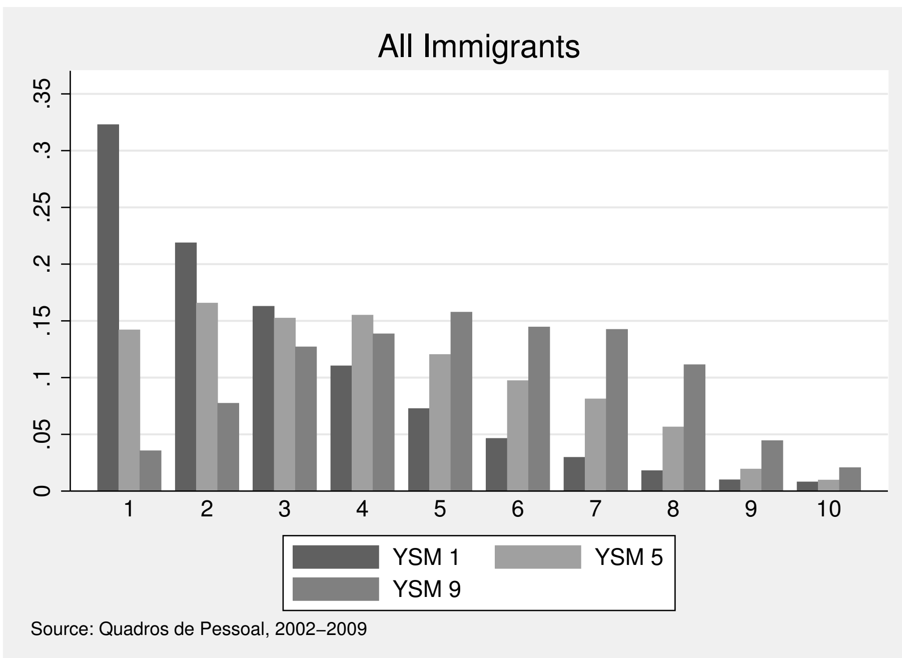
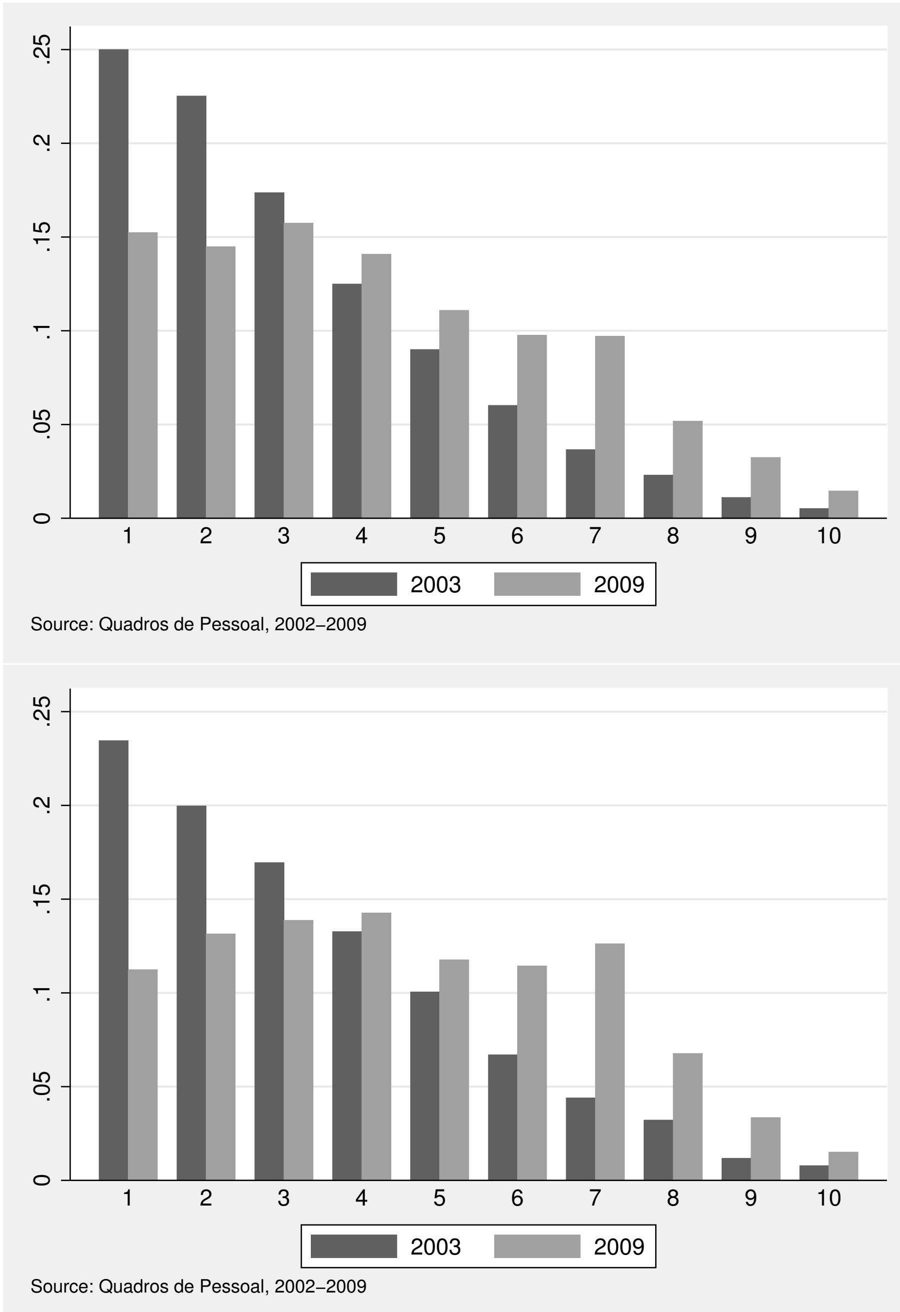


Figure 4: Representation of Immigrant Wages in the Distribution of Native Wages by Year since Migration



Note: The graphic illustrates the representation of immigrant wages after 1, 5 and 9 years in the country in the native wage distribution. With years spent in the country, the distribution of wages of immigrants comes closer to the one of the natives.

Figure 5: Representation of Immigrant Wages in the Distribution of Native Wages by Years since Migration, 2003 Cohort



Note: The top graphic is for all immigrants of the 2003 cohort and the bottom one is for immigrants of the 2003 cohort who remain in the data every year the "stayers". The comparison group is natives who are in the data in 2003 and natives who are in the data in 2009.

Figure 6: Climbing up the 'Firm Quality Ladder'

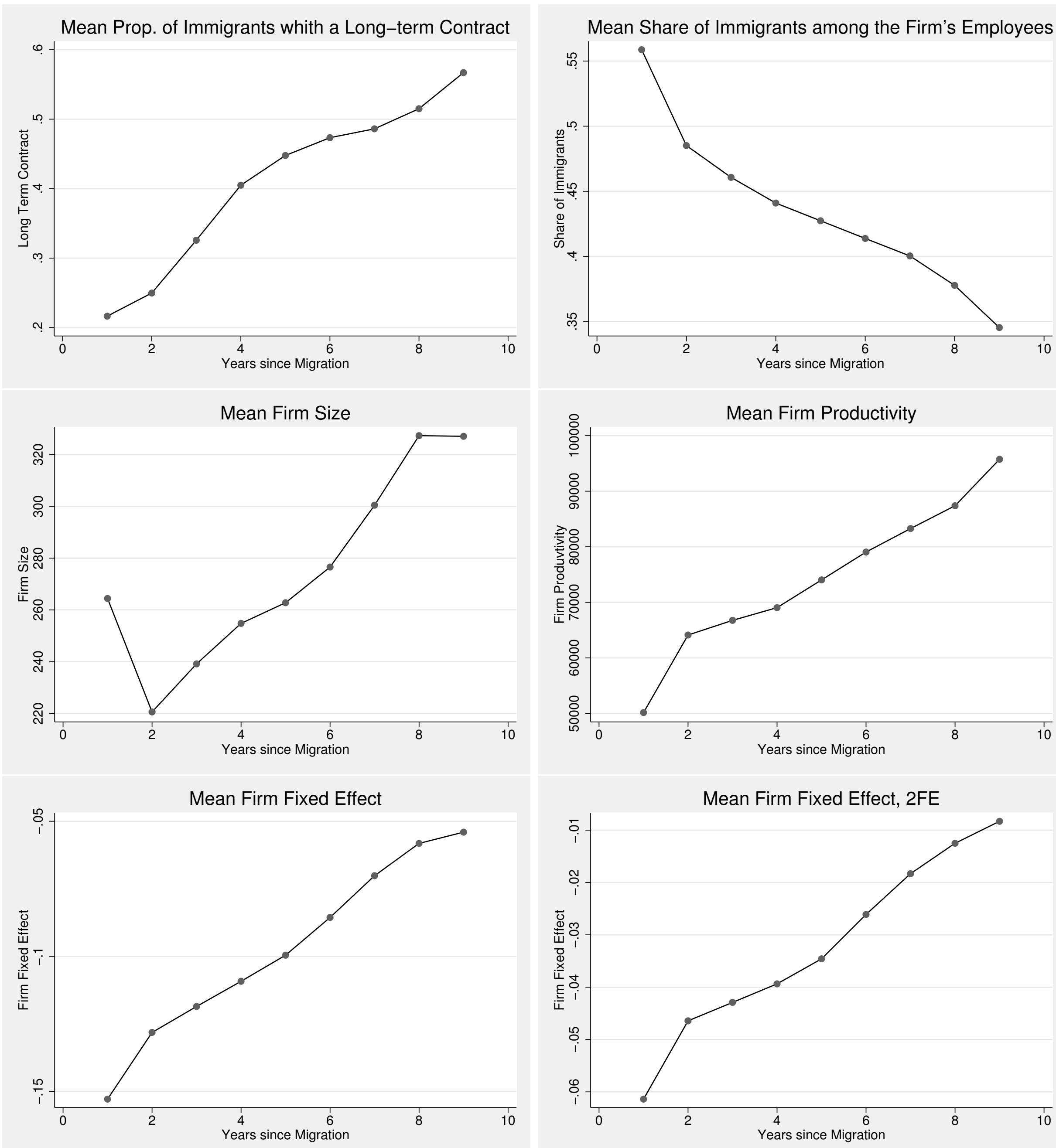


Figure 7: Climbing up the 'Firm Quality Ladder', 2003 Cohort

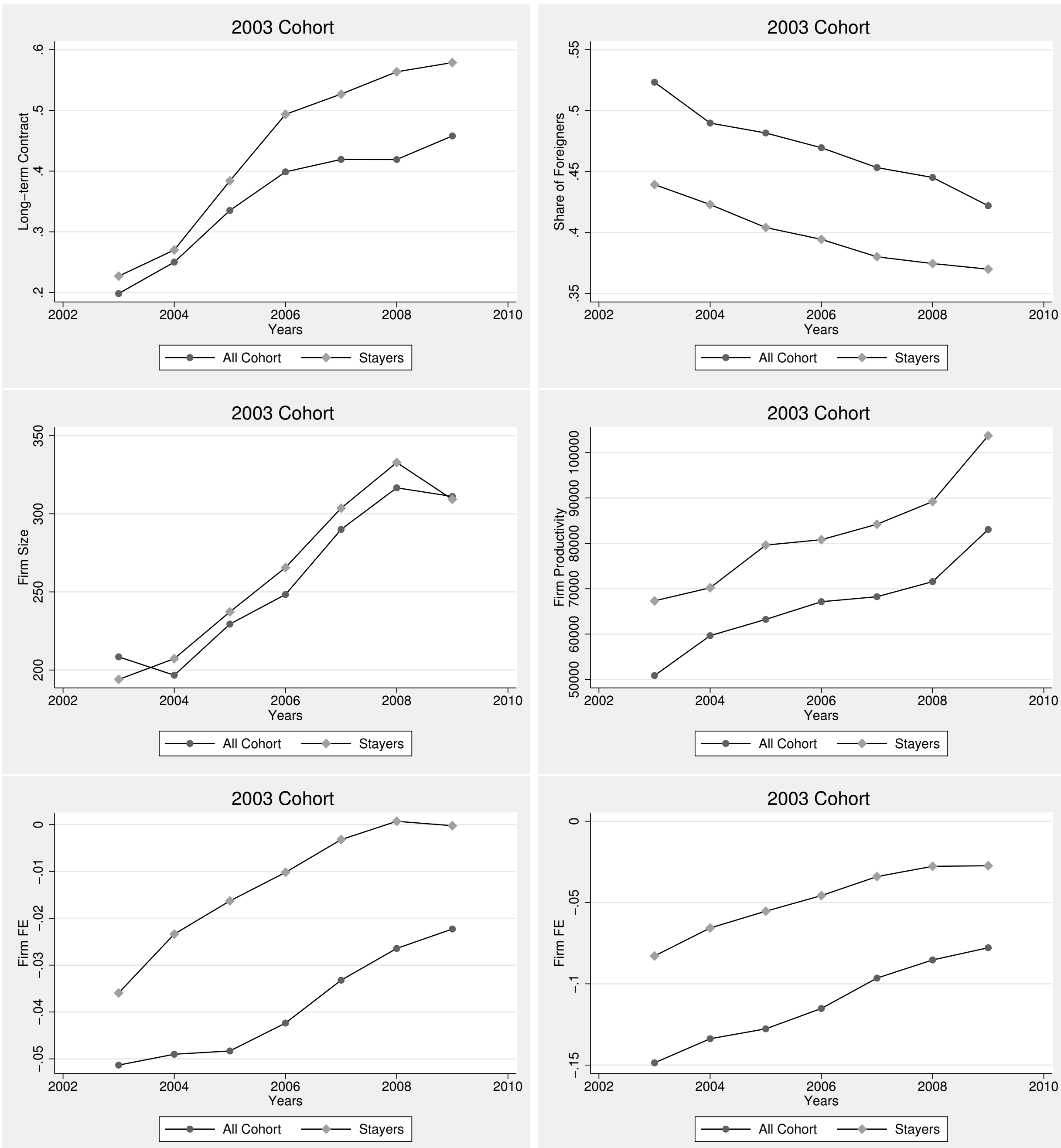
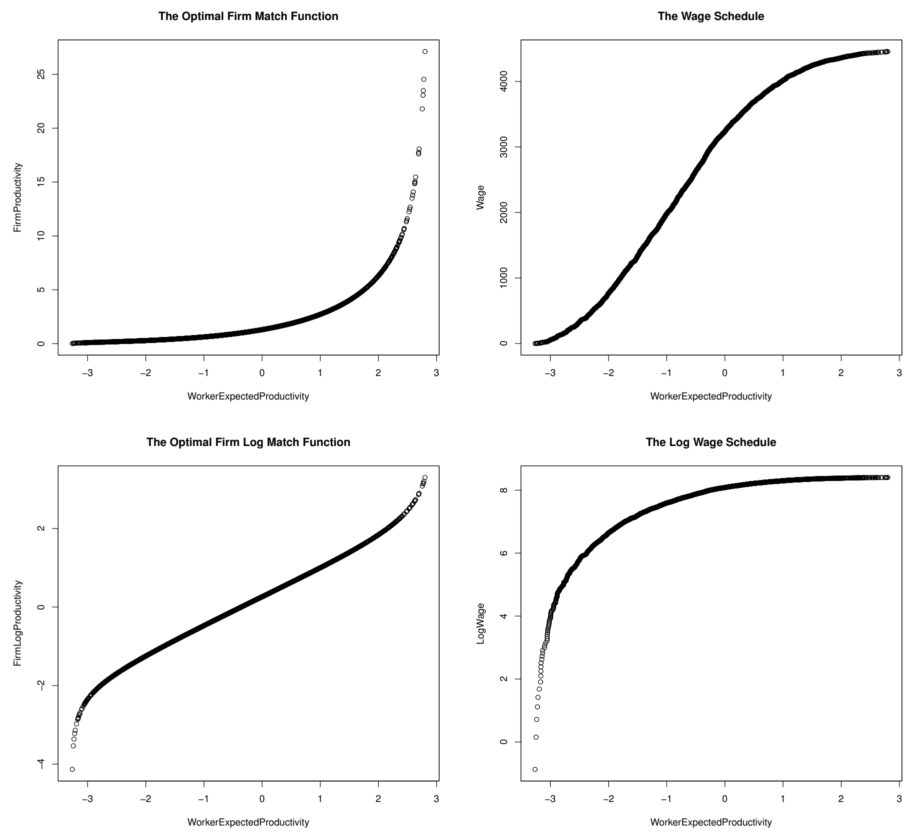
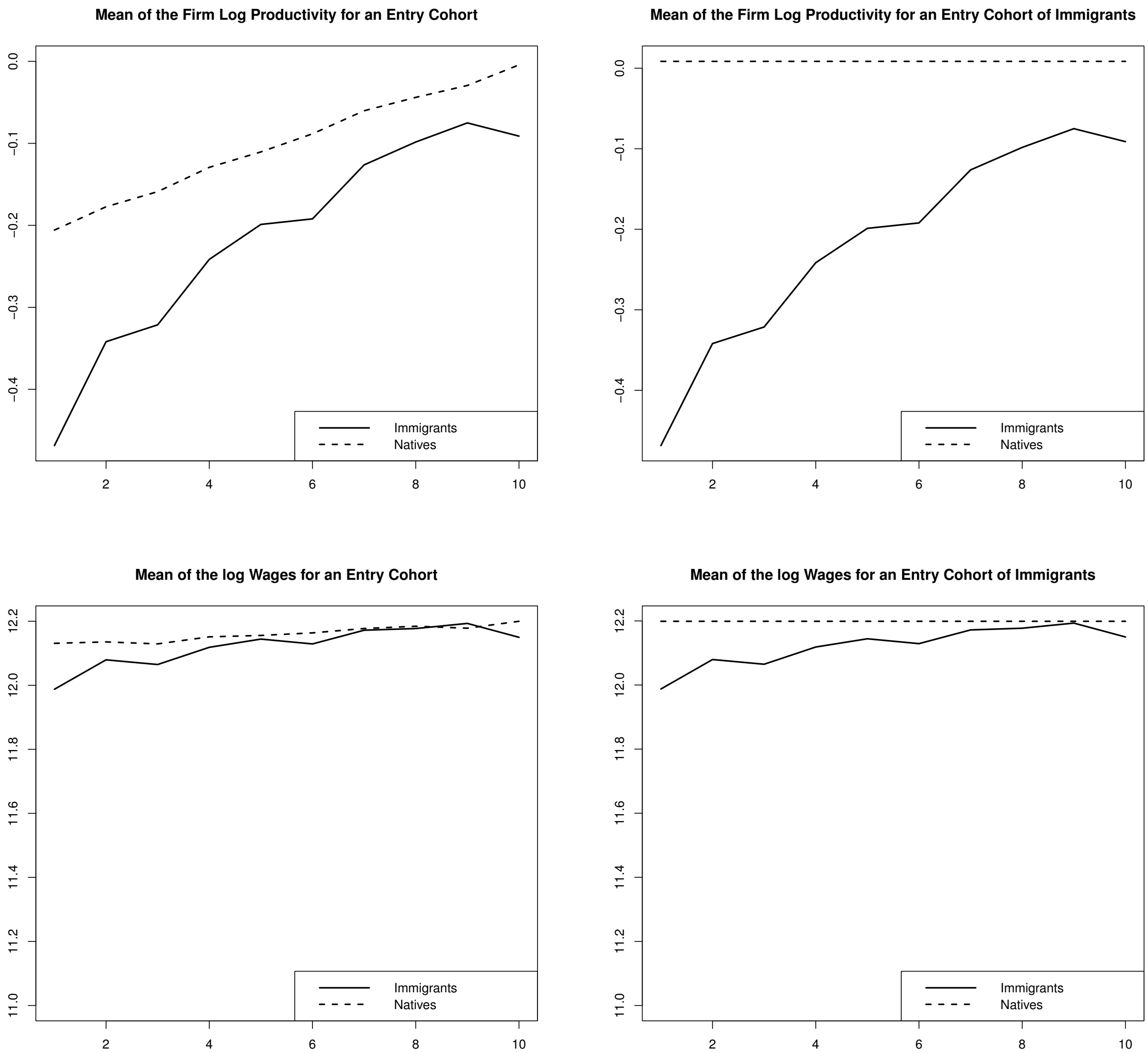


Figure 8: An Employer Learning Model with Firm and Worker Heterogeneity



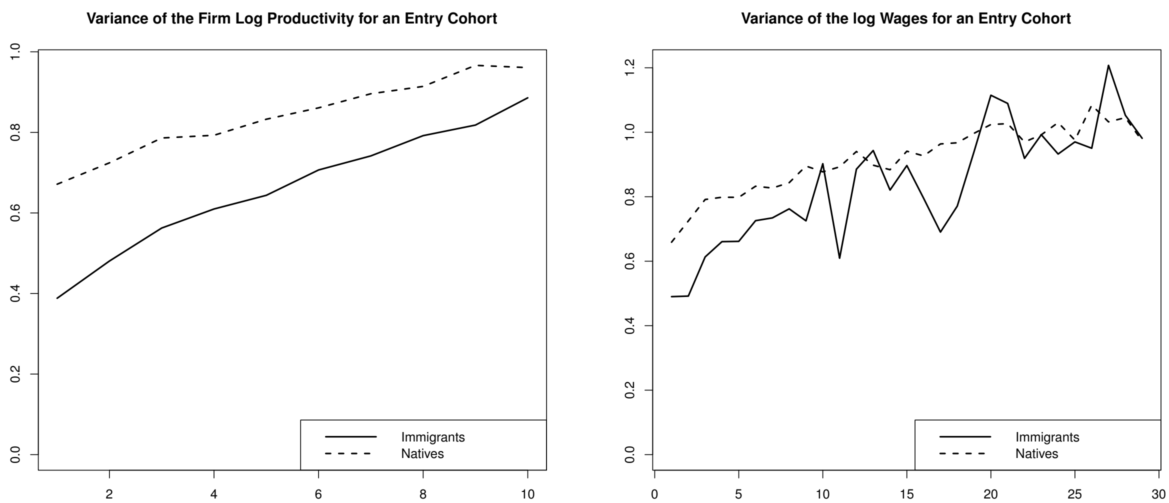
Note: The plots of the expressions derived in the model are drawn setting all means equal to 0, $\mu_q = \mu_a = \mu_s = \mu_\epsilon = \mu_c = 0$ and $\sigma_q^2 = 0.5$, $\sigma_a^2 = 1.5$, $\sigma_s^2 = 1$, $\sigma_\epsilon^2 = 30$, $\sigma_c^2 = 1$.

Figure 9: Predictions on the Mean Log Firm Productivity and the Mean Log Wages



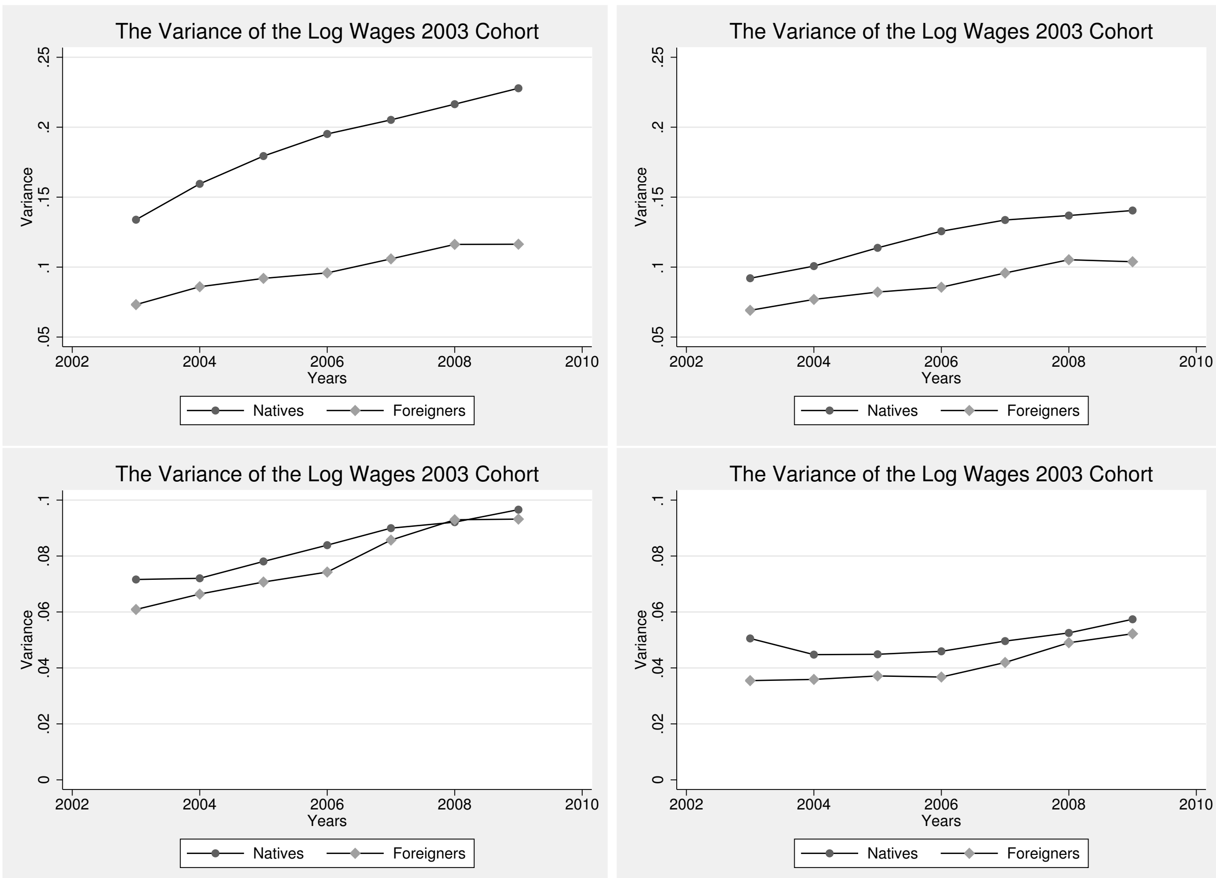
Note: The top left and the bottom left graph compare immigrants of an entering cohort with the natives of the same cohort. The figures on the right compare immigrants of an entering cohort to all natives in the economy. The plots of the expressions derived in the model are drawn setting all means equal to 0, $\mu_q = \mu_a = \mu_s = \mu_\epsilon = \mu_c = 0$ and $\sigma_q^2 = 0.5$, $\sigma_a^2 = 1.5$, $\sigma_s^2 = 1$, $\sigma_\epsilon^2 = 30$, $\sigma_c^2 = 1$.

Figure 10: Predictions on the Variance of Log Firm Productivity and the Variance of Log Wages



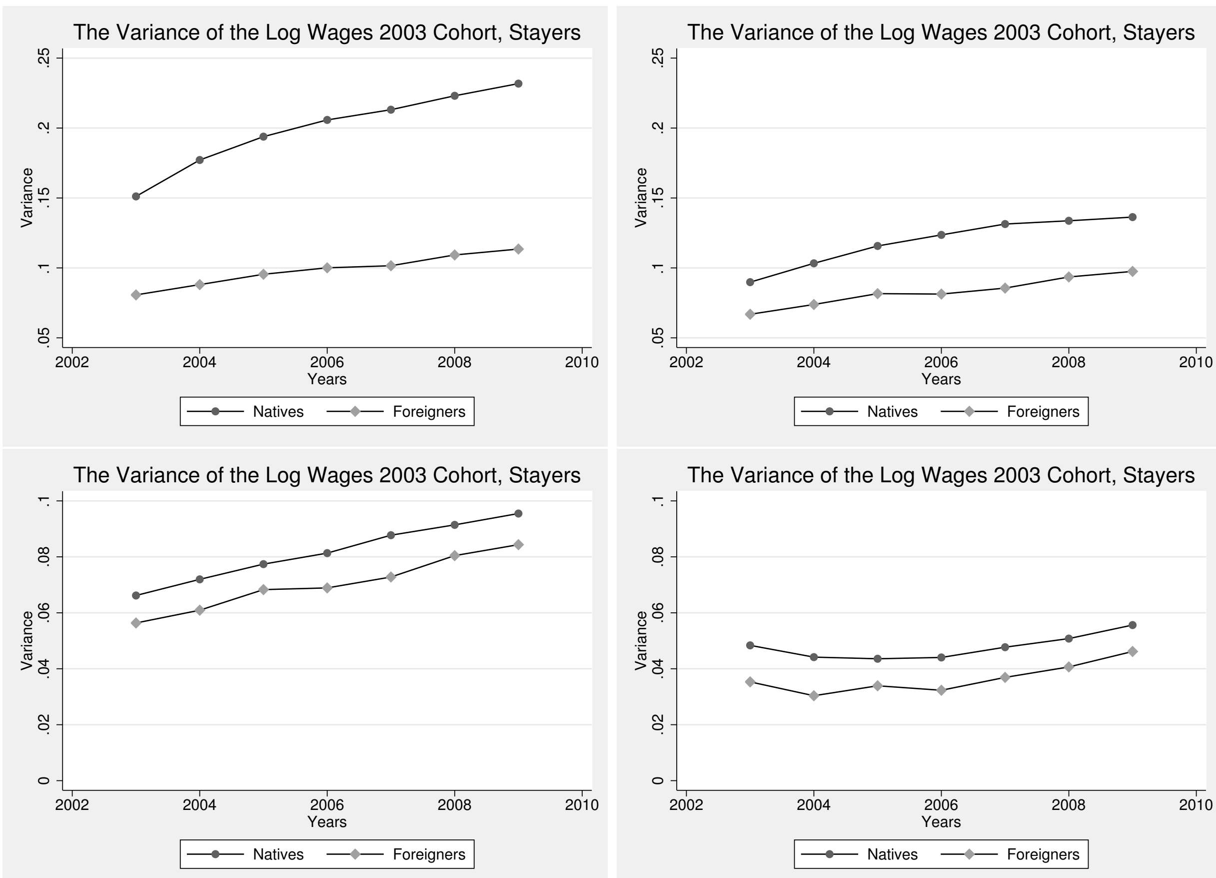
Note: The plots of the expressions derived in the model are drawn setting all means equal to 0, $\mu_q = \mu_a = \mu_s = \mu_\epsilon = \mu_c = 0$ and $\sigma_q^2 = 1$, $\sigma_a^2 = 1.5$, $\sigma_s^2 = 0.5$, $\sigma_\epsilon^2 = 30$, $\sigma_c^2 = 1$.

Figure 11: The Variance of Log Wages



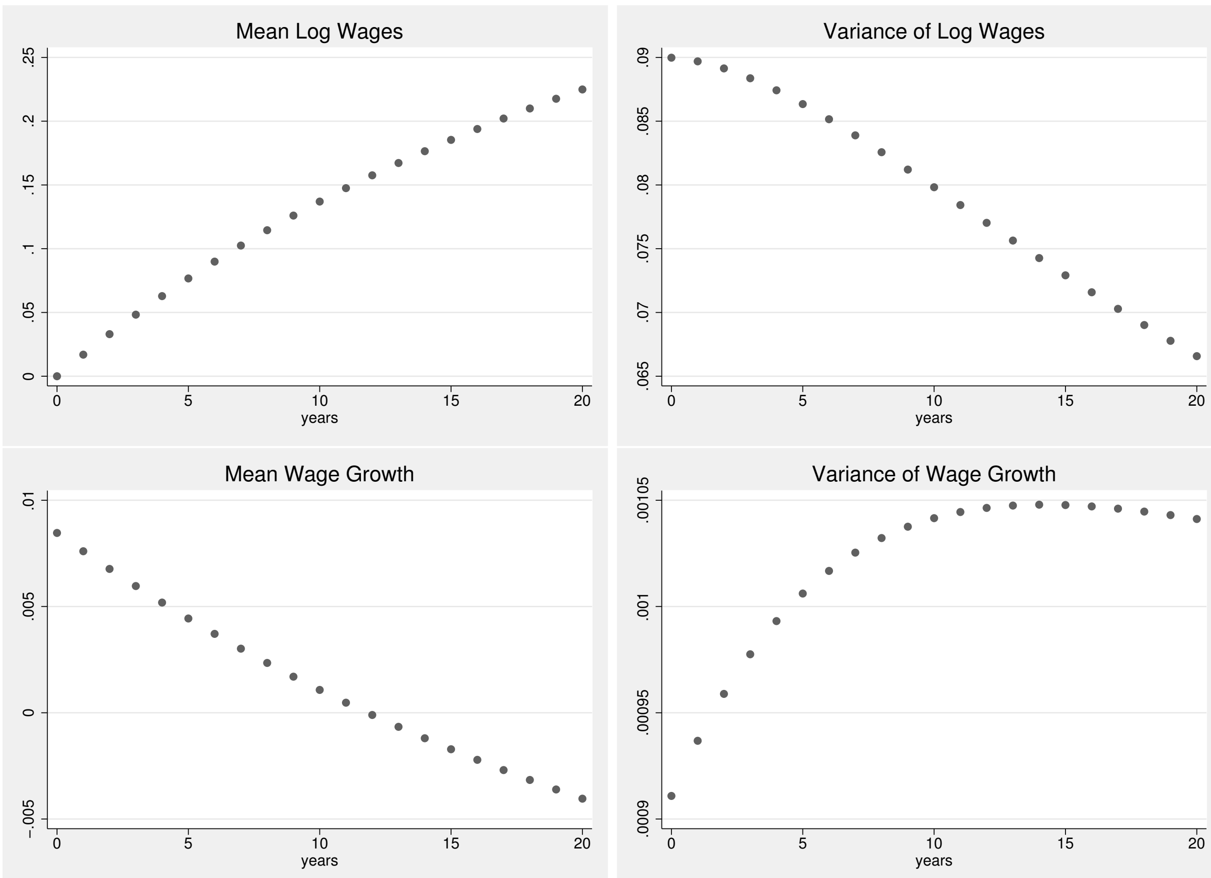
Notes: The plots represent the variance of the residual by year and cohort for all natives and immigrants of the 2003 cohort estimated by least squares from the following specification:
$\ln(HW)_{ijt} = origin_i * cohort_i * year_t + \epsilon_{it}$, and controlling progressively by age group and industry (top right), occupation (bottom left) and firm heterogeneity (bottom right).
The variance of log wages is higher for immigrants than for natives and increasing for both groups over time. Firm heterogeneity explains the increase in the variance in particular in the first years in the labour market.

Figure 12: The Variance of Log Wages, Stayers



Notes: The plots are the same than those in figure 11 but consider only workers from the 2003 cohort who remain employment each year. The patterns are very similar, which show that selection out of the labour market does not affect the results.

Figure 13: Predictions on the Mean and Variance of Wages of a Search Model



Notes: The plots represent the patterns of the mean and variance of log wages and wage growth for an entry cohort. Workers are assumed to stay in employment every period. The probability to receive a wage offer in any given period is set to 0.1.
The decrease in the variance of wages of a cohort over time is not compatible with the stylized facts in section 5.

Table 1: Population Selected Means

	Natives	All Immigrants	East. Europ.	Brazil	Africa
Age	38.7	35.1	36.6	32.6	35.3
YSM	0	3.3	3.6	3.0	3.2
By Origin					
East.Eur.	0	0.49	1	0	0
Brazil	0	0.22	0	1	0
Africa	0	0.20	0	0	1
By Region					
Alentejo	0.05	0.06	0.07	0.06	0.02
Algarve	0.04	0.14	0.19	0.11	0.08
Centro	0.22	0.18	0.26	0.15	0.07
Lisboa	0.29	0.49	0.32	0.55	0.77
Norte	0.40	0.13	0.16	0.13	0.06
By Industry					
Manufacturing	0.31	0.16	0.24	0.12	0.06
Construction	0.18	0.42	0.46	0.34	0.56
Wholesale and retail trade	0.19	0.10	0.08	0.13	0.07
Hotels and restaurants	0.04	0.09	0.04	0.18	0.06
Transport, storage and communication	0.08	0.05	0.06	0.06	0.02
Real estate, renting and business activities	0.09	0.13	0.09	0.13	0.19
Number of Workers		117,964	47,279	34,913	23,810
Number of Observations	8,506,801	339,986	152,008	89,001	65,977

Notes: This table shows the mean age for natives and immigrants of the three main origin groups and the "years since migration" (YSM) for immigrants; the distribution of immigrants by origin; and the distribution of immigrants and natives by region and industry. Only recent immigrants who have entered the labour market after 2001 are considered in the analysis. All the differences in means between groups are very significantly different from 0.
Source: Quadros de Pessoal, 2002-2009.

Table 2: Immigrant Wage Catch up

	(1)	(2)	(3)	(4)	(5)	(6)
FG	-0.353	-0.254	-0.152			
	(0.0012)	(0.0012)	(0.0011)			
YSM	0.009	0.009	0.008	0.010	0.010	0.009
	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)
Age (quartic)	Yes	Yes	Yes	Yes	Yes	Yes
Region		Yes	Yes		Yes	Yes
Industry		Yes	Yes		Yes	Yes
Occupation			Yes			Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Individual FE				Yes	Yes	Yes
N	7,543,209	7,543,209	7,543,209	7,543,209	7,543,209	7,543,209
R^2	0.105	0.456	0.608	0.313	0.324	0.332

Notes: The dependent variable is log hourly wages. Standard errors are in parentheses.
'FG' is a dummy for foreigners. 'YSM' is the interaction between 'FG' and years since migration. 'Region' is a set of 27 dummy variables (nutse3) accounting for the region of the country the establishment is located in; 'Industry' is a set of 211 dummy variables accounting for the industry of the establishment at the 3 digit level (cae rev2.1); 'Occupation' is a set of 110 dummy variables accounting for the occupation of the individual at the 3 digit level (cnp94).
FG measures the wage gap and YSM the wage catch up. Sorting into regions, sectors and occupations explains half of the wage gap between natives and immigrants. Immigrants wages grow at a rate of approximately 1 percentage point faster than natives. The catch up is not correlated to immigrants moving industries or occupations. Estimations with and without individual heterogeneity are similar and show that the result is not driven by selection.
Source: Quadros de Pessoal, 2002-2009.

Table 3: Immigrant Wage Catch up by Origin Group

	East.Eur. (1)	Brazil (1)	Africa (1)	East.Eur. (4)	Brazil (4)	Africa (4)
FG	-0.377	-0.314	-0.346			
	(0.0016)	(0.0024)	(0.0024)			
YSM	0.010	0.020	0.006	0.013	0.011	0.003
	(0.0004)	(0.0007)	(0.0006)	(0.0005)	(0.0007)	(0.0007)
Age (quartic)	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Individual FE				Yes	Yes	Yes
N	7,395,761	7,334,379	7,319,209	7,395,761	7,334,379	7,319,209
R^2	0.100	0.148	0.096	0.315	0.315	0.315

Notes: The dependent variable is log hourly wages. Standard errors are in parentheses.
See table 2 for the definitions of the variables used.
The wage gap upon entry is highest for immigrants from Eastern Europe and lowest for Brazilians. The wage catch up rate accounting for individual fixed effects is above 1 percentage point for Brazilians and Eastern Europeans but immigrants from Africa lag substantially behind.
Source: Quadros de Pessoal, 2002-2009.

Table 4: Job Mobility

	(1)	(2)	(3)	(4)	(5)
FG	0.211	0.191	0.117	0.083	0.080
	(0.0013)	(0.0013)	(0.0013)	(0.0013)	(0.0013)
YSM	-0.021	-0.017	-0.010	-0.008	-0.007
	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)
Age		-0.036	-0.022	-0.020	-0.019
		(0.0011)	(0.0011)	(0.0011)	(0.0011)
Quartic in Age		Yes	Yes	Yes	Yes
Tenure			-0.023	-0.019	-0.019
			(0.0001)	(0.0001)	(0.0001)
Cubic in Tenure			Yes	Yes	Yes
Hourly wage			-0.001	-0.001	-0.001
			(0.00003)	(0.00003)	(0.00005)
Region				Yes	Yes
Industry				Yes	Yes
Occupation					Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Cst	0.071	0.582	0.400	0.368	0.389
N	5,731,442	5,731,442	5,731,442	5,731,442	5,731,442
R^2	0.010	0.011	0.049	0.081	0.082

Notes: The dependent variable is 1 if the worker will be working in a different firm next period, 0 if he stays with the same employer. Standard errors are in parentheses.
See table 2 for the definitions of the variables used.
The probability of changing employers is higher for immigrants than for natives. This probability declines with years spent in the labour market.
Source: Quadros de Pessoal, 2002-2009.

Table 5: Immigrant Wage Catch-up and Firm Fixed Effects

	(1)	(2)	(3)	(4)	(5)
YSM	0.010	0.010	0.009	0.006	0.006
	(0.0003)	(0.0003)	(0.0003)	(0.0002)	(0.0002)
Age (quartic)	Yes	Yes	Yes	Yes	Yes
Region		Yes	Yes		
Industry		Yes	Yes		
Occupation			Yes		Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes	Yes
Firm FE				Yes	Yes
N	7,543,209	7,543,209	7,543,209	7,543,209	7,543,209
R^2	0.313	0.324	0.332	0.945	0.945

Notes: The dependent variable is log hourly wages. Standard errors are in parentheses.
See table 2 for the definitions of the variables used.
These regressions control for firm fixed effects in the wage catch-up estimations. Comparing the estimates for γ in this table and table 2 shows that the coefficient decreases from 1ppt to 0.6ppt, or from 0.9 to 0.6ppt when controlling also for occupations. Changing firms accounts for a third of the immigrant wage catch-up.
Source: Quadros de Pessoal, 2002-2009.

Table 6: Immigrant Wage Catch-up and Firm Fixed Effects by Origin Group

	East.Eur. (1)	East.Eur. (2)	Brazil (3)	Brazil (4)	Africa (5)	Africa (6)
YSM	0.009	0.008	0.006	0.006	-0.001	-0.001
	(0.0002)	(0.0002)	(0.0004)	(0.0004)	(0.0004)	(0.0004)
Age (quartic)	Yes	Yes	Yes	Yes	Yes	Yes
Region						
Industry						
Occupation		Yes		Yes		Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE Yes	Yes	Yes	Yes	Yes	Yes	
N	7,395,761	7,395,761	7,334,379	7,334,379	7,319,209	7,319,209
R^2	0.945	0.946	0.946	0.946	0.946	0.946

Notes: The dependent variable is log hourly wages. Standard errors are in parentheses.
See table 2 for the definitions of the variables used.
Comparing the estimates in this table to those in table 3, the estimated γ decreases from 1.3ppt to 0.9ppt for Eastern Europeans and from 1.1ppt to 0.8ppt for Brazilians. A third of the wage catch-up occurs when changing firms for these two groups. All of the wage catch-up for immigrants from Africa occurs when changing firms as the estimated γ is close to 0 in this estimation.
Source: Quadros de Pessoal, 2002-2009.

Table 7: The Variance of the Wage Growth

FG	0.0072	0.0056
	(0.0009)	(0.0022)
EXP	-0.0025	-0.0026
	(0.0009)	(0.0002)
YSM		0.0004
		(0.0005)
Year FE	Yes	Yes
N	56	56
R^2	0.808	0.807

Notes: The dependent variable is the variance of the residual estimated from equation (4) for a origin-cohort at each calendar year. 'FG' is a dummy for foreigners.'EXP' are the years of experience in the labour market and 'YSM' is the interaction between 'FG' and 'FG'. Standard errors are in parentheses.
In line with the model, the variance of the wage growth is higher for immigrants than for natives and both decrease over time.

Table 8: Competing Theories of the Distribution of Wages

	Learning Model	Search Model	Human Capital Model
Basic Set up	Employer learning with complementarities between worker and firm type	On-the-job-search	Human capital accumulation with complementarities between worker and firm type
Immigrants and Natives	Higher initial uncertainty about immigrant productivity	Lower initial search capital for immigrants	Lower initial human capital for immigrants
Immigrants and Natives over Time		Immigrants accumulate search capital faster than natives	Immigrants accumulate human capital faster than natives
Other Features	Firms value certainty over the worker's productivity		Decreasing returns to human capital accumulation
Stylized Facts			
Immigrant wage catch up	✓	✓	✓
High but decreasing job mobility for immigrants	✓	✓	✓
Switching firms accounts for part of the catch up	✓	✓	✓
Variance of wages increases over time	✓	X	if heterogeneous accumulation of human capital
Variance of the wage growth decreases over time	✓	X	if heterogeneous accumulation of human capital

A Data Appendix

The data used in the paper is a linked employer-employee panel. The information is collected yearly by the Ministry of Labour in Portugal and the questionnaire is compulsory for all firms that employ at least one wage earner. All firms, establishments and workers have a unique identifer. An observation is a worker-firm match in a given year.

A.1 Building the Panel

Pooling all observations from 2000 until 2009, the initial data has 27m observations. In this section, I present details on the checks which were made to construct the panel adequately.

Workers are identified by their social security number. I start by identifying workers with an invalid social security number. In most cases, an invalid social security number is coded with a 0. It may be that immigrants as they first appear in the data have not been attributed a social security number. Deleting these observations would lead to ignoring information related to the first year in the panel and underestimating the number of years spent in formal employment. In order to recover the potential first year in the panel of immigrant observations, I match observations with a 0 social security number with observations in the following year by gender, date of birth, nationality (Portuguese or not), and firm identifier. The profile of an individual with an invalid social security number may hence only be recovered if he works in the same firm the following year. This correction allows to recover 240,595 observations. 478,347 observations still have an invalid social security number after this correction and are hence deleted.

I exclude workers who have several jobs at some point in their careers. The paper focuses on the career of immigrants and in particular on the importance of job mobility. The cases where workers have multiple jobs would need special attention. I discard these profiles: 2.8m observations in total, 18% of immigrant and 10% of native observations.

I then check for basic inconsistencies in the workers' profiles. Individuals for whom there are changes in gender or in immigrant status over time are allocated the gender and immigrant status reported more than half the times. 50,208 and 90,695 observations are dropped when after this correction no conclusion is reached. Individuals with a decreasing age profile are also identified and dropped from the analysis: 305,661 observations, 1.3% of native and 1.4% of immigrant observations. A last profile consistency check concerns wages. Individuals with an inconsistent wage growth profile (log hourly wage growth smaller than -0.5 or bigger than 2) are deleted[29]. In total, 1,073,426 observations were deleted: 4.6% of native and 5.9% of immigrant observations.

A.2 Sample Selection

For the analysis, I use only a sub-sample of individuals from the full panel. I restrict the analysis to men, as the careers of women would need a separate analysis. 44% of native observations are from female workers but only 35% of immigrants.[30] This leads to discarding 8.4m observations. Only individuals working in the mainland of Portugal are considered. Workers who work in the islands (Madeira, Açores) at some point of their career are excluded: 3% of immigrant and 4.7% of native observations. The data has a low coverage of agriculture, the whole industry is hence excluded. 5% of immigrant observations and 2.5% of native observations are deleted. Family workers and self-employed workers were dropped from the sample, only wage earners were considered to make wage progression comparisons meaningful. This accounts to excluding 13% of native but only 4% of immigrant observations. Part-time workers are also excluded, which accounts to 3.8% of native and 3.3% of immigrant observations.

A.3 Immigrant Cohorts and Origin Groups

A.3.1 Origin Groups

I exclude immigrants from the EU15 from the analysis. These immigrants benefit from the same conditions in the labour market than native workers and have very different characteristics than the other immigrant groups. The three main immigrant origins are Eastern and South-Eastern Europe, the former Portuguese African colonies (African Countries of Portuguese Official Language), and Brazil. The residual group represents less than 10% of the total number of immigrant observations in the data. The countries considered in the Eastern and South-Eastern Europe group are Slovakia, Poland, the Czech Republic, Hungary, Slovenia, Latvia, Estonia, Lithuania, Romania, Russia, Moldova, Ukraine and the former Yugoslavia. The countries belonging to the PALOP are Cape Verde, Mozambique, Angola, Guinea Bissau and São Tomé and Príncipe. Similarly to the consistency checks above, workers

[29] This correction follows Cardoso (2005)

[30] 71% of the observations for Eastern European immigrants are from male workers.

who exhibit changes in origin are identified and attributed the origin declared over half the times. Workers for which no conclusion may be drawn have the origin variable set to missing.

A.3.2 Cohorts

The paper focuses on immigrants from the new immigration wave to Portugal. I consider only immigrants first tracked in the data after 2001. All immigrants already in the data in 2000 are dropped from the sample.[31] This amounts to dropping approximately 7% of all immigrant workers in the data between 2000 and 2009.

The information on the date of arrival in the country is not available. The first time an immigrant is observed in the panel is used as a proxy. This captures the first time the worker is in formal employment, since the data set covers all wage earners in the private sector in Portugal. The cohort is defined as the first year the immigrant appears in the data and the years since migration are calculated as the difference between the calendar year and the cohort year. Moreover, a correction using the tenure variable is made to this calculation. Immigrants in their first year in the panel are assumed to have arrived in the country at their arrival in the firm. Consider for example an immigrant who is first observed in the data in 2003, but whose tenure indicates that he has already worked in the same firm for two years. He is considered to have been in the country since 2001.

Tenure for the purposes of the analysis refers to the time spent working in the same firm. If an individual's tenure is reported decreasing in the same firm (this may, for instance, be due to a change in contract) then the number of years considered as tenure is the time since the beginning of the first contract with the firm. After this correction, if there are still different dates of entry in the firm across the years, the correct value is considered to be the one taken over half of the times. When no conclusion may be reached after these corrections, the individual's tenure is set to missing.

[31] I use the whole panel from 1987 to check whether immigrants who are classified as new immigrants are in the data at an earlier point in time. I find that less than 10% of the immigrant observations considered in the analysis can be tracked before 2000. The correction using only the year 2000 is thus an acceptable correction.

A.4 Specific Data Issues and Robustness Checks

A.4.1 Dealing with the Missing Year of 2001

The data for the year of 2001 is not available. The analysis in the paper starts the analysis in 2002. I use the year 2000 to identify immigrants who are already in the country in 2000.

The missing data for 2001 poses several challenges and particularly in defining the immigrant cohorts. Workers who first start working in 2001 but change employers between 2001 and 2002 are allocated to the 2002 cohort; whereas workers who remain with the same employer are allocated to the 2001 cohort. A fraction of the 2002 cohort is made up of workers who have an extra year of experience in the Portuguese market. If movers are positively selected, these extra workers are also the "best" workers of the 2001 cohort. Figure 1 in section 2 shows that the pattern of the mean wages for the immigrants of the 2002 cohort does not appear to be very different from the one of the other cohorts.

I perform another robustness check: I redefine cohorts as two-year instead of one-year cohorts. I classify immigrants who first appear in the data in 2001[32] or 2002 as belonging to the first cohort; immigrants who are first tracked in 2003 or 2004 belong to the second cohort, etc. The years since migration variable is re-calculated accordingly. Figure 14 plots the mean wages for these newly defined cohorts over time. I re-estimate all the main empirical specifications in section 3 using this two-year cohorts and find little difference in the main results.

A.4.2 Dealing with the Changes in the Industry Classification in 2007

In 2007, the classification used for the industries in Portugal changed.[33] I use the 'old' classification in all the analysis. I do not use the official table created by the Portuguese Institute of Statistics to convert the new classification into the old one. This would lead to over-estimate the frequency with which workers change industries as the classifications are very different. In fact, when I consider firms which existed in 2006 and 2007 and which are all classified in a given 'new' industry in 2007, there is a very large dispersion in the industries the firms belonged to in 2006. For all firms which can be tracked in the data before 2007, I assign the industry observed before 2007 in the 'old' classification to the observations from 2007 until 2009. I then drop all observations belonging to firms who enter the

[32]The correction using the tenure variable allows to allocate immigrants to the 2001 cohort even if the data for 2001 is missing.

[33]The classification until 2006 is cae rev 2.1 and from 2007 it is cae rev 3.

market in 2007 and later.

One may worry that excluding these observations may lead to a selection bias. I perform two robustness checks to address this concern. First, I re-do all the main estimations in the main empirical section which do not use the industry dummies including the firms entering the market after 2007; second, I re-do the analysis excluding the years after 2007. I find little difference in the main results.

B Model Appendix

B.1 The Variance of the Expected Productivity for a Cohort

I calculate the variance of the distribution of the expected worker productivity ($\mu_{x,k}$) for a given cohort after x years in the labour market.

For immigrants:

$$\mu_{x,fg} = \frac{\sigma_\epsilon^2}{x(\sigma_a^2 + \sigma_s^2) + \sigma_\epsilon^2}(q + \mu_a + \mu_s) + \frac{\sigma_a^2 + \sigma_s^2}{x(\sigma_a^2 + \sigma_s^2) + \sigma_\epsilon^2}\sum_{l=0}^{x-1} y_l$$

Replacing $\sum_{l=0}^{x-1} y_l = x(a + s + q) + \sum_{l=0}^{x-1} \epsilon_l$,

$$\mu_{x,fg} = q + \frac{\sigma_\epsilon^2(m_s + m_a) + (\sigma_a^2 + \sigma_s^2)(x(a + s) + \sum_{l=0}^{x-1} \epsilon_l)}{x(\sigma_a^2 + \sigma_s^2) + \sigma_\epsilon^2}$$

q, a, s and ϵ are independent random variables. The variance of the above expression is hence:

$$V(\mu_{x,fg}|I_x) = \sigma_q^2 + \frac{x^2(\sigma_a^2 + \sigma_s^2)^3}{(x(\sigma_a^2 + \sigma_s^2) + \sigma_\epsilon^2)^2} + \frac{x\sigma_\epsilon^2(\sigma_a^2 + \sigma_s^2)^2}{(x(\sigma_a^2 + \sigma_s^2) + \sigma_\epsilon^2)^2}$$

Similarly for natives:

$$\mu_{x,nat} = \frac{\sigma_\epsilon^2}{x\sigma_a^2 + \sigma_\epsilon^2}(q + \mu_a + s) + \frac{\sigma_a^2}{x\sigma_a^2 + \sigma_\epsilon^2}\sum_{l=0}^{x-1} y_l$$

$$V(\mu_{x,nat}|I_x) = \sigma_q^2 + \sigma_s^2 + \frac{x^2(\sigma_a^2)^3}{(x\sigma_a^2 + \sigma_\epsilon^2)^2} + \frac{x\sigma_\epsilon^2(\sigma_a^2)^2}{(x\sigma_a^2 + \sigma_\epsilon^2)^2}$$

B.2 The Distribution of the Changes in Risk-adjusted Expected Productivity for a Cohort

The change in worker risk-adjusted expected productivity from year $x-1$ to year x

$$\Delta_{x,k} = \left(\mu_{x,k} - \frac{1}{2}\sigma^2_{x,k}\right) - \left(\mu_{x-1,k} - \frac{1}{2}\sigma^2_{x-1,k}\right)$$

follows a normal distribution. I calculate the mean and variance of its distribution for immigrants and natives of a given cohort.

The mean of $\Delta_{x,k}$ is the mean of $-\frac{1}{2}\sigma^2_{x,k} + \frac{1}{2}\sigma^2_{x-1,k}$ as the mean of expected productivity over a cohort of workers is constant over time.

For immigrants:

$$M(\Delta_{x,fg}) = \frac{1}{2}\frac{\sigma^2_\epsilon(\sigma^2_s + \sigma^2_a)^2}{(\sigma^2_\epsilon + x(\sigma^2_a + \sigma^2_s))(\sigma^2_\epsilon + (x-1)(\sigma^2_a + \sigma^2_s))}$$

For natives:

$$M(\Delta_{x,nat}) = \frac{1}{2}\frac{\sigma^2_\epsilon\sigma^4_a}{(\sigma^2_\epsilon + x\sigma^2_a)(\sigma^2_\epsilon + (x-1)\sigma^2_a)}$$

The mean change in expected productivity is higher for immigrants than for natives, as there is initially more uncertainty about immigrant productivity. The mean decreases for both groups with time spent in the market and tends to 0 at the limit.

The variance of $\Delta_{x,k}$ is the variance of $\mu_{x,k} - \mu_{x-1,k}$ as $\sigma^2_{x,k}$ is constant across workers of the same cohort in all periods in the market.

For immigrants:

$$\mu_{x,fg} - \mu_{x-1,fg} = q + \frac{\sigma^2_\epsilon(m_s + m_a) + (\sigma^2_a + \sigma^2_s)(x(a+s) + \sum_{l=0}^{x-1}\epsilon_l)}{x(\sigma^2_a + \sigma^2_s) + \sigma^2_\epsilon}$$

$$-q - \frac{\sigma^2_\epsilon(m_s + m_a) + (\sigma^2_a + \sigma^2_s)((x-1)(a+s) + \sum_{l=0}^{x-2}\epsilon_l)}{(x-1)(\sigma^2_a + \sigma^2_s) - \sigma^2_\epsilon}$$

Re-writing:

$$\frac{\left((x-1)(\sigma_a^2+\sigma_s^2)+\sigma_\epsilon^2\right)\left(\frac{\sigma_\epsilon^2(m_s+m_a)+(\sigma_a^2+\sigma_s^2)(x(a+s)+\sum_{l=0}^{x-1}\epsilon_l)}{x(\sigma_a^2+\sigma_s^2)+\sigma_\epsilon^2}\right)}{\left(x(\sigma_a^2+\sigma_s^2)+\sigma_\epsilon^2\right)\left((x-1)(\sigma_a^2+\sigma_s^2)+\sigma_\epsilon^2\right)}$$

$$-\frac{\left(x(\sigma_a^2+\sigma_s^2)+\sigma_\epsilon^2\right)\left(\frac{\sigma_\epsilon^2(m_s+m_a)+(\sigma_a^2+\sigma_s^2)((x-1)(a+s)+\sum_{l=0}^{x-2}\epsilon_l)}{(x-1)(\sigma_a^2+\sigma_s^2)-\sigma_\epsilon^2}\right)}{\left(x(\sigma_a^2+\sigma_s^2)+\sigma_\epsilon^2\right)\left((x-1)(\sigma_a^2+\sigma_s^2)+\sigma_\epsilon^2\right)}$$

Noting that a, s and ϵ are independent random variables, collecting terms in a, s and ϵ, and calculating the variance:

$$V(\Delta_{x,fg})=\sigma_\epsilon^2\frac{((\sigma_a^2+\sigma_s^2)^2(x-1)+(\sigma_a^2+\sigma_s^2)\sigma_\epsilon^2)^2+(\sigma_a^2+\sigma_s^2)^4(x-1)+\sigma_\epsilon^2(\sigma_a^2+\sigma_s^2)^3}{[(x(\sigma_a^2+\sigma_s^2)+\sigma_\epsilon^2)((x-1)(\sigma_a^2+\sigma_s^2)+\sigma_\epsilon^2)]^2}$$

Similarly for natives:

$$V(\Delta_{x,nat})=\sigma_\epsilon^2\frac{(\sigma_a^4(x-1)+\sigma_a^2\sigma_\epsilon^2)^2+\sigma_a^8(x-1)+\sigma_\epsilon^2\sigma_a^6}{[(x\sigma_a^2+\sigma_\epsilon^2)((x-1)\sigma_a^2+\sigma_\epsilon^2)]^2}$$

As time spent in the market goes by, there is less uncertainty about the worker's productivity and the expected worker productivity becomes more stable. The variance of the expected productivity decreases with time for an entry cohort. The initial variance is higher for immigrants as there is relatively more that is learnt in the first years about their productivity. The difference in profiles of the two groups decreases over time.

Figure 14: Mean Hourly Wages for Immigrants by Two-year Cohort