ABSTRACT

Title of dissertation: ESSAYS ON LABOR ECONOMICS: HUMAN CAPITAL RISK AND LABOR MARKET OUTCOMES AND LEARNING BY DOING IN MEDICINE

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This dissertation consists of two essays. In the first essay I show that there are substantial differences in unemployment durations and reemployment outcomes for workers coming from different occupations. I argue that this variation can be explained in part by differences in occupational employment risk, arising from two sources: (1) the diversification of occupational employment across industries; and (2) the volatility of industry employment fluctuations, including sectoral co-movements. I define and estimate a measure of occupational employment risk (OER), which I relate to unemployment durations and wage losses. My results indicate that unemployed workers in high employment risk occupations, as defined by the OER measure, have 5 percent lower hazard ratios of leaving unemployment to a job in the same occupation and have around 5 percent higher wage losses upon reemployment than workers in low OER occupations. Among occupational

switchers, workers in higher OER occupations have 11.5 percent higher wage losses than workers in lower OER occupations.

In my second essay, I and my co-authors estimate the effect of physician's experience on health outcomes. It is a common belief that experience can improve the level of skills, which suggests that there may be some learning by doing with practice. Economists have tried hard to empirically determine the existence of learning by doing in the medical area, because of its important policy implications. However, it is difficult to define and measure health outcomes since they are affected by patient selection and underlying conditions, making it hard to disentangle learning by doing from other effects. In this paper, we use a clean-cut medical procedure that allows us to overcome those confounding issues. We use refractive eye surgery, an operation with a well-defined eligibility criterion and objective measures of previous condition and posterior outcome, which depend minimally on post-surgical care. The data used in the study is a two-year longitudinal census of refractive surgery patients from one of the largest ophthalmologic clinics in Colombia. We collected the data from individual patients' chart and we observe all information the surgeon accessed pre- and post-surgery. We find that the learning is coming more from the improvement in the surgical center's ability to translate the surgical plan into the desired eyesight correction rather than from the accumulation of the physician experience.

ESSAYS ON LABOR ECONOMICS:
HUMAN CAPITAL RISK AND LABOR MARKET OUTCOMES
AND
LEARNING BY DOING IN MEDICINE

by

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DEDICATION

To God that gave me the strength.

To this country that opened the door.

To my mother that stood by me every step of the way.

To my husband that never let me fall.

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TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

Part I

How Hard Is It to Get Another Job? Occupational Employment Risk and its Consequences for Unemployment Duration and Wages

1.1 Introduction

This paper documents substantial differences in unemployment durations and re-employment outcomes across workers coming from different occupations. It argues that this variation comes in part from the fact that some occupations have a more diversified portfolio of employment opportunities than others. For instance, occupations employed by many industries in the economy, like 'accountants', have a well diversified portfolio of employment options, while occupations employed only by a handful of quite volatile industries, like 'earth drillers', have a much more concentrated portfolio of employment choices.

Looking at the data, one can observe a large variation in average unemployment durations and wage losses across occupations (see table and figure 1.1).[1] Figure 1.2 presents occupational differences in average wage change upon re-employment for occupational stayers and occupational switchers.[2] We can see from this figure that wage loss variation is present regardless of whether workers switch occupations or not upon re-employment.[3] One of the striking features of these figures is that differences in unemployment duration and wage losses are present even among closely related occupations with seemingly similar level of skills, education, training, and

[1]These averages are reported for 45 'detailed occupational codes', which is an intermediate occupational classification (between two and three-digit codes) given by the Current Population Survey (CPS).

[2]Occupational stayers are workers reemployed in the same occupation they held in their previous job, while occupational switchers are workers that change occupation upon re-employment.

[3]I also examined whether this observed variation on wage losses were due to an uneven distribution of displaced workers across occupations - since they may suffer greater wage losses upon re-employment than than non-displaced workers. However, I still find the same large variation, whether or not they switched occupations upon re-employment. Displaced workers are workers that report losing their jobs due to layoff or plant closing.

work performed. For instance, there are large differences in duration and wage outcomes between low skill blue-collar occupations, like 'cleaning and building services' and 'handlers and laborers,' and between high skill white collar occupations like 'engineering and science technicians' and 'other technicians'. This suggests that variation in workers characteristics alone, especially in educational attainment, cannot explain why individuals in some occupations face longer unemployment spells and greater wage losses than individuals in other closely related occupations.

Past studies of unemployment duration and wage determination have acknowledged the relevance of an individual's occupation either directly, by differentiating workers between blue and white collar or main occupational groups, or indirectly by controlling for occupation in their analysis. However, only recently have studies tried to investigate why occupations are important to employment and wages. For a long time, economists have considered firm-specific skills to play a major role in earnings determination.[4] Conflicting findings regarding the magnitude of tenure effects on earnings profile led Neal (1995) and later Parent (2000) to examine whether industry-specific human capital is more important in explaining earnings than firm-accumulated skills. Both studies find evidence in favor of industry-specific skills.

Most recently, a growing line of work has been emphasized occupation rather than industry as the level of human capital specificity that is relevant to earnings. Kambourov and Manovskii (2002) and Poletaev and Robinson (2003 and 2004)

[4]See Abraham and Faber (1987), Altonji and Shakotko (1987) and Topel (1991). For a complete discussion of the literature see Willies (1986).

show that the evidence for industry specific capital is weak and that the data is consistent with a more general skill measure of human capital, like occupation. They find that when occupation or a set of skills specific to occupations are taken into account, industry and firm-specific human capital lose their importance in explaining earnings. Their results suggest that occupation captures an important component of human capital which is relevant to earnings determination.[5] In light of this new evidence, unemployed workers have an incentive to look for a job in the occupation they held previously, so that they can retain and therefore capitalize on their occupation-specific human capital.

Another aspect of human capital that has attracted attention in the recent years is the labor income risk associated with different skills. It has become common in the literature to assume that individuals with different skills or levels of accumulated human capital face different labor income risk.[6] In this paper, however, I show that there is another aspect of human capital risk that has not been studied before and that seems to have an important role in explaining observable differences in unemployment duration and wage losses across occupations.

In particular, I analyze differences in the diversification of employment opportunities faced by each occupation. I argue that differences in this risk arise from the large variation in the distribution of occupational employment across industries

[5] Occupations are, in general, classified based on an exclusive set of specific skills and skill demands which uniquely define them. Among this set of specific skills are the nature of work performed, education, training, and work credentials.

[6] Most studies measure human capital risk as differences in the variance of labor income associated with different levels of skills. See for example Grossmann (2005) and Huggett et al. (2005).

and from the fact that industries have different employment volatilities. The combination of these two facts implies that some occupations have a more diversified portfolio of employment opportunities than others. This suggests that the individuals employed in more diversified occupations potentially face lower unemployment risk than individuals employed in occupations with lower diversification, which may translate into shorter unemployment spells and/or lower wages losses upon re-employment. I call this phenomenon Occupational Employment Risk (OER).

Regarding the distribution of occupational employment, occupations can differ in both the number of different industries that employ them[7] and in how concentrated across these industries their employment is. Looking at the data, one can see that there is a quite large variation in the number of industries that employ different occupations. For instance, in the 1990 Census data the occupation 'accountants' is employed by 157 out of 158 three-digit industries, while the occupation 'earth drillers' is only employed by 13 of these industries (see figure 1.3).[8]

Second, occupations vary enormously in the concentration of their employment across industries. It is not uncommon to see occupations with more than 75% of their employment concentrated in one or two industries, regardless of how many industries employ the occupation. These differences in occupational employment concentration across industries can be well summarized by a Herfindahl Index of employment concentration.[9] Table 1.2 presents the Herfindahl index for each occu-

[7] In a sense this captures how transferable occupational skills are across industries.

[8] Appendix A.2 provides details on occupational and industry codes.

[9] A Herfindahl index of employment concentration can be obtained for each occupation by summing, across all industries, the squared shares of the occupation's employment in each industry. This index is bounded between 0 and 1 and the higher is its value, the more concentrated across

pation. Similar to unemployment duration and wage loss, there is large variation in the concentration of occupational employment across industries. Some occupations, like 'financial records' or 'handlers and laborers', have very low Herfindahl values and therefore low industry employment concentration, while occupations like 'teachers' and 'construction laborers' have their employment highly concentrated in few industries. Figure 1.4 graphs the Herfindahl values for all occupations shown in table 1.2. Even within major occupational groups, there is large variation in the concentration of occupational employment.

Aside from differences in the distribution of occupational employment, variation in industries' employment fluctuations are also important to occupational employment opportunities and should be taken into account when studying occupational employment risk. Given the uneven distribution of occupational employment across industries, differences in industries' employment fluctuations[10] can greatly affect the portfolio of employment opportunities faced by each occupation. Returning to the case illustrated in figure 1.3, both 'accountants' and 'earth drillers' are employed by the construction industry, which is highly volatile. We can see from the figure that more than 80% of 'earth drillers' are employed by the construction sector and only few other industries employ them. Among those are 'metal mining', 'non metal mining' and 'cement, concrete and plaster products', all of which are very volatile and exhibit strong temporal co-movement with construction. So if

industries the occupational employment is.

[10]Some industries face more frequent and/or larger shocks than others. For example, low aggregate demand or high oil prices can affect some industries more heavily than others. Sectors like construction, transportation and services, for instance, are usually more volatile than other sectors.

the construction sector is hit by an idiosyncratic shock and lays off many workers, including 'earth drillers' and 'accountants', 'earth drillers' would probably have a harder time finding a new job in the same occupation, since the construction industry is their main employer, and the other industries that employ them are probably comoving with construction (being affected by the same shock). Unemployed earth drillers can change occupation in order to shorten their unemployment spell; however, we know from our previous discussion that if they do so they are likely to have a higher wage loss, since they lose their occupation-specific human capital. Accountants, however, can more easily leave the construction sector and look for an accountant job in a different industry. In fact, only 5.2% of accountants are employed in construction and they can work for any other industry in the economy, some of which will not be comoving with construction.

In this paper, I combine the specific-human capital preservation motive with employment risk variation to explain the differences in unemployment duration and wage losses across occupations. In order to do so, I define a measure of occupational employment risk (OER), which I estimate using data from the Quarterly Census of Employment and Wages, years 1979-2000. I then relate this measure to unemployment duration and wage loss using a constructed weekly panel of employment and demographic histories for 5,579 males in the NLSY79, which includes employer characteristics for up to five jobs each individual held during any year in the period 1979-2000. I find, as expected, that workers in high risk occupations, as defined by the OER measure, have lower hazard ratios of leaving unemployment to a job in the same occupation and have higher wage losses than workers in low risk OER occupations, especially if they switch occupations.

The paper is divided into five sections. Section 1.2 discusses the methodology used in order to measure occupation employment risk. Section 1.3 estimates the effect of OER on unemployment duration, while Section 1.4 relates this risk measure to wage losses. Section 1.5 presents conclusions and suggestions for future work.

1.2 Measuring Occupational Employment Risk (OER)

In this section, I define and construct a measure that depends on the diversification of occupational employment across industries and on the level of industry employment volatility, including co-movements. In a sense, the employment opportunities of an occupation can be seen as a portfolio of industries where the weights are the shares of occupational employment in each industry and the rates of return are the industry volatilities. To my knowledge, this study is the first to define and calculate a measure of employment risk associated with particular occupations, although a number of studies in the literature have estimated either the risk associated with aggregate employment volatility or different industries' unemployment risk. Neumann and Topel (1991) measure unemployment risk for workers in a particular locality as the variance of the within-market local demand uncertainty, $e'V$, where e is the vector of local industry employment shares and V the vector of estimated sectoral local employment shocks. Based on the assumption that workers are mobile within local markets[11], they show that the sectoral composition of the market forms an implicit "portfolio of employment opportunities in which less specialized markets may achieve lower unemployment." The authors find that their measure explains differences in unemployment rates among geographically distinct labor markets.[12] Through the use of a similar measure, Shea (2002) finds that interindustry co-movement is responsible for 95% of the variance of manufacturing employment.[13] Using 126 three-digit U.S. manufacturing industries over the period 1959-1986, he estimates aggregate employment risk by decomposing annual employment growth into an average of industry growth rates, weighted by the industries' share of employment.

My idea builds upon the fact that occupational employment is distributed unevenly across industries. Some occupations are employed in many industries, while others are only employed in a small number of industries. Meanwhile, different industries have different cyclicalities. In this context, it is reasonable to expect that different occupations may have diverse levels of employment risk associated with them. Occupations used in a larger number of industries may potentially face a lower employment risk given that they have more diversified employment opportunities. In order to examine whether this is really the case, I construct a measure of occupational employment risk (OER) which considers two important

[11] Their argument is based on the assumption that if there are many goods and if skills are transferable, workers are mobile within local markets.

[12] In addition, they show that within-market changes in demand uncertainty had positive, but only minor effects on within-market changes in unemployment.

[13] Shea estimates that the average pairwise correlation of annual employment growth is 0.34 and that, even after aggregating industries to 20 two-digit industries codes, co-movement is still responsible for over 86% of manufacturing employment variation. For more on co-movements, see Long and Plosser (1983) and Horvath (1998).

dimensions of risk: the concentration of occupational employment across industries and the volatility and co-movement of disaggregated industry employment. The OER measure is calculated in a fashion similar to Neumann/Topel and Shea.

The concentration component of the OER measure is obtained by calculating the shares of occupational employment in each industry. S_{vj} is the share of occupation v in industry j, defined as follows:

$$S_{vj} = \frac{emp_{vj}}{emp_v} \tag{1.1}$$

where emp_{vj} is the employment of occupation v in industry j and emp_v is the total employment in occupation v. I assume the shares to be in steady-state and compute them from the 1990 Census Public Use Microdata Series (PUMS) by constructing an occupation-by-industry employment matrix. I must make a steady-state assumption due to the lack of annual data on occupational employment by industry for the time period I consider. The limitation of making such an assumption is that if the occupational employment shares are changing over time, my measure of OER would not capture these trends.[14] However, this issue is minimized by the fact that most of the trends in shares occur at the three-digit occupational classification level, while I use a more aggregated occupational classification, which makes the shares more robust to changes over time. Nevertheless, as a robustness check, I also estimated a version of OER using 1980 Census shares and I obtained similar results.[15] I use 1990 shares since 1990 is the midpoint of my analysis.

[14]Note that the steady-state assumption of the shares of occupational employment in each industry is not necessarily inconsistent with the well-known phenomenon of skill upgrading within industries, as long as all industries are shedding less-skilled workers at the same rate.

[15]The overall correlation of the shares of occupational employment in each industry between

The volatility component, Ω_ε, is constructed using the variance-covariance matrix of disaggregated industry employment growth rates, ε_{jt}, $j = 1, ...J$ and $t = 1978, ...2000$, which I estimate using data from the Quarterly Census of Employment and Wages (QCEW) over the period 1978 to 2000.[16] In particular, note that Ω_ε incorporates not only the variance of industry employment but also the co-movements among industries.[17] The QCEW contains information on the number of establishments, employment, and total wages of employees covered by various unemployment insurance programs. A nice feature of this data set is that it provides industry employment data for every four-digit industry at national, state, MSA and county levels for the period 1975-2004.[18] The main limitation, however, is the change in industry codes over the time period available (years 1975-1987 use the 1972 SIC, 1988-2000 use the 1987 SIC and 1990-2004 use the NAICS). I deal with this issue by matching industry codes between the first two time periods in order to make the industry classification consistent through 1978-2000. The criterion I used was to merge 3-digit industry codes if one or more of their 4-digit industries are reported to be combined. Details about the industry code matching may be found in the appendix at the end of the paper.[19]

1980 and 1990 is 0.98. Calculating this correlation separately for each occupation, I find the lowest correlation to be quite high (0.79 for 'Personal Services Occupations').

[16]Specifically, $\varepsilon_{jt}=\Delta log(emp_{jt})$.

[17]I have tried different specifications for estimating Ω_ε. In particular, using industry employment shocks estimated by controlling for industry specific characteristics with and without year dummies, I obtain similar results, regardless of the specification I use, so I opted for the simplest specification.

[18]Data for certain establishments under government ownership are not disclosed, so the total employment in these industries will be somewhat underestimated.

[19]For an extensive discussion of the criteria applied and the constructed crosswalk, see Tristao (2005).

I next assume that the growth rate of employment for a particular occupation can be (first-order) approximated as a weighted average of industry employment growth rates, where the weights are the shares of occupational employment in each industry:[20]

$$OEG_{vt} \cong \sum_{j=1}^{J}(S_{vj} * \varepsilon_{jt}), \qquad v = 1, ..., V; \quad j = 1, ..., J. \tag{1.2}$$

where J is the number of industries, V is the number of occupations and OEG_{vt} is a first-order approximation of the growth rate of employment in occupation v at time t.

My benchmark measure of occupational risk is calculated as the implied variance of the (unobserved) growth rate of occupational employment:

$$OER_v = Var(OEG_{vt}) = S_{vj}\Omega_{\varepsilon}S'_{vj}. \tag{1.3}$$

where S_{vj} is a $1 \times J$ vector of occupation $v's$ industry shares and Ω_{ε} is a $J \times J$ matrix of variances and covariances of $j's$ employment growth rates. It is worth noting that this measure has a lower bound at zero but is unbounded from above.

The OER measure is estimated for 158 3-digit industry codes and 46 'detailed' occupational codes,[21] which is an intermediate occupational classification (between two and three-digit occupational codes) given by the Current Population Survey

[20] This assumption, however, would not be robust to deskilling, even if deskilling was uniform across industries. This happens because by calculating the product of these shares with the correspondent industry employment growth - which implies the occupational employment, is growing at the industry employment growth rate - we may overestimate the occupational employment growth of occupations that are disappearing. For instance, suppose 50% of the occupation 'typist' is employed in industry A and the other 50% is employed in industry B, and that although the employment in both industries are growing by 10%, they are both laying-off 50% of their 'typists'. According to equation (2), 'typists' employment would grow by 10%, while in fact, it decreased by 50%.

[21] See appendix A.2 for a description.

(CPS). There are two main advantages to using this classification. The first is that workers may consider their skills to fit more than one three-digit occupation, which could lead them to search for a job in closely related occupation. For example, a worker whose three-digit occupation is a 'Payroll and Timekeeping Clerk' may also see himself as a 'Billing Clerk' [22] and consider jobs in both positions. Second, a more aggregate classification reduces the problem of measurement errors from occupational misclassifications, which is an issue in other longitudinal studies using occupations.[23] Nevertheless, the detailed occupational code (from now on referred as DOC), is still quite a rich classification, with three times as many occupational categories as the two-digit code.

Figure 1.5 presents the OER measure for different occupations. One can see that there is a large variation in this measure of employment risk across occupations, even within closely related occupational groups. In the next two sections, I relate this measure to unemployment duration and wage loss in order to examine whether workers in higher employment risk occupations indeed face longer unemployment spells and wage losses than workers in lower employment risk occupations.[24]

1.3 OER Measure and Unemployment Duration

In this section, I estimate the effect of OER on the hazard rate of leaving unemployment and, consequently, on the length of unemployment spells. In light

[22]These two occupations are classified as being closely related by the Occupational Outlook Handbook published by the Bureau of Labor Statistics (BLS).

[23]See Kambourov and Manovskii (2002 and 2005) and Neal (1995) for discussions.

[24]The correlation between the OER measure and the average unemployment duration and wage loss is is 0.18 and -0.17, respectively.

of recent evidence showing the relevance of occupation-specific human capital to earnings, unemployed workers have an incentive to look for a job in the occupation they held previously, so they can retain and therefore capitalize on their occupation-specific human capital. This suggests that it is important to distinguish between two exit modes out of unemployment: finding a job in the same or in a different occupation. In order to accomplish this, I use a continuous-time competing risk model, which I estimate by using a Cox Proportional Hazard model with multiple spells and time-varying covariates.

The main reason for choosing this specific regression model is that it allows me to estimate the relationship between the hazard rate and explanatory variables without imposing any parametric assumption about the shape of the baseline hazard function, $h_0(t)$.[25] Not having to parameterize $h_0(t)$ is desirable in this context because it eliminates the need to make assumptions on how the hazard changes over time. Incorrect assumptions on the shape of $h_0(t)$ would produce incorrect results regarding how the covariates affect the hazard. The only assumption made concerning the shape of $h_0(t)$ is that it is the same for everyone.[26] The Cox model is often called semiparametric because the effect of the covariates is parameterized and is assumed to shift the baseline hazard function multiplicatively. The hazard

[25]Cox (1972) proposed a method for estimating the covariates without having to make any assumptions about the shape of the baseline hazard function, which in fact is not even estimated. This method relies on the assumption of proportional hazard and is estimated by partial likelihood rather than maximum likelihood.

[26]See Kalbfleisch and Prentice (2002) for a rigorous treatment and Cleves et al. (2004) for an intuitive discussion.

rate for the ith subject in the data is:

$$h(t/x_i(t)) = h_0(t)e^{(x_i(t)\beta_x)} \tag{1.4}$$

The baseline hazard can be estimated separately, conditional on the estimates of β_x. I specify the relative hazard to be:

$$e^{(x_i(t)\beta_x)} = exp(\beta_1 OER_v + \beta_x X_i(t) + \beta_z Z_i(t)) \tag{1.5}$$

where OER_v is the occupational employment risk measure for occupation v. X_{it} is a vector of demographic characteristics which include age, measures of ability, a dummy for race, marital status and educational attainment. The measures of ability are the first two principal components of the age-adjusted Armed Services Vocational Aptitude Battery (ASVAB) scores, obtained by following the two-step methodology presented by Cawley et al. (1995) and Kermit et al. (1997). The appendix at the end of the paper provides details.[27] $Z_i(t)$ is a vector containing relevant work history information, including years of work experience and tenure in the previous job, a dummy for receiving unemployment compensation during the unemployment spell, and the local unemployment rate.[28]

Construction of the Panel

I restrict the sample to unemployment spells whose duration was less than 53 weeks in occupations for which there were at least 20 observations. I make these restrictions to obtain more reliable estimates, by reducing classical measurement

[27]The ASVAB is a set of ten tests measuring knowledge and skill in different areas.

[28]In order to capture nonlinear effects, I also include quadratic terms for age, ability, experience and tenure.

error in the data and by not including possibly discouraged workers.[29] In order to exclude the period of high job turnover at the beginning of individuals' careers, I further restrict the sample by considering only spells in which the individual was at least 21 years old at the beginning of the spell (see Neal (1995)). Moreover, I consider only completed spells, which I define to be a transition from employment to unemployment and then back to employment again, except for the last spell in the sample, which may be censored.[30] The duration of a spell is the difference in weeks between the end and the beginning of the spell.

The data set I use to assess the relevance of the OER measure for unemployment duration and wages is the National Longitudinal Survey of Youth 1979 (NLSY79). The NLSY79 is a nationally representative sample of 12,686 young men and women who were 14-22 years old when they were first surveyed in 1979. Detailed information on these individuals' demographic characteristics and labor force participation has been collected since 1979.[31] This paper uses the unbalanced panel of civilian males, covering 1979-2000, which contains 5,579 individuals. I restrict the sample to males in order to avoid labor force participation issues that arise when including women in the sample.

Relative to other micro data sets, the NLSY79 has two distinct features that makes it the best data to answer my particular question. First, the NLSY79 work

[29] Out of the 45 detailed occupational codes, there were 16 codes for which there were less than ten observations, representing 1.4% of the spells. Unemployment spells with a duration of more than 52 weeks were less than 2% of the sample.

[30] A worker is considered to be unemployed by the NLSY if he or she did not work at all during the survey week and is currently searching or has searched for a job in the four weeks prior to the survey.

[31] Data was collected annually from 1979 to 1993, and biennially from 1994 to the present.

history data is available on a weekly basis. Since a significant number of unemployment spells are very short, this high frequency is quite important.

Second, and most importantly, the NLSY79 is one of few data sets that provides a complete work history for a specific cohort, which allows researchers to analyze completed unemployment spells.[32] This is one of the most desirable attributes of a data set for studying labor force transitions and unemployment duration, and it constitutes a significant advantage of the NLSY79 over the Current Population Survey (CPS) data, where unemployment spells are incomplete and cohorts change over time. Most studies analyzing unemployment duration in the U.S. use CPS data on spells in progress. Based on the steady-state assumption that flows in and out of unemployment are constant over time, existing studies either estimate the expected length of spell duration for a synthetic cohort of individuals entering unemployment (using continuation rates) or estimate the average completed spell length for the currently unemployed workers by 'doubling' the average duration of their spells.[33] However, when steady-state conditions do not hold, both estimators can be biased. Rising unemployment will cause the steady-state method to underestimate completed spell lengths, while decreasing unemployment will cause this method to overestimate the length of spells.[34] In addition to the advantages men-

[32]It is possible for the NLSY to construct a complete work history for each respondent, regardless of period of non-interview, because its survey questions are designed to recover the starting and ending dates for each labor force status change since the date of the last interview. See Appendix A.1. for details.

[33]For some of the most recent and influential papers using the CPS data see Darby et al. (1997), Baker (1992), Shimer and Abraham (2002) and Shimer (2005). Some exceptions are Dynarski and Sheffrin (1986) and (1990) using the PSID.

[34]For studies discussing the technical difficulties in measuring completed spells see Sider (1985) and Kiefer et al. (1985).

tioned above, the NLSY79 also has ability measures and has lower attrition rates than other longitudinal data sets, such as the Panel Study of Income Dynamics (PSID). The downside of using the NLSY79 instead of the CPS is that I am able to analyze only individuals of a specific cohort, which is still relatively young. In 2000, the individuals' age range was 35 to 43 years old.

The NLSY79 collects detailed information on new and previously reported employers for whom a respondent has worked since the date of last interview. For every survey year, it reports up to five employers.[35] Using start and end dates of employment, as well as the job number assigned to each employer in every survey round (which can vary across rounds), I linked all employers across survey years and further to the weekly work history files.[36] This allowed me to merge employer and job characteristics, such as industry and occupational codes, with the work history file. I also merge employees' main demographic characteristics, creating a weekly panel of employment and demographic histories for up to five jobs each individual held during any year in the period 1979-2000. This panel allows me to obtain good measures of work experience and tenure within given employer, which I calculate weekly by accumulating the number of weeks reported working and working for a particular employer, respectively.

Issues that normally arise with the use of occupational codes (and to a less ex-

[35] In fact, the NLSY79 collects information for all employers for whom a respondent has worked since the date of last interview. According to the NLSY documentation files, however, the number of respondents who report more than five jobs in each survey is less than one percent of those interviewed.

[36] Since employers can receive different job numbers across years, it is necessary to use beginning and ending dates as well as a series of other supporting variables which jointly taken indicate, for every current survey employer the job number it received in the previous survey and whether it is a new job.

tent, industry codes) are (i) individuals doing the same job can be coded as having different occupations and (ii) the same individual working in the same occupation can be coded differently across survey rounds, generating spurious occupation mobility. As I mentioned in the last section, in order to minimize measurement errors from misclassifications of occupational descriptions, I use a more aggregated occupational classification, which combines closely related occupations, but which still contains three times as many occupational categories as the two-digit code. Taking advantage of my panel of individual work histories within each employer, I eliminate the second type of problem by defining the occupation in each job to be the mode of occupational codes ever reported for that employer, instead of the code reported in every survey round for that job. This is a significant improvement over previous studies that have used reported occupation codes in the NLSY79,[37] provided that one accepts the assumption that there is no genuine occupational change for individuals working for a given employer. A similar procedure was applied to industry codes.[38]

Table 1.3 shows the basic characteristics of the sample. The last two columns present the same statistics conditional on remaining in the same occupation and switching occupation upon reemployment, respectively.[39] One can see from this

[37]Neal (1999) assumes each employer's industry and occupational codes to be the first one ever reported.

[38]For the NLSY79 civilian-male sample, I estimate a significant amount of within-employer 3-digit occupation and industry miscoding over time. In fact, more than 88.9% of within employer 3-digit occupational code changes and more than 88.4% of within-employer 3-digit industry changes are spurious, transitory changes. Genuine within-employer changes represent, respectively, only 6.66% and 7.92% of true occupational and industry mobility at the 3-digit level.

[39]The omitted category are spells for which no occupational code was reported either for the previous job or the new job, or both.

table that around 44% of completed unemployment spells end in occupational mobility and that workers who switch occupations seem to be different from workers who remained in the same occupation. In comparison to workers who switch, a larger fraction of stayers are white, single, have a college degree, have more experience and tenure, and report having used unemployment insurance. In addition, more occupational switchers report having been displaced than occupational stayers.[40]

Results

Table 1.4 shows the estimated hazard ratios of the competing risk model, obtained by estimating a Cox PH model. The coefficients can be read as the ratio of the hazards of leaving unemployment implied by a one-unit change in the corresponding covariate. The proportionate change is obtained by subtracting one from the estimated hazard ratios provided in the table 1.4.[41] One can see that, indeed, the measure of occupation employment risk seems to affect the hazard of leaving unemployment. In particular, a one-unit increase in the OER measure reduces the hazard of leaving unemployment to a job in the same occupation by more than 25%. Translating, a one standard deviation increase in OER represents a 5.1% decrease in the hazard of finding a job in every week of unemployment. All else equal, a worker in a high OER occupation faces a longer unemployment spell than a worker in a low OER occupation. The OER measure has no effect on the

[40]Displaced workers are workers that report losing their jobs due to layoff or plant closing.

[41]Notice that the benchmark coefficient is one rather than zero since the hazard rate is the exponentiated coefficient.

hazard of leaving unemployment to a job in a different occupation, however.

Turning to other covariates, I find that being white increases the hazard of leaving unemployment to a job in the same occupation by 42%, but has no effect on leaving unemployment to a job in a different occupation. In comparison with high school dropouts, workers with a college degree have a 56.7% lower hazard rate of getting a job in the same occupation and a 6.5% lower hazard getting a job in a different occupation, although the latter result is not statistically significant. An extra year of experience and tenure increases the hazard of leaving unemployment to a job in the same occupation by 13.4% and 23.5%, respectively. An additional year of experience increase the hazard of getting a job in a different occupation by 6.3%, while an additional year of tenure reduces it by 16.8%. Having received unemployment insurance increases by 24.1% the hazard of leaving unemployment to a job in the same occupation, while it decreases by 28.4% the hazard of getting a job in a different occupation. A one percentage point increase in the local unemployment rate seems to have no effect on finding a job in the same occupation but reduces by 2.7% the hazard of finding a job in a different occupation.

1.4 OER Measure and Wage Change

In order to assess whether OER has any effect on earnings losses when controlling for other covariates, I examine its impact on the change in log wage between post- and pre-unemployment jobs. In particular, I estimate an Ordinary Least Squares regression, where unemployment spells are the unit of observation. Since the sample includes multiple spells per individual, I use clustered standard errors to account for the additional correlation. I estimate the following equation:

$$\Delta lnw = \beta_0 + \beta_1 OER + \beta_2 X + \beta_3 Z + \beta_4 slength + \epsilon \tag{1.6}$$

X and Z are the same matrices of covariates used to estimate the effects of OER on the hazard rate of leaving unemployment. All these covariates refer to pre-unemployment values. *slength* is the total weeks of unemployment, which I expect to have a negative estimated coefficient, given that workers tend to lower their reservation wage as their unemployment spell length increases. In this context, when explicitly accounting for *slength* in the regression, it's coefficient measures the effect of OER on wage changes through increases in unemployment duration and lower reservation wages while the OER coefficient measures its direct effect on wage gain or loss upon reemployment. In order to assess the total effect of OER on wage, I also run the regressions without spell length.

I examined the effect of OER on earnings losses for three different samples: occupation stayers, occupational switchers and the full sample. I expect it to increase wage losses, especially for occupational switchers. The results are shown in table 1.5. In fact, we can see that an increase in the OER measure increases the wage loss for all three samples. This effect is statistically significant for occupational switchers (with and without spell length) and for the full sample (only with spell length). In particular, a one-unit increase in the OER measure increases the hourly wage loss by 4.88% for all workers and 11.5% for occupational switchers. For a one standard deviation increase in OER, the corresponding numbers are 1% and

2.3%, respectively. In addition, longer unemployment spells translate into higher wage losses, with each extra week of unemployment increasing the hourly wage loss by 0.1% for the full sample and by 0.2% for occupational stayers.[42] Similarly, an extra year of tenure increases wage loss by 2.1% for the full sample and by 6.2% for occupational switchers.

These results, combined with those for unemployment duration, suggest that workers in high risk occupations, as defined by the OER measure, have an incentive to remain in the same occupation in order to avoid incurring higher wage losses, even if this means facing longer unemployment spells.

1.5 Conclusions

This paper shows an aspect of human capital risk which has not been examined before and which seems to have an important role in explaining observable differences in unemployment duration and wage losses across occupations. I argue that this risk arises from the large differences in the distribution of occupational employment across industries and from the fact that industries have different employment volatilities. These two facts imply that some occupations have a more diversified portfolio of employment opportunities, suggesting that the individuals employed in these occupations potentially face lower unemployment risk than individuals employed in occupations with less diversification.

[42] So high OER occupations face 4.88% of wage loss plus 0.1% for every extra week of unemployment they have, while workers in high OER occupations that switched occupations had 11.5% of wage lost of plus 0.2% for every extra week of unemployment.

Using data from the decennial Census and the Quarterly Census of Employment and Wages, I estimate a measure of Occupational Employment Risk (OER). I find a large variation in this risk across occupations. I then relate the OER measure to occupational unemployment durations and wage losses upon reemployment, using data from the NLSY79. Applying a competing risk duration model, I find that workers in high risk occupations, as defined by the OER measure, have lower hazard ratios of leaving unemployment to a job in the same occupation and have higher wage losses than workers in low OER occupations, especially if they switch occupations.

A next step in this research would be to investigate whether workers receive compensating wage differentials for this type of risk and how this risk affects their employment duration and incidence of unemployment. Preliminary exploration of this issue indicates that workers in high OER measure occupations receive wage compensating differentials and have longer employment spells than workers on low OER occupations. In particular, it would be interesting to estimate a multiple state transition model with three possible labor market states - employment, unemployment and out-of-the labor force - and examine the effects of the OER measure on the probabilities of exiting and entering these states. As in Martinez-Granado (2002), we could allow for unobservable individual heterogeneity, duration dependence, lagged duration dependence and state dependence. Another possibility would be to write a Mortensen-Pissarides model with the OER measure, which would suggest that high OER jobs should be more durable and have more flexible wages than low

OER jobs.

The type of risk documented and analyzed in this paper may affect the occupational and career choice of individuals, the search strategy of unemployed workers, and individual decisions about consumption and precautionary savings. With respect to career choice, we could ask if individuals take into account the risk associated with specific occupations when they make career choice decisions. With respect to search strategy of unemployed individuals, it is worth noting that OER is closely related to the trade off between accepting a job today or waiting for a better offer tomorrow. As shown in the paper, the risk associated with specific occupations affects, on one hand, the wage that individuals receive upon reemployment, and on the other hand, the time they have to wait to receive an offer. It follows, then, that occupational employment risk may imply different outcomes in the optimal search of unemployed individuals.

Finally, it would be interesting to study whether OER risk affects precautionary savings. This should have implications for wealth holdings and consumption behavior. In the context of a life cycle model, the type of risk implied by occupational employment diversification would affect the transition matrix between being employed/unemployed, which would affect optimal asset holdings. The relevant question would be to quantify this effect either with a realistic life cycle model or with some other empirical strategy.

1.6 Tables

Table 1.1: Average Unemployment Duration and Wage Change by Occupation.

(CPS) Detailed Occupation Title	Duration	Std. Err.	Wage Change	Std. Err.
Executive, Administrators, and Managers, exc. Pub. Adm.	10.04	(0.78)	-0.06	(0.04)
Management Related Occupations	12.79	(1.93)	-0.06	(0.06)
Engineers	9.16	(1.67)	-0.16	(0.11)
Teachers, Except College and University	5.73	(1.15)	-0.07	(0.07)
Other Professional Specialty Occupations	9.15	(0.96)	0.11	(0.07)
Engineering and Science Technicians	10.77	(1.47)	-0.05	(0.07)
Technicians, Except Health Engineering, and Science	6.94	(1.50)	0.14	(0.06)
Sales Representatives, Finance, and Business Service	11.35	(2.12)	-0.02	(0.05)
Sales Representatives, Commodities, Except Retail	10.83	(1.16)	-0.17	(0.05)
Sales Workers, Retail and Personal Services	12.22	(1.90)	0.03	(0.07)
Financial Records, Processing Occupations	6.44	(1.47)	0.01	(0.04)
Mail and Message Distributing	10.42	(1.92)	0.04	(0.02)
Other Administrative Support Occupations, Including Clerical	9.10	(0.79)	0.01	(0.04)
Protective Service Occupations	11.95	(1.81)	-0.07	(0.05)
Food Service Occupations	10.57	(0.80)	0.01	(0.03)
Health Service Occupations	11.23	(2.08)	0.00	(0.03)
Cleaning and Building Service Occupations	13.31	(1.43)	0.05	(0.04)
Personal Service Occupations	10.55	(3.34)	-0.06	(0.07)
Mechanics and Repairers	10.31	(0.78)	0.00	(0.03)
Construction Trades	9.61	(0.58)	0.01	(0.02)
Other Precision Production Occupations	11.01	(0.89)	-0.01	(0.03)
Machine Operators and Tenders, Except Precision	9.41	(0.71)	-0.02	(0.02)
Fabricators, Assemblers, Inspectors, and Samplers	9.18	(0.70)	0.02	(0.02)
Motor Vehicle Operators	10.02	(0.84)	0.01	(0.04)
Other Transportation Occupations and Material Moving	11.12	(1.16)	-0.02	(0.02)
Construction Laborer	9.72	(0.57)	0.01	(0.03)
Freight, Stock and Material Handlers	11.01	(0.97)	-0.02	(0.04)
Other Handlers, Equipment Cleaners, and Laborers	11.62	(0.87)	0.02	(0.04)
Farm Workers and Related Occupations	12.22	(0.79)	0.03	(0.04)
Forestry and Fishing Occupations	6.49	(1.24)	0.15	(0.10)
Overall	10.14	(1.82)	-0.01	(0.02)
Number of obs.	6246		3619	
Number of clusters	2216		1778	
F-Test*	2.08		189.22	
Prob > F	0.0007		0.0000	

*F-test for equality of duration and wage loss across occupations. Across industries, we cannot reject the null hypothesis of equality.

Table 1.2: Measure of occupational employment concentration.

(CPS) Detailed Occupation Title	Herfindahl Index
Public Administration	0.162
Other Executive, Administrators, and Managers	0.035
Management Related Occupations	0.046
Engineers	0.103
Mathematical and Computer Scientists	0.065
Natural Scientists	0.076
Health Diagnosing Occupations	0.461
Health Assessment and Treating Occupations	0.421
Teachers, College and University	0.951
Teachers, Except College and University	0.720
Lawyers and Judges	0.580
Other Professional Specialty Occupations	0.054
Health Technologists and Technicians	0.346
Engineering and Science Technicians	0.073
Technicians, Exc. Health, Engineering, and Science	0.045
Supervisors and Proprietors, Sales Occupations	0.065
Sales Representatives, Finance, and Business Service	0.348
Sales Representatives, Commodities, Exc Retail	0.089
Sales Workers, Retail and Personal Services	0.083
Sales Related Occupations	0.125
Supervisors - Administrative Support	0.042
Computer Equipment Operators	0.034
Secretaries, Stenographers, and Typists	0.038
Financial Records, Processing Occupations	0.027
Mail and Message Distributing	0.454
Other Adm. Support Occupations, Incl. Clerical	0.035
Private Household Service Occupations	1.000
Protective Service Occupations	0.343
Food Service Occupations	0.505
Health Service Occupations	0.257
Cleaning and Building Service Occupations	0.079
Personal Service Occupations	0.190
Mechanics and Repairers	0.054
Construction Trades	0.551
Other Precision Production Occupations	0.105
Machine Operators and Tenders, Except Precision	0.067
Fabricators, Assemblers, Inspectors, and Samplers	0.115
Motor Vehicle Operators	0.106
Other Transportation Occupations and Material Moving	0.090
Construction Laborer	0.833
Freight, Stock and Material Handlers	0.157
Other Handlers, Equipment Cleaners, and Laborers	0.028
Farm Operators and Managers	0.474
Farm Workers and Related Occupations	0.205
Forestry and Fishing Occupations	0.309

Table 1.3: Sample Statistics.

Variables	All sample	Stayers	Switchers
Age	28.07	27.52	26.61
	(0.11)	(0.24)	(0.17)
White	79.81%	84.27%	76.53%
Married	44.92%	40.52%	51.94%
Years Schooling	12.13	11.82	12.00
	(0.06)	(0.10)	(0.11)
HS	70.52%	72.56%	68.91%
College	8.03%	3.92%	7.07%
Experience	4.98	4.65	3.79
	(0.10)	(0.21)	(0.14)
Tenure	1.34	1.63	0.87
	(0.07)	(0.18)	(0.05)
Received UI	41.77%	56.08%	34.36%
Displaced	19.99%	14.13%	24.28%
Number of spells	5344	1460	1143
N. of clusters	2216	743	738

Note: (1) Standard deviations are in parentheses; (2) 2,741 unemployment spells (out of 5344) did not report occupational code either for the previous or the new job or both.

Table 1.4: Unemployment Duration: Cox PH Estimated Hazards.

	Same Occupation		Different Occupation	
	coef.	std	coef.	std
OER	0.746	(0.125)†*	0.997	(0.196)
White	1.423	(0.131)**	0.998	(0.087)
Age	0.788	(0.148)	1.102	(0.245)
Age^2	1.004	(0.003)	0.997	(0.004)
Ability Factor 1	1.028	(0.021)	1.013	(0.018)
Ability Factor 1^2	0.996	(0.006)	0.998	(0.005)
Ability Factor 2	0.996	(0.006)	0.935	(0.043)
Ability Factor 2^2	1.016	(0.030)	0.977	(0.032)
High school	1.034	(0.099)	1.010	(0.091)
College	0.433	(0.127)**	0.914	(0.162)
Married	0.923	(0.072)	1.032	(0.084)
Experience	1.134	(0.070)*	1.063	(0.076)
Experience^2	0.993	(0.004)†	0.999	(0.006)
Tenure	1.235	(0.064)**	0.832	(0.063)*
Tenure^2	0.989	(0.005)*	1.013	(0.011)
Unemp. Ins.	1.241	(0.095)**	0.716	(0.058)**
Unemp. Rate	0.999	(0.016)	0.973	(0.013)*
Weeks of unemployment	11019		11019	
N. of clusters	2035		2035	
Wald chi2(17)	118.51		47.28	

**, *, †: significant at 1%, 5% and 10%, respectively; †* Significant at 8%.
Note: (1) Standard deviations are in parentheses; (2) Ability factors 1 and 2 are the first two principal components of the age-adjusted ASVAB scores.

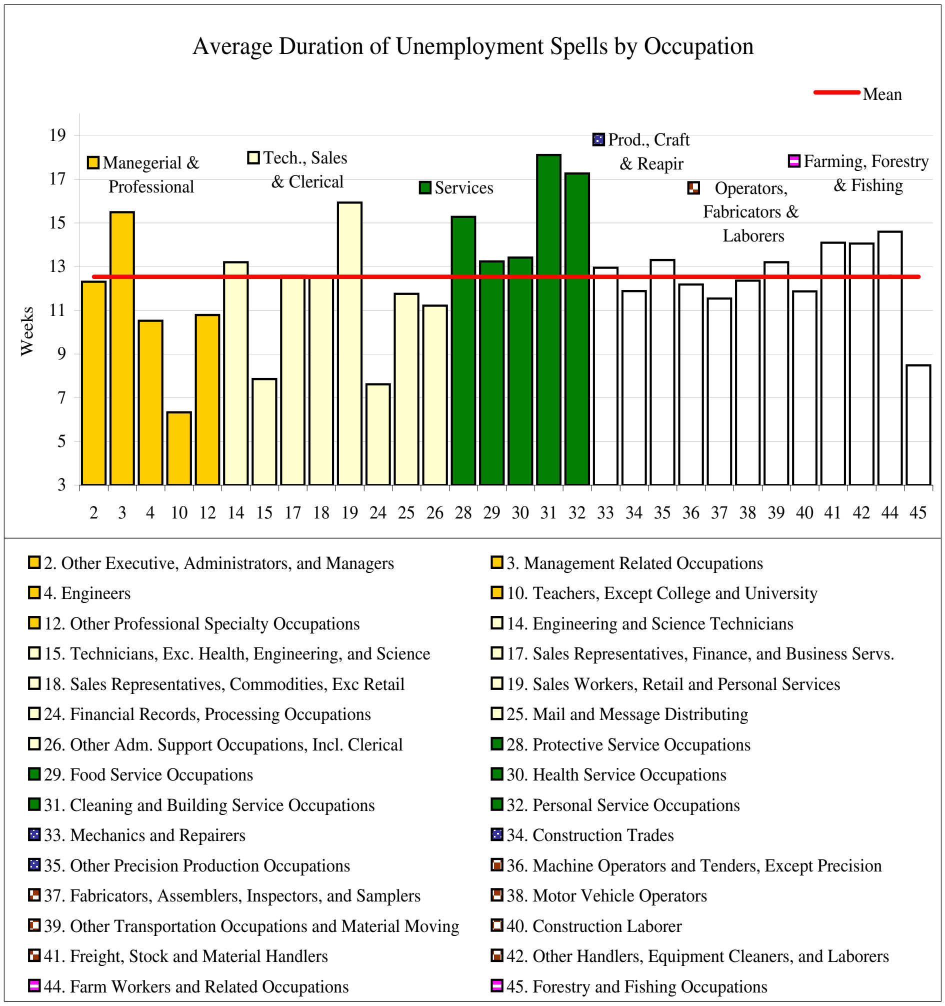
Table 1.5: Wage Change: OLS estimates.

	All sample		Stayers		Switchers	
OER	-0.04882	-0.05233	-0.00505	-0.01145	-0.11451	-0.11500
	(0.03513)†	(0.03491)	(0.05019)	(0.04958)	(0.05414)*	(0.05418)*
White	-0.01447	-0.01193	-0.01319	-0.01060	-0.02328	-0.02284
	(0.01511)	(0.01499)	(0.01561)	(0.01548)	(0.03587)	(0.03582)
Age	-0.01539	-0.01191	-0.01328	-0.01076	-0.02471	-0.01864
	(0.02843)	(0.02866)	(0.02760)	(0.02788)	(0.06519)	(0.06515)
Age^2	0.00028	0.00021	0.00023	0.00017	0.00043	0.00032
	(0.00049)	(0.00050)	(0.00048)	(0.00049)	(0.00111)	(0.00111)
Ability Factor 1	0.00326	0.00366	0.00375	0.00430	0.00285	0.00324
	(0.00372)	(0.00374)	(0.00375)	(0.00379)	(0.00867)	(0.00864)
Ability Factor 1^2	0.00045	0.00040	-0.00026	-0.00019	0.00246	0.00225
	(0.00111)	(0.00112)	(0.00121)	(0.00122)	(0.00241)	(0.00239)
Ability Factor 2	0.01511	0.01460	0.01772	0.01772	0.01340	0.01232
	(0.00743)*	(0.00743)*	(0.00785)*	(0.00785)*	(0.01536)	(0.01528)
Ability Factor 2^2	0.00505	0.00498	0.00747	0.00796	0.00343	0.00280
	(0.00464)	(0.00466)	(0.00489)	(0.00497)	(0.00980)	(0.00978)
High School	0.00703	0.01231	-0.00436	0.00059	0.03728	0.04314
	(0.01822)	(0.01836)	(0.01637)	(0.01666)	(0.04525)	(0.04479)
College	-0.03445	-0.02905	-0.00214	0.00294	-0.05741	-0.04974
	(0.03952)	(0.03974)	(0.04666)	(0.04681)	(0.06894)	(0.06871)
Married	0.01805	0.01603	-0.00446	-0.00666	0.06441	0.06326
	(0.01513)	(0.01521)	(0.01557)	(0.01574)	(0.03295)†	(0.03306)†
Experience	0.00326	0.00350	-0.00211	-0.00201	0.02008	0.02044
	(0.01003)	(0.01004)	(0.00881)	(0.00883)	(0.02277)	(0.02271)
Experience^2	-0.00001	-0.00001	0.00000	0.00000	-0.00002	-0.00002
	(0.00001)	(0.00001)	(0.00001)	(0.00001)	(0.00003)	(0.00003)
Tenure	-0.02110	-0.02126	-0.01123	-0.01140	-0.06172	-0.06297
	(0.00829)*	(0.00836)*	(0.00752)	(0.00759)	(0.02680)*	(0.02693)*
Tenure^2	0.00004	0.00004	0.00002	0.00002	0.00011	0.00011
	(0.00002)*	(0.00002)*	(0.00001)	(0.00001)	(0.00006)†	(0.00006)†
Spell length	-0.00137		-0.00175		-0.00094	
	(0.00047)**		(0.00060)**		(0.00076)	
Constant	0.23556	0.17132	0.24317	0.19142	0.29421	0.19481
	(0.39435)	(0.39557)	(0.37861)	(0.38099)	(0.91489)	(0.91009)
Number of spells	3462	3462	2212	2212	1250	1250
Number of clusters	1691	1691	1246	1246	884	884
F-Test	1.78	1.35	1.30	0.97	1.71	1.61
Prob > F	0.0290	0.1619	0.1864	0.4836	0.0390	0.0660
R-squared	0.0112	0.0127	0.0248	0.0071	0.0070	0.0227

**, *, †: significant at 1%, 5% and 10%, respectively.
Note: (1) Standard deviations are in parentheses; (2) Ability factors 1 and 2 are the first two principal components of the age-adjusted ASVAB scores.

1.7 Figures

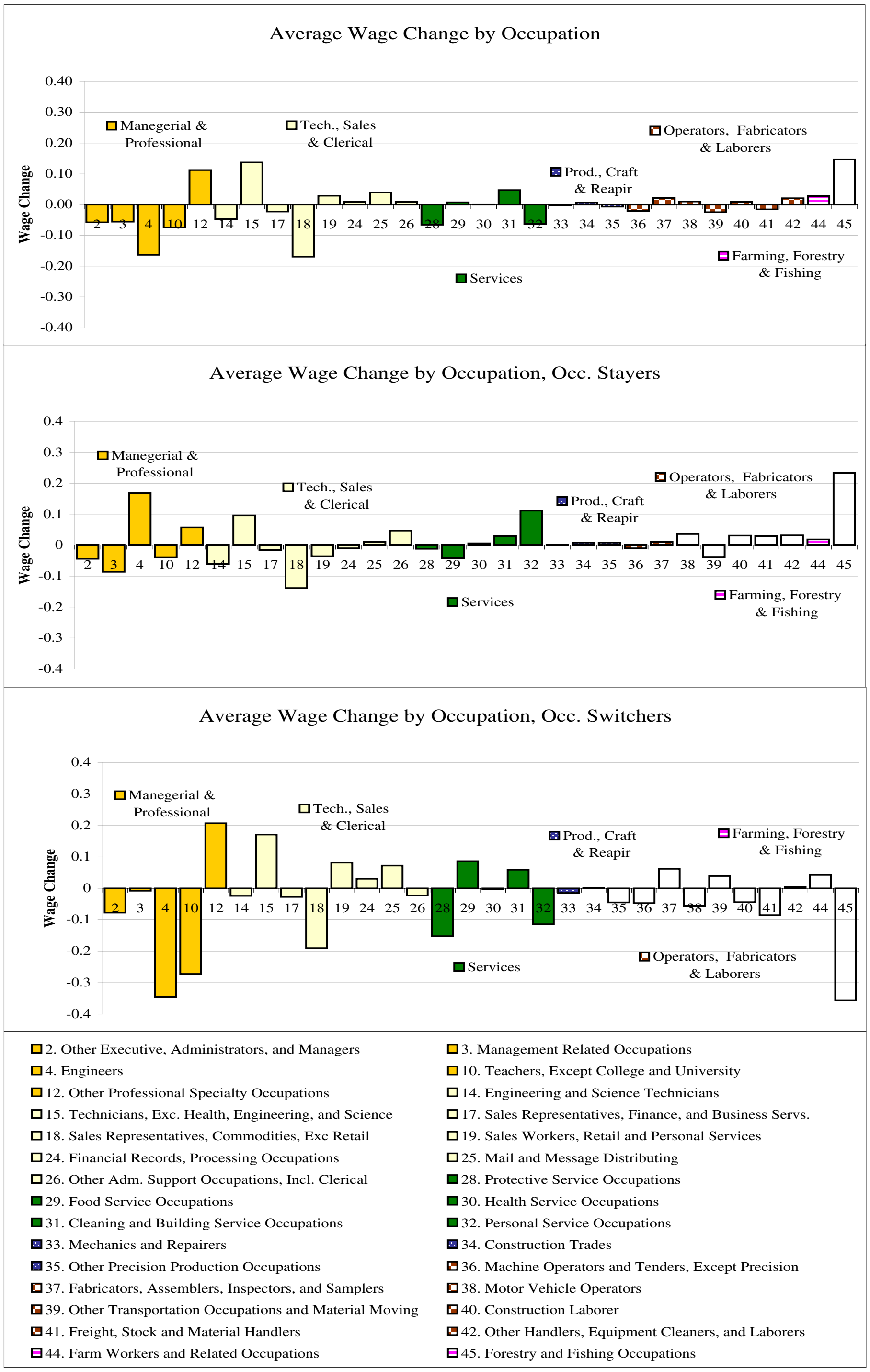
Figure 1.1: Average unemployment duration by occupation



Source: NLSY79, 1979-2000.

*Occupations with less than twenty observations are omitted from the analysis.

Figure 1.2: Average wage change by occupation



Source: NLSY79, 1979-2000.

*Occupations with less than twenty observations are omitted from the analysis.

Figure 1.3: Example: accountants and earth drillers employment distribution across industries

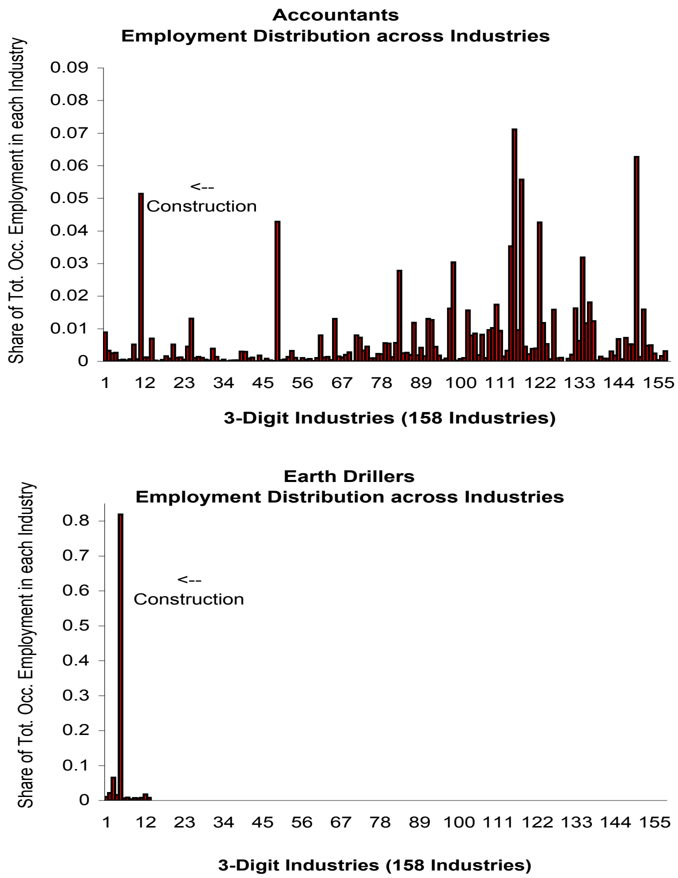
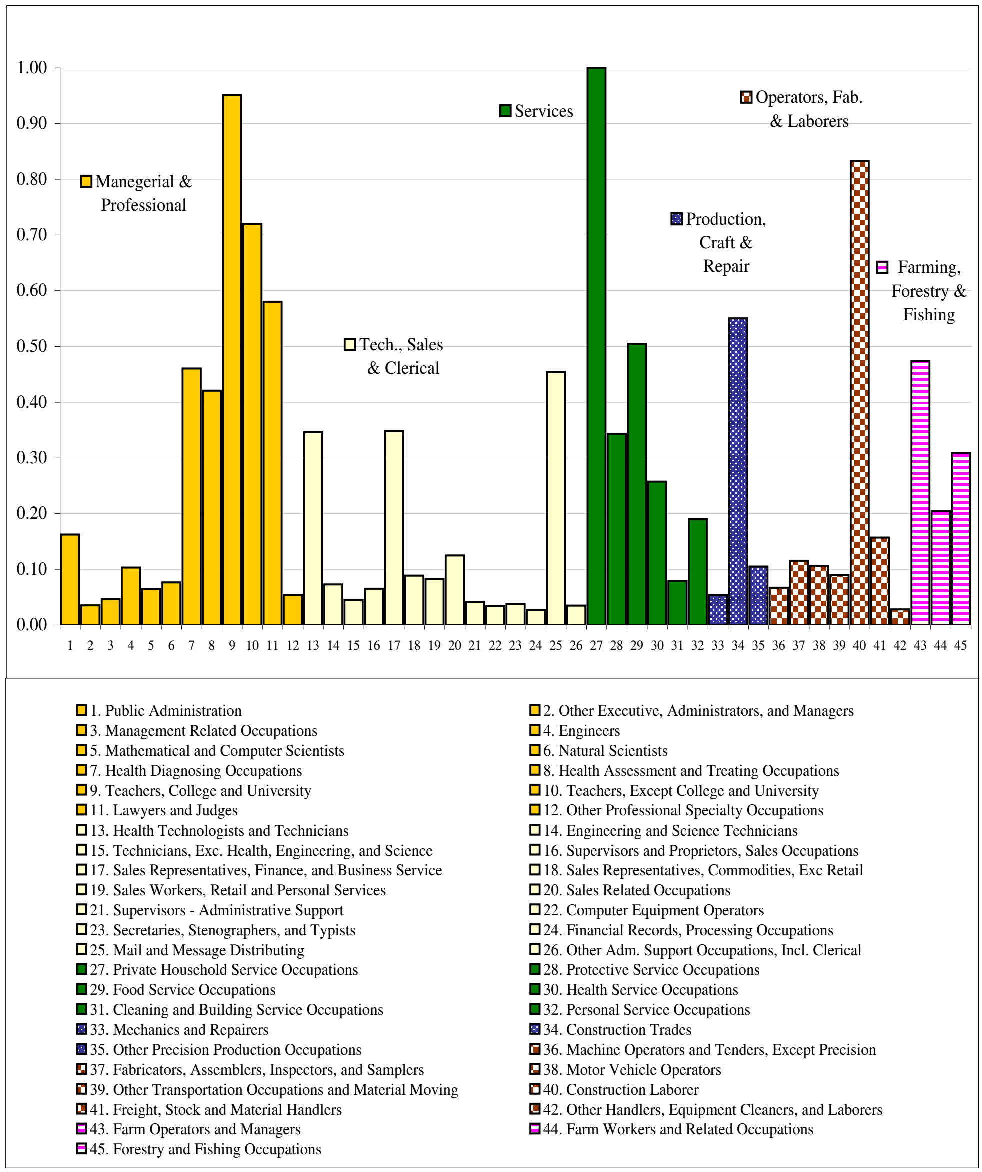
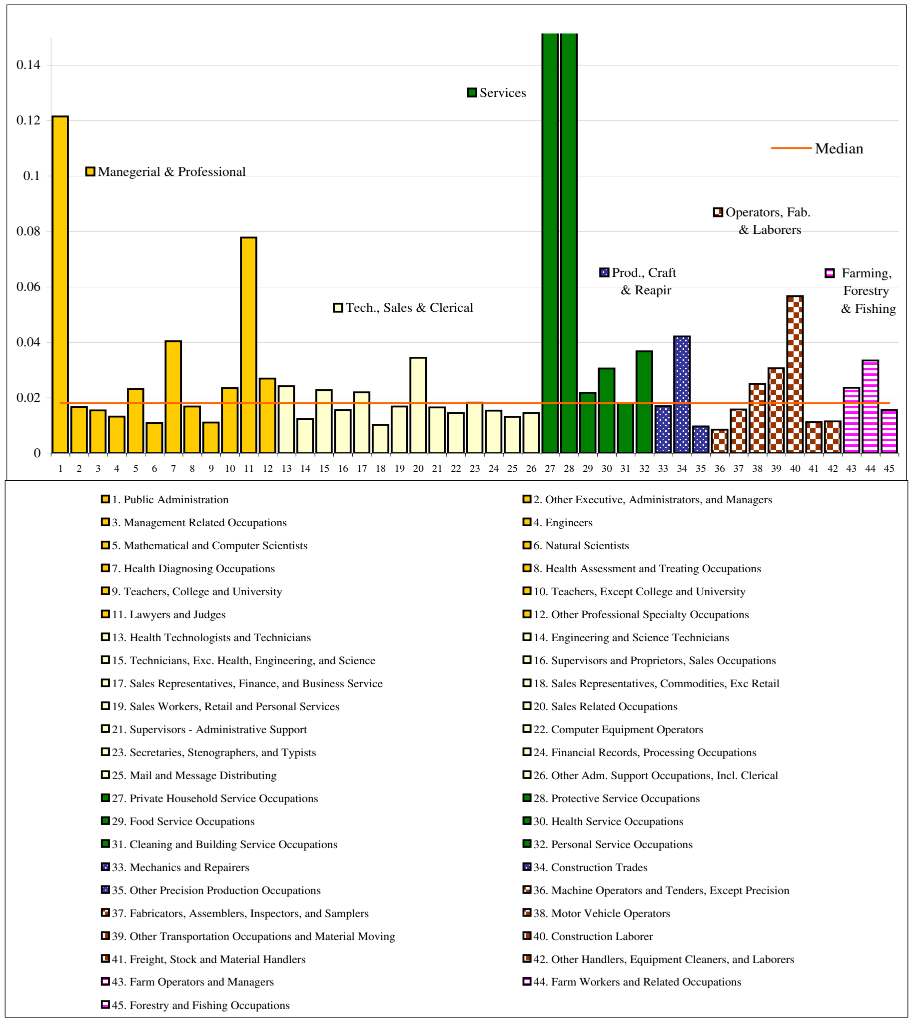


Figure 1.4: Herfindahl index of employment concentration by occupation



Source: 1990 Census & QCEW 1979-2000.

Figure 1.5: Occupational employment risk measure.



*OER for occupations 27 and 28 are 0.30 and 1.35, respectively. I have truncated them at 0.35 in figure 5 for better visualization.
Source: 1990 Census & QCEW 1979-2000.

Appendix A

Appendix for Part I

A.1 Weekly Labor Status

The NLSY79 Work History Data provides week-by-week records of the respondents labor force status from January 1, 1978, through the current survey date. At each year's survey, information is collected on jobs held and periods not working since the date of the last interview.[1] Since the questions in the NLSY survey are constructed to collect a complete history for each respondent, regardless of period of non-interview, it is possible to construct for each respondent, a continuous, week-by-week labor force status record.[2] In particular, the respondents labor force history is constructed by filling in the weeks between the reported beginning and end dates for different activities (or "inactivities") with the appropriate labor status code.

One of the reported issues with the weekly labor status series is the presence of "split gaps" during employment gaps. "Split gaps" occur during an employment gap in which individuals report being unemployed for part of the gap and out of the labor force for the other part of it.[3] Since "split gaps" are coded such that

[1] A job held any day of a week is counted as a job for the whole week.

[2] For example, a respondent last interviewed in 1987, and not interviewed again until 1990, will have a complete labor force history, as information for the intervening period will be recovered in the 1990 interview. The NLSY "Work Experience" section reports that although there may be potential inconsistencies generated by this method, it does not compromise the quality and/or completeness of the work history record. For details, see Appendix 18 of the Documentation Files.

[3] Although the start and stop dates for the whole gap will be those actually reported by the

the unemployment spell falls between two out-of-labor force spells, they are not considered to be completed unemployment spells and are therefore, not included my the sample.

The NLSY weekly labor status variable, WK, can assume the following values:

$$wk = \begin{cases} 0, & \text{cannot account for week due to invalid starting and end dates;} \\ 2, & \text{cannot determine whether unemployed or out-of-the labor force;} \\ 3, & \text{employed but cannot account for all of the time with employer;} \\ 4, & \text{unemployed;} \\ 5, & \text{out of the labor force;} \\ 7, & \text{active military service;} \\ > 7, & \text{employed.} \end{cases}$$

About 1% of the weeks in the male, not military sample, have wk equal to 0. When employed, the assigned code is the actual survey number multiplied by 100 plus the job number for that employer in that year. Based on this classification, I generated a weekly employment status which assumes the values:[4]

$$empstat = \begin{cases} employed & \text{if wk} = 3 \text{ or wk}>7; \\ unemployed & \text{if wk} = 4 \text{ or } (\text{wk}_t{=}2)\&(2 \leq \text{wk}_{t-1} \leq 4) \text{ or } (\text{wk}_t{=}2)\&(\text{wk}_{t-1} > 7); \\ other & \text{if empstat} \neq \ 1 \ or \ 2; \end{cases}$$

respondent, the assignment of the unemployed and out-of-labor-force states will not represent actual dates reported by the respondent. Instead, they represent only the number of weeks that a respondent reported having held each status, with the unemployed status being arbitrarily assigned to the middle portion of the gap. For further details in "split gaps," see Appendix 18 in the NLSY documentation.

[4]It is worth noting that I do not include individuals who ever work in the military.

A.2 Industry and Occupational Codes

The Census defines an industry as a group of establishments that produce similar products or provide similar services. Although many industries are closely related, each one of them has a unique combination of inputs and outputs, production techniques, occupations, and business characteristics. Occupations are classified based upon work performed, skills, education, training, and credentials. The classification system covers all occupations in which work is performed for pay or profit, and is intended to classify workers at the most detailed level possible.

The universe used by the Census for occupation and industry variables are individuals age sixteen or older who worked within the previous five years and are not considered new workers.[5] Occupation and industry codes report the person's primary occupation and industry, which are considered to be the ones in which the person earns the most money; however, if the respondent was not sure about their income, his/her primary occupation and industry was then the ones at which s/he spent the most time. If a person listed more than one occupation and/or industry, the samples use the first one listed. The occupational codes were assigned based in the questions: (1) what kind of work was this person doing? and (2) what were this person's most important activities or duties? While the industry codes were assigned based in the following three questions: (1) for whom did this person work? (name of company, business, organization, or other employer), (2) what kind of business or industry was this? and (3) is it mainly manufacturing or, wholesale

[5] "New workers" are defined as persons seeking employment for the first time who have not yet secured their first job.

trade, or retail trade or other?

Matching Industry Codes

In order to estimate the OER measure, I calculate the concentration of occupational employment across industries and the volatility and comovement of disaggregated industry employment. Given the fact that there is no single data set with occupational employment by industry during the period of analysis, 1979-2000, I combine data from two different sources to compute both components of the OER measure.

I use data from the 1990 Census to calculate the concentration component of the OER measure, which is obtained by calculating the shares of occupational employment in each industry. The volatility component was estimated using data from the Quartely Census of Employment and Wages (QCEW), 1978-2000. However, these two data sources use different industry classification systems. The Census uses the Census Industrial Classification (which I will call CIC), while the QCEW uses the Standard Industrial Classification System (SIC). So in order to estimate OER from these two data sets, I need to match the industry codes across the industry classification systems. In addition, both classification systems experience changes over time. Therefore, it is necessary to match industry codes across classification systems and over time in order to have consistent industry codes over the period of analysis. An extensive discussion of all criteria applied in this matching is given by Tristao (2005). I choose the 1980 Census Industry and Occupational codes as the base codes for this study. I discuss the occupational codes' matching in the next subsection of this appendix.

Over time changes within classification systems can be mainly classified into three categories: (1) change in the code value assigned for a given industry; (2) merges and splits in existing industry codes, resulting in the creation of a new code or disappearance of an existent one; and (3) new industry codes due to a new industry in the economy. The changes between the Census 1980 and 1990 Industry Classification Systems were minimal and the criteria I use to deal with them can be summarized by using the correspondent 1980 code for changes of type (1), combining industry codes into a single code for changes of type (2) and adding new codes to the closest miscellaneous category with a correspondence in 1980 codes for the type (3).

The QCEW data uses the 1972 SIC codes for the years 1975-1987 and the 1987 SIC codes for the period 1988-2000. The match within the SIC system was made through the correspondences offered by the 1987 standard industrial classification manual, which provides a 4-digit code crosswalk between the 1972 SIC and 1977 SIC and between the 1977 SIC to 1987 SIC. Based in this crosswalk, I merge 3-digit industry codes if one or more of their 4-digit industries are reported to be combined. I choose the 1987 SIC codes as the base code for this particular match.

In order to merge the Census industry codes and the Standard Industry Classification codes, I use a Census crosswalk between 1990 Census Industry codes and the 1987 SIC codes. The match between these two systems required further 3-digit industry code merges to maintain group comparability across classification systems and time.[6] After the matches, I obtain 158 industry codes, which constitutes a 33% reduction from the number of 3-digit industries in 1980 and 1990 CIC codes. Figure A illustrates the match.

Matching Occupation Codes

The OER measure is calculated for every CPS detailed occupational code based on the 1980 Census occupational codes. However, the data for calculating the shares of occupational employment across industries come from the 1990 Census PUMS, which uses the 1990 Census occupational codes. Therefore, in order to have consistent occupational codes, I match the codes between both classification systems. The changes between them were minimal and can be classified into two types: (1) a change in the code value assigned for a given occupation; and (2) merges and splits in existent industry codes, resulting in the creation of a new code or disappearance of an existing one. The procedure I apply in matching the codes is to use the corresponding 1980 code for changes of type (1), and to combine occupational codes into a single code for changes of type (2).

The data set I use to assess the relevance of the OER measure for unemployment duration and wages is the National Longitudinal Survey of Youth 1979 (NLSY79). The NLSY79 uses the 1970 Census occupational codes in reporting the occupations for up to five jobs each individual held during any survey round.[7] Since

[6] See Census technical paper #65.

[7] For the main job or CPS job only, it also provides the 1980 Census occupational codes.

the OER measure is calculated for 1980 Census occupational codes, I match the 1970 Census occupational code to the 1980 Census codes. It is worth noting that there are significant changes between these two classification systems. The Bureau of Census technical paper 59 provides, for each occupation, a quantification of the employment relationship between these two systems, which I use in generating the correspondences between them. The criterion I use is to assign, for each 1970 occupational code, the 1980 occupational code that received the largest share of the 1970 occupational code's employment. Over 76% of all occupations in the 1970 code had over 75% of its employment going to a single occupation code in 1980.[8]

A.3 Construction of Age-Adjusted Ability Measure

The measures of ability used in this paper are calculated from the Armed Services Vocational Aptitude Battery (ASVAB), which is a set of ten tests that measure knowledge and skill in the following areas: (1) general science; (2) arithmetic reasoning; (3) word knowledge; (4) paragraph comprehension; (5) numerical operations; (6) coding speed; (7) auto and shop information; (8) mathematic knowledge; (9) mechanical comprehension; and (10) electronics information.

Since the NLSY79 respondents had different ages and educational levels when they took the tests, and the scores on these "ability" tests may increase with age and education, it was necessary to adjust the ASVAB test scores for both factors. I

[8]Around 40% of all occupations in the 1970 code had over 99% of its employment going to a single occupation code in 1980, while 86% had over 50% of its employment going to a single occupation code in 1980. Only 3.4% of all occupations in the 1970 code had the highest percentage of their employment assigned to a 1980 code as less than 50%.

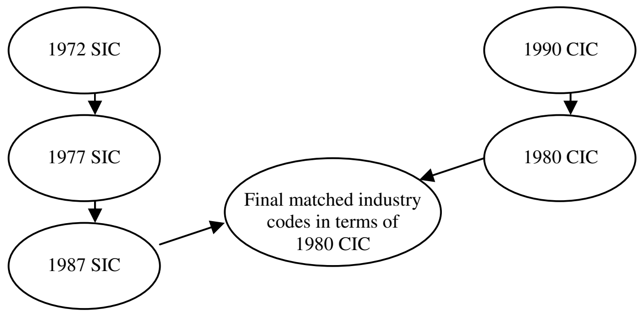
Table A.1: ASVAB Principal Components.

Component	**Eigenvalue**	**Diff.**	**Proportion**	**Cumulative**
1	6.74144	5.81295	0.6741	0.6741
2	0.9285	0.37823	0.0928	0.767
3	0.55027	0.10989	0.055	0.822
4	0.44038	0.13468	0.044	0.8661
5	0.30571	0.03699	0.0306	0.8966
6	0.26871	0.04837	0.0269	0.9235
7	0.22034	0.0115	0.022	0.9455
8	0.20884	0.02749	0.0209	0.9664
9	0.18134	0.02687	0.0181	0.9846
10	0.15448	.	0.0154	1
Eigenvectors, 1st and 2nd PC	**1st PC**	**2nd PC**		
General science residuals	0.34016	-0.17568		
Arithmetic reasoning residuals	0.33150	0.13789		
Word knowledge residuals	0.34340	-0.07447		
Paragraph comprehension residuals	0.32602	0.02441		
Numerical operations residuals	0.28267	0.52215		
Coding speed residuals	0.27085	0.49544		
Auto and shop knowledge residuals	0.29872	-0.43598		
Mathematics knowledge residuals	0.31038	0.23927		
Mechanical comprehension residuals	0.32052	-0.28386		
Electrical Information residuals	0.32958	-0.31302		

follow the two-step methodology presented by Cawley et al. (1995) and Kermit et al. (1997), which uses principal components analysis in order to measure age-adjusted ASVAB scores.

The ASVAB scores are adjusted for age by regressing each test score on age dummy variables and an indicator variable of whether the respondent had completed high school when the tests were administered (Kermit et al. (1995)). Principal components analysis is performed on the ordinary least square residuals from these regressions. See Heckman (1995) on using the first two principal components and Kermit et al. (1997) for an application of this procedure. The estimates are presented in table A.1.

Figure A.1: Industry code matching



Part II

Does Experience Make Better Doctors? Evidence from Lasik and Other Refractive Eye Surgeries

(Coauthored with Juan M. Contreras and Beomsoo Kim)

2.1 Introduction

It is a common belief that experience can improve the level of skills. In general, as workers accumulate years of experience, they get better at their jobs. Athletes and musicians, to mention perhaps the most stylized cases, practice over and over again until they master the techniques. This common perception suggests that there may be some learning by doing with practice.

In the last decade a heated debate has arisen among policymakers, consumers' organizations, health insurance plans and health professionals on whether or not to regionalize medical care. This debate was fueled by the findings of recent studies showing strong evidence that high-volume hospitals and high-volume physicians have lower post-operative mortality than hospitals and physicians with a lower number of cases.[1]

One plausible explanation for this high-volume better-outcome relationship is that there is learning by doing in the provision of medical care. If indeed practice makes perfect in medicine, then policymakers can improve health outcomes of medical procedures by concentrating resources on few a high-volume hospitals rather than many smaller hospitals. The idea is that by assigning resources to few hospitals, their physicians will have a high volume of procedures, master the procedures with practice, and obtain better results.

The alternative hypothesis to learning by doing is selective referral. In this

[1]Hewitt (2000), Birkmeyer et al. (2002), Ho (2002), Epstein (2003), Birkmeyer et al. (2003), Sarrazin and Rosenthal (2004) and Ho (2004). For a review of the literature on volume-outcome see Halm et al. (2002).

case, patients needing certain high-risk procedures or with high-risk conditions look for physicians that have a reputation for obtaining good outcomes, which does not necessarily depend on the amount of experience they have. For instance, variation in outcomes may be due to the physician's ability. High-ability doctors may have better outcomes, regardless of how much experience they have. Their outcomes will build their reputation, attracting more patients.

Economists have attempted to empirically determine the existence of learning by doing; especially in production processes.[2] In medicine, this task is particularly complicated due to the fact that medical outcomes are hard to define and measure, and are generally affected by patient selection and underlying conditions, that make it difficult to disentangle learning by doing from other effects.

Patient selection and the presence in some patients of underlying conditions like diabetes and high blood pressure can seriously cloud the analysis of learning by doing. Patients in more severe states (with higher probability of an adverse outcome) may look for more experienced physicians.[3] So, more experienced surgeons may in fact face higher adverse outcome rates, not because their experience did not improve the outcome, but because they treat more severe cases on average. The opposite bias could also exist if more experienced doctors charge higher prices and rich people have better underlying conditions. Therefore, in examining the physician experience-outcome relation, it is very important both to address the patient selection problem and to take into account patients' underlying conditions.

[2]See Alchian (1963), Argote et al. (1990), Gruber (1992), Gruber (1994) and Benkard (2000).
[3]Patients in more severe conditions may value more physician's experience than other patients, given that sicker patients have higher expected returns from having better care.

Previous studies have used sophisticated types of surgery and post-operative mortality to analyze the volume-outcome relationship.[4] The reason for using surgery is that it requires a lot of practice. A surgeon needs sophisticated skills to perform surgery and people believe that those skills can be highly affected by their level of experience. Post-operative mortality is used as an indicator of a bad outcome due to the difficulty of precisely measuring (and even observing in the data) the success of a surgery.[5]

The caveats of the approach taken by previous studies in examining the volume-outcome relationship are that: (1) they all use medical procedures in which the outcome is highly affected by patient observed and unobserved underlying conditions, (2) they cannot identify the effect of physician's experience on the outcome from the effect of the medical team that assisted the procedure and (3) they have a very restricted measure of outcome, which does not capture a whole range of possible outcomes, like obtaining the best surgery outcome or obtaining a poor surgery outcome leading to morbidity or future death outside the observed post-operative period. Furthermore, past studies have observed only physicians' yearly current volume of procedures rather than their experience, so they cannot estimate a true learning curve.

In this paper, we use a type of surgery which has a clear measure of outcome

[4]The most common used surgeries are coronary angioplasty, coronary artery bypass, myocardial infarction, carotid endarterectomy, pediatric cardiac surgery, surgery for ruptured and unruptured abdominal aortic aneurysm, total hip replacement and cancer surgeries (pancreatic, breast, colorectal, lung and gastric).

[5]In most studies, post-operative mortality is usually defined to be death within 30 days of the surgery.

and for which the outcome is not as much affected by patient's underlying conditions as other medical procedures, once patients are eligible for the surgery. Also the procedure is performed by only one doctor so there is no need to worry about the effect of the quality or experience of a medical team on the outcome. In addition, we use an exceptional data set, in which patient selection is highly minimized, and that allows us to observe a time series of each physician's procedures and their outcomes over time, so we can see if there is a true learning curve.

The procedures in question are different types of refractive eye surgery and, in particular, Lasik surgery. Refractive surgeries are surgical procedures to correct nearsightedness, farsightedness and astigmatism. In these procedures, the surgeon uses a special laser to reshape the cornea changing its focusing power. LASIK (Laser-Assisted In Situ Keratomileusisis) is a special kind of refractive surgery in which the surgeon creates a thin flap on the cornea with a special tool. The flap is folded back, and a laser is used to remove certain amount of corneal tissue. The surgeon then places the flap back down again (see figure B.1).[6]

Refractive laser surgery is voluntary and there are few eligibility criteria to be met to undergo the procedures.[7] For patients who are eligible for surgery, outcomes should depend mostly on two inputs: labor (skill of the ophthalmologist) and capital (the machine used for surgery). The few patients' underlying conditions that could

[6]In comparison with other refractive surgery procedures, Lasik became a very popular due to the fast vision recovery and to the minimal pain.

[7]The presence of a subclinical keratoconus, a corneal warpage syndrome, irregular astigmatism or thin cornea are generally contraindications to having refractive surgery. Also Lasik is not recommended for patients with autoimmune diseases (e.g., lupus, rheumatoid arthritis) and immunodeficiency states (e.g., HIV). Some doctors also do not operate on patients younger than 18 years old or with diabetes. For details see Pallikaris and Siganos (1997) and FDA guidelines on Laser surgeries.

potentially affect outcome, like age and pre-surgery eyesight, can be easily observed and controlled for.[8]

We have full access to the individual medical charts of the population of patients that underwent refractive surgery in one of the major ophthalmologic clinics and surgical centers in Medellin, Colombia. This clinic has 30 doctors, 29 of whom perform refractive surgery. This surgical center opened in July 2003 with a brand new Schwind Esiris laser machine and currently has the biggest market share in Medellin.[9] We have two years of data with a total of $3,314$ refractive surgery cases (eyes). We collected information not only on pre-surgery eyesight measures and surgical plans, but also on all post-surgery follow-ups during the subsequent two-year period. In addition, we observe basic demographic characteristics for patients, such as gender, age, marital status, date and place of birth, occupation, neighborhood and city of residence. The key feature of this data, however, is that we can observe the time series of procedures performed by each physician, which allows us to test for the existence of learning by doing in this medical procedure. If indeed practice makes perfect, then we should observe a learning curve, that is, we should observe an improvement in physicians' outcomes as they accumulate experience.

This paper is divided into four sections. Section 2.2 describes the data, the measures of outcome and the empirical methodology we implemented. Section 2.3

[8]For example, in comparison with Lasik surgery, the outcome of coronary surgeries can be affected by age, gender, body surface area, operative priority, cardiac function as measured by left ventricular ejection fraction, previous myocardial infarction, the presence of left main stem coronary artery disease, previous cardiac surgery, peripheral vascular disease, diabetes, renal function, hypertension, angina, dyspnoea (breathlessness) and smoking.

[9]Their market share is estimated to be around 57% of all refractive surgery procedures done in Medellin. There are only three other surgical centers in the city, two of which use a much older laser technology.

presents and discusses our findings, and section 2.4 concludes.

2.2 Empirical Methodology

2.2.1 Data

The data used in this study is the population of patients that underwent refractive surgery in one of the major ophthalmologic clinics and surgical centers in Medellin, Colombia. We collected the data directly from the individual patient charts of CLOFAN (Clinica Oftalmologica de Antioquia).

CLOFAN owns a surgical center in which a whole range of eye surgeries are performed, including different types of refractive surgeries. This surgical center opened in July 2003 with a brand new Schwind Esiris laser machine. This equipment is used not only by the CLOFAN doctors but also by doctors from other clinics that rent the equipment and facilities for their own surgeries. Twenty-nine out of thirty CLOFAN doctors perform refractive surgeries in this surgical center.[10]

Before July 2003, some doctors of CLOFAN performed refractive surgery in two other surgical centers in Medellin using older laser technology. However, despite the fact that some of the physicians did not perform their first laser eye surgery in CLOFAN, the outcomes of refractive surgery are known to be particular to the combination of surgeon, laser machine and environment (Pallikaris and Siganos

[10] Although in theory, CLOFAN doctors could use other surgical centers' machines', they have high incentives not to do so since CLOFAN's equipment is the best available technology in the city, and using other surgical centers' machines, would require them to pay rent. Moreover, CLOFAN doctors as a group need to perform a certain number of surgeries a month to make their equipment pay-off its cost and generate some profit.

(1997)). Every machine uses its own specific inner algorithm to convert the surgical plan into laser beam cuts, which also depend on environmental conditions such as temperature and humidity in the surgical room; the surgeon has to weight all these circumstances when performing the surgery and has to adapt every time these conditions change. In particular, the amount and shape of laser energy necessary to obtain the desired correction is based on a "nomogram" which each surgeon or surgical center develops for the surgeries based on the typical response of patients treated.[11]

We have two years of data (from July 2003 until August 2005) with a total of $3,892$ surgery cases (each case is an eye) and $2,042$ patients. All surgeries in our data were done by one of the twenty-nine CLOFAN doctors who performs refractive surgery. From the patients' charts we collected pre-surgery eyesight measures, surgical plans, and all post-surgery follow-up evaluations. We also recorded basic patient demographic characteristics such as gender, age, marital status, date and place of birth, occupation, neighborhood and city of residence. Moreover, limited information on patient and family medical history and patient's health insurance coverage is also available to us.[12] In addition, the patient chart also includes a report on basic information on the surgery: time of surgery (to the precision of seconds), type of procedure, specific technique, blade and ring used, temperature

[11] In the case of CLOFAN, all doctors use the same nomogram developed and periodically updated by the surgical center based on a sample of treated patients. Section 2.3.3 discusses in more detail the potential effects of the nomogram and its updates on surgeries' outcome.

[12] Most of the reported medical history data were related to eyesight problems. Although 99.6% of patients reported having some type of health insurance coverage, refractive surgery is not covered by health plans. Once patients have paid for the surgery, any additional costs of re-treatment are covered by the clinic.

and humidity in the room, software version, diameter of the cornea, and whether or not there was any complication during the surgery.

We collected data on all refractive surgeries performed by the CLOFAN doctors, most of which consist of three procedures: LASIK, ORK and MULTIZONE. All these procedures are used to correct nearsightedness, farsightedness and astigmatism and they vary on the type of flap the surgeon cuts in the cornea and the technique he/she applies for the laser beam cuts. Table 2.1 provides some basic statistics. Although we have data from July 2003 until August 2005, which give us $3,892$ surgery cases (eyes) and $2,042$ patients, we only use data until January 2005, in order to have a six-month window for post-surgery follow-ups' evaluations.

Table 2.1: Basic statistics (July-2003 to January-2005)

Number of doctors performing refractive surgery	29
Number of refractive surgeries	2,827
LASIK	2,320
ORK	322
MULTIZONE	182
Number of patients	1,480
Patient average age	38.89 (13.35)*
% Male patients	0.35

* Standard deviation.

In our data, we cannot verify selective referral since we do not observe if the patient was referred to a particular doctor by a friend or if he/she was assigned by the front desk. We know, however, that a large number of patients are assigned to particular doctors by the front desk, which distributes patients based on an arbitrary rule that does not depend directly on doctors' experience or outcomes, but rather on the past month's earnings. Since CLOFAN doctors are shareholders of the clinic and surgical center, the clinic tries to equalize their earnings through the assignment of patients that come to the clinic without a referral.[13] In this sense, although the assignment of doctors to patients is not completely random, the fact that the clinic bases its assignment rule not on experience but on past earnings should reduce bias due to selective referral. And if differences in doctor ability are driving the assignment of patients not assigned by the front desk, we can control for ability by incorporating doctor fixed effects into our analysis.

The key feature of this data is that we can observe the order of all refractive surgeries performed by each physician over time using this new technology. Thus the nature of this data allows us to test for the existence of learning by doing in this medical procedure. If indeed practice makes perfect, then we should observe a learning curve; that is, we should observe an improvement in the physicians' outcomes as they accumulate experience.

2.2.2 Measures of Eyesight and Outcomes

This section describes eyesight measures generated by ophthalmologist examinations. Initially, the patient is asked to read several letters of different sizes. This visual acuity exam provides the *Snellen measure* on a scale between 20/10 to 20/800, depending on the letter sizes the patient is able to read. In some cases, the patient cannot read any letters and the value is called "finger counting".

This first examination is informative, but in order to determine refractive

[13] Notice that this will not affect the cross-section variation in experience for surgeons within a cohort since refractive surgeries are only some of the procedures performed by CLOFAN doctors.

error and prescribe a corrective lens, the ophthalmologist needs to perform a refraction assessment.[14] A lens prescription consists of three measures – the sphere, the cylinder and the axis – and is expressed as $sphere = cylinder * axis = 20/xx$, where units are called "dioptries". The first number is the correction in the sphere of the eye and determines the degree of myopia or near-sightedness (if negative) or the degree of hyperopia or far-sightedness (if positive). The second and third numbers are, respectively, the correction on the cylinder and on the axis, which determine the degree of astigmatism. The last two numbers, "$20/xx$", determines the visual acuity the correction given by the three first numbers $xxx = xxx * xxx$ can provide. In other words, it expresses the best possible visual acuity that the patient can get. A value of zero for the first number or second number in the expression above means a perfect sphere or a perfect cylinder, which implies that the patient does not have myopia/hyperopia or astigmatism.

In order to measure the cornea and get values for the sphere, the cylinder and the axis, the doctor has several options; one is to measure the cornea directly with an automated refractometry; an other possibility is to try several combinations of lenses to correct the vision, which is called a subjective examination. The subjective evaluation is a doctor's evaluation of the correction required from the optical lenses to produce eyesight in the Snellen measure scale. These exams can be conducted with the eye muscles relaxed using eyedrops ("dilated" measures) or without the use of drops. The choice of the measurement method depends on the doctor's preferences.

[14]Refraction refers to how light waves are bent as they pass through your cornea and lens.

After the cornea measurement, the doctor makes a plan for the surgery which determines the correction to be performed for each defect. After the surgery, the doctor performs several follow-up examinations where he measures eyesight either with the Snellen scale, refractometry or with subjective evaluation.

Table 2.2: Crosswalk across different eye sight measures

Snellen Measure	Spherical Equivalent		
	Myopia	Hyperopia	
		$Age < 37$	$Age > 37$
20/800	-4		
20/400	-3.25		5
20/300	-3		4.5
20/250	-2.75		4
20/200	-2.5		3.5
20/160	-2.25		3
20/150	-2.25		3
20/125	-2	9	2.75
20/100	-1.75	8	2.5
20/80	-1.5	7	2.25
20/70	-1.25	6.25	2
20/60	-1.25	6.25	2
20/50	-1	5.25	1.75
20/40	-0.75	4.625	1.5
20/30	-0.5	3.625	1
20/25	-0.25	2.5	0.5
20/20	0	0.875	0
20/16	0		
20/12.5	0		
20/10	0		

In order to have a single outcome measure we need to overcome two difficulties with the data. The first is that we need to combine the refraction data into a single measure that captures not only myopia/hyperopia but also astigmatism. This measure is called the Spherical Equivalent (SE) and it is a standard metric used by ophthalmologists. The Spherical Equivalent is obtained by dividing the degree of astigmatism (or the cylinder deviation) by 2 and adding this number to the degree of myopia (hyperopia). For example, if the subjective evaluation is (-2.5) = (-3.5) x 180 (which means a myopia of -2.5 dioptries and an astigmatism of -3.5 dioptries, measured in the 180 degrees axis), the spherical equivalent would be equal to (-3.5/2) + (-2.5) = -4.25. For a perfect eye, the spherical equivalent should be zero but any measure between -0.5 and 0.5 dioptries is considered a good eyesight.

The second problem comes from the fact that not all doctors take all measures before and after surgery. Some doctors prefer to report only the *Snellen measure*, while others report also or only the refraction measures. Fortunately, it is possible to construct a crosswalk across different eye sight measures using equivalences well known to ophthalmologists. The crosswalk is presented in table 2.2.[15]

2.2.3 Econometric Model

The main question of this paper is whether we observe learning by doing in refractive eye surgery and, in particular, Lasik surgery. We define learning by doing to be the improvement in surgery outcomes due to the accumulated experience of the physician in performing a specific medical procedure. Our empirical strategy aims to identify this effect. However, in doing so, we need to consider that there may be other types of learning that could affect surgeries' outcome. For instance, as time passes, doctors may have some general learning of the procedure coming from sources like specialized magazines, professional congresses or other types of surgeries. Also, there may be some learning in the clinic and in the surgical center which are passed on to the doctors and affect outcomes through updates in the

[15] We constructed this crosswalk under the supervision of an optometrist using the following references Weatherly (2002), Gillet and Goldblum (2004) and Commission for Safety, Rehabilitation and Compensation of Commonwealth Employees 2006 Report on the visual system.

nomogram they all use in their surgeries.

Even if our data set contains a very good measure of physician experience in performing refractive surgery, it is hard to disentangle the effect of learning by doing from the general learning that comes with time. This happens because both effects are highly collinear since experience accumulates with time. With respect to the learning coming from the nomogram, we can effectively identify it since we know all the dates the nomogram was updated.

One of the nice features of the data is that it contains different measures of outcomes. In our analysis, we use five of these measures. The first is the absolute value of the post-surgical Spherical Equivalent taken in the last follow-up (in a six month window) observed at least 2 weeks after the surgery. We take the absolute value because it is the deviation from zero that matters, while the sign indicates only the kind of eye problem (myopia or hyperopia). The second measure we use is a dummy for success or failure of the procedure. A Spherical Equivalent between -0.5 and 0.5 dioptries is considered a good outcome and a success. Values outside this window are considered a failure. The third measure is an indicator of whether the patient needed at least one re-treatment (new surgery).[16] The fourth measure is the number of required follow ups visits after the surgery. And finally, the fifth outcome measure is the absolute value of the achieved minus the attempted correction, a measure that ophthalmologists consider important since it indicates the how good was their correction with respect to the surgical plan. It is worth noting that the attempted outcome is not always a spherical equivalent of zero. For

[16] It is worth noting that not all surgeries that failed (outside ± 0.5D) required a re-treatment.

instance, based on the patient's lifestyle (occupation, recreational activities, etc), age, eyeglass prescription and accommodation of the eye muscles, the physician may consider that a full correction is not attainable or advisable. Moreover, the physician may decide to specialize one eye for nearsightedness and the other eye for farsightedness. The fifth measure of outcome is only used in the initial exploration of the data, since using this measure as a dependent variable would imply introducing a decision variable into the left hand side of the regression, imposing a coefficient of one on this covariate.

So in order to test for learning by doing effects, we estimate the following equations:

$$Outcome_{ijk} = X_j\beta + Y\delta + \mu_{ijk} \tag{2.1}$$

where $Outcome_{ijk}$ is the outcome for the surgery on the i^{th} eye ($i = [left, right]$) of patient j operated on by doctor k. A perfect outcome has a value of zero; deviations are due to the existence of post-operative myopia/hyperopia and/or astigmatism. We only consider first surgeries in our sample, although we accumulate all surgeries (1st surgeries and re-treatments) when calculating doctor's experience. $X_j = [Age, Sex, Presurgery\ eyesight]$ is a vector of patient characteristics. $Y = [n_k,\ nomogram\ updates'\ dummies,\ time\ trend]$ is a vector of learning effects, where n_k is the number of surgeries performed by doctor k before surgery ij;[17] this is the variable of interest, since its coefficient measures the slope of the learning curve. If the hypothesis of learning by doing is true, doctors should get

[17] The initial nomogram (starting July 2003) was updated on December 2003 and May 2004.

better outcomes (i.e. measures of spherical equivalent closer to zero) in the n^{th} surgery than in the $n^{th}-1$ surgery, so that we should expect a negative sign on the coefficients in δ.

Other important identifying issue is that the learning curve may be flat in some portions or the learning speed may be different at certain range of surgeries. We try to examine the importance of these non-linearities by introducing a spline in the previous regression and by estimating a piecewise linear regression in addition to equation (2.1).[18] The spline we use have knots at surgeries number 50, 100 and 160; these knots were chosen based on the breaks we observe in most of next section figures. In the piecewise linear regression, we rewrite the Y vector to be $Y = [Y^*,\ time\ trend]$, where:

$$Y^* = \alpha_1(I = S_1) + \alpha_2(I = S_2) + \alpha_3(I = S_3) + \theta_1 n_{S_{1k}}(I = S_1) + \theta_2 n_{S_{2k}}(I = S_2) + \theta_3 n_{S_{3k}}(I = S_3)$$

2.3 Results

2.3.1 Initial Exploration of the Data

We start with a description of outcomes, using the outcome measure that is most commonly used in previous medical analysis, which compares the achieved correction with the attempted correction. Figure 2.1 shows graphs for Lasik surgeries and for all refractive surgeries. A perfect outcome lies on the 45 degree line

[18] A spline allows different slopes at different range of observations.

where the achieved correction equals the attempted correction, i.e. the surgery plan defined by the doctor is successfully implemented.

Outcomes that lie below the 45 degree line are undercorrections, while outcomes that lie above the 45 degree line are overcorrections, such as when the patient had myopia before the surgery and end ups with some degree of hyperopia after it. We can observe from figure 2.1 that there is a larger dispersion in the degree of hyperopia corrections than on the myopia ones which suggest that doctors obtain better results in myopia than in hyperopia surgeries.

We turn next to investigate the main question of the paper, which is if we observe a learning curve in the data. A learning curve would imply that the outcomes improve with the number of surgeries. For all our measures of outcome, a learning curve would show a negative slope in the plot of the number of previous surgeries vs. outcomes.

Figures 2.2 through 2.9 show simple graphs that suggest learning by doing for the Lasik procedures and for all refractive procedures in the case of outcome number 1 (final spherical equivalent obtained after the surgery), outcome number 2 (percentage of final spherical equivalents outside the window $[-0.5, 0.5]$ dioptries), outcome number 3 (whether the patient needed at least one re-treatment), outcome number 4 (the number of required follow ups visits after the surgery) and outcome number 5 (absolute value of the attempted minus the achieved correction). The graphs plot average outcome across doctors by number of surgeries.

None of the graphs exhibits a positive slope and most show a mild downward

Figure 2.1: Achieved vs. Attempted Correction in the Eyesight.

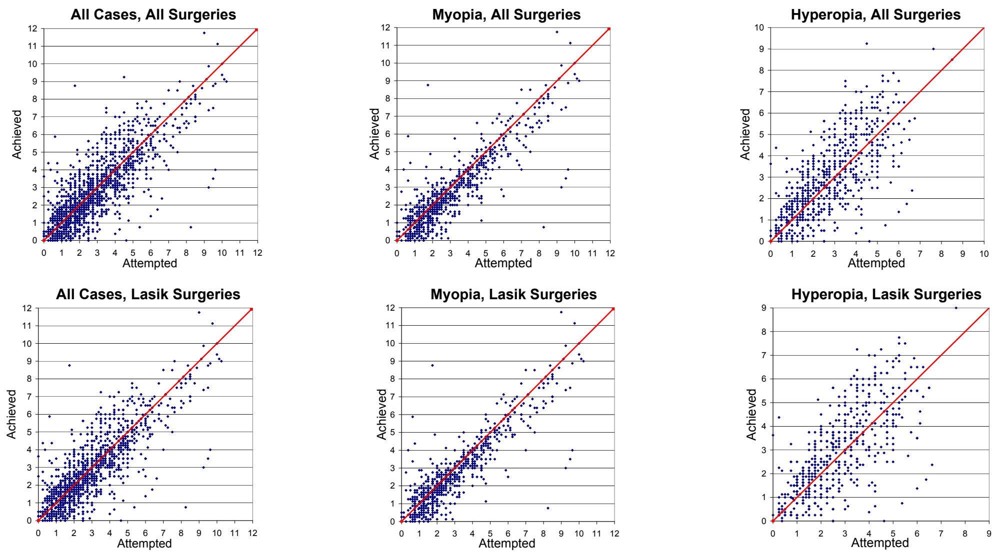


Figure 2.2: Absolute Value of Final Spherical Equivalent for All refractive Surgeries.

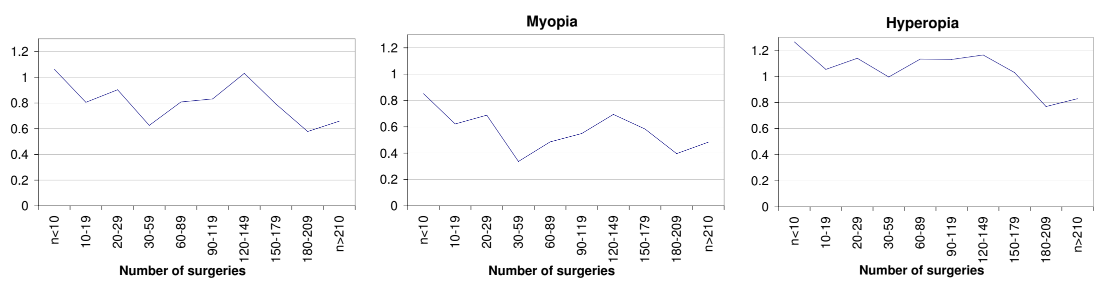


Figure 2.3: Absolute Value of Final Spherical Equivalent for Lasik Surgeries.

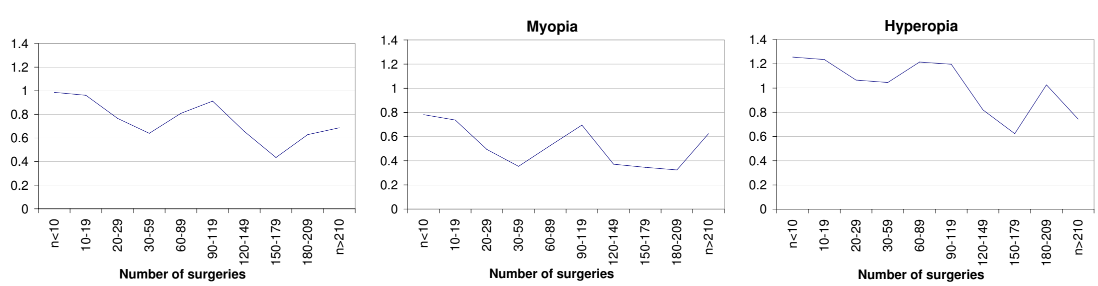


Figure 2.4: % of Bad Outcomes for All refractive Surgeries.

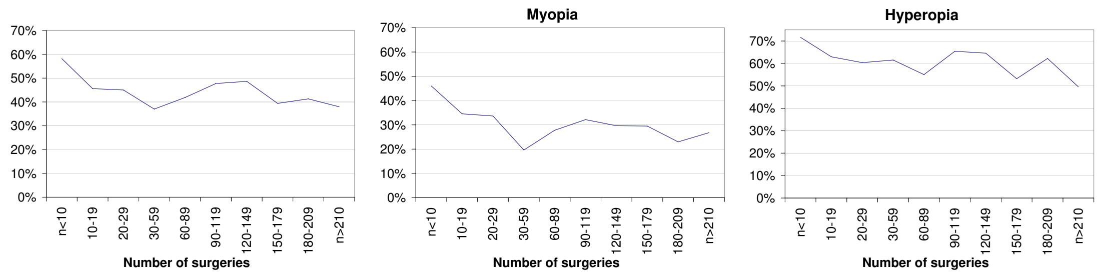


Figure 2.5: % of Bad Outcomes for Lasik Surgeries.

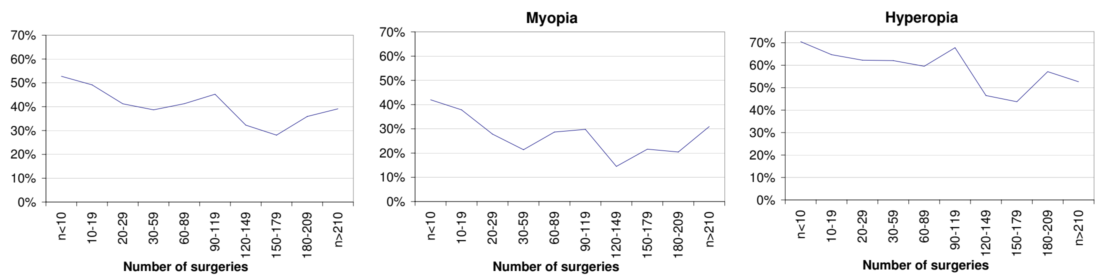


Figure 2.6: Abs. value of Achieved minus Attempted Correction for All refractive Surgeries.

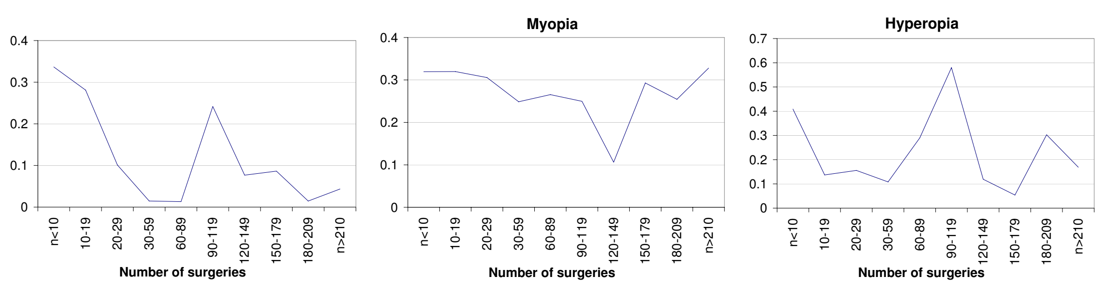


Figure 2.7: Abs. value of Achieved minus Attempted Correction for Lasik Surgeries.

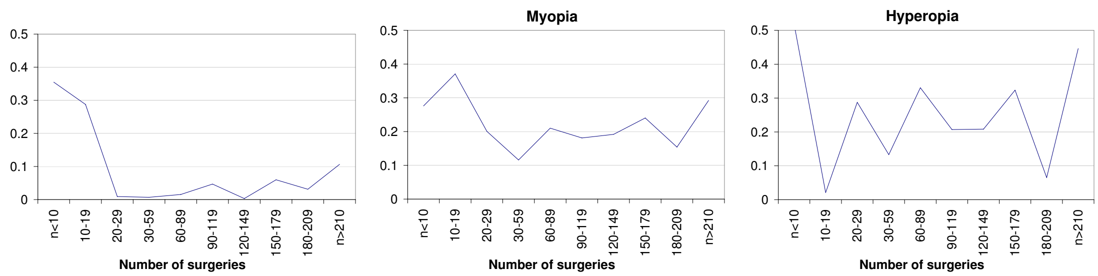


Figure 2.8: Indicator of whether the patients need at least one retreament, All refractive surgeries (left) and Lasik Surgeries (right).

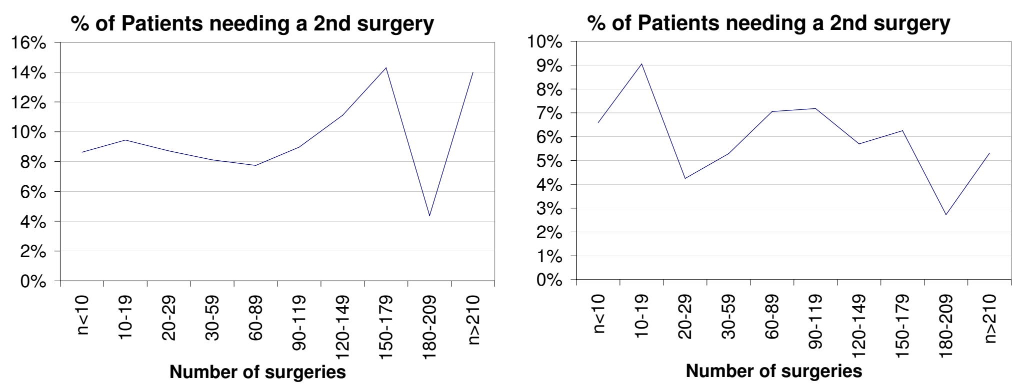


Figure 2.9: Number of required follow up visits after the surgery, All refractive surgeries (left) and Lasik Surgeries (right).

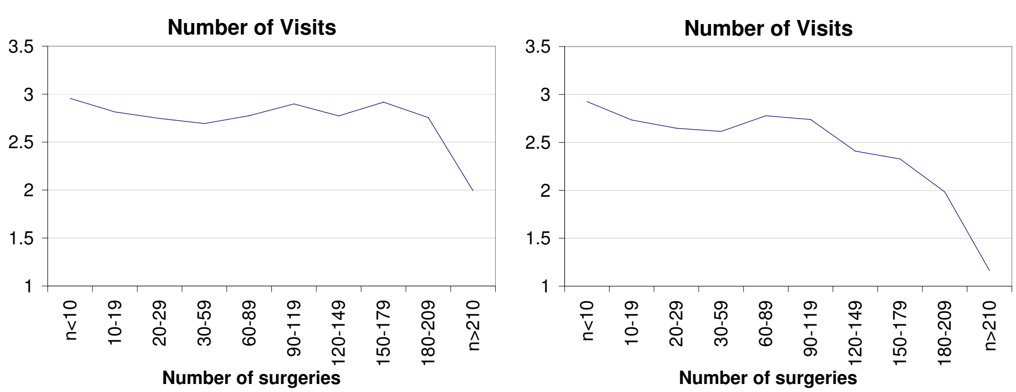
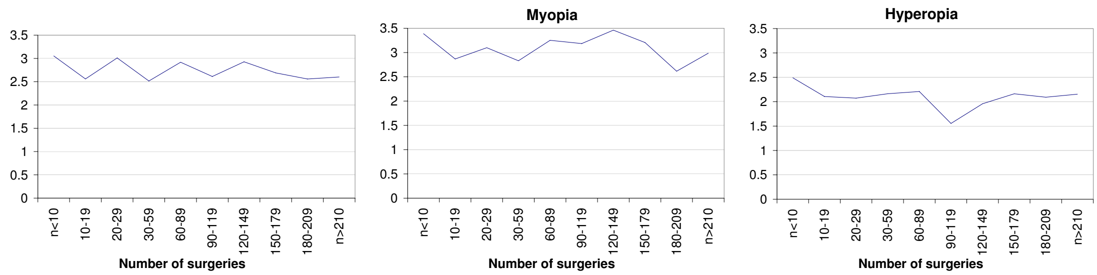


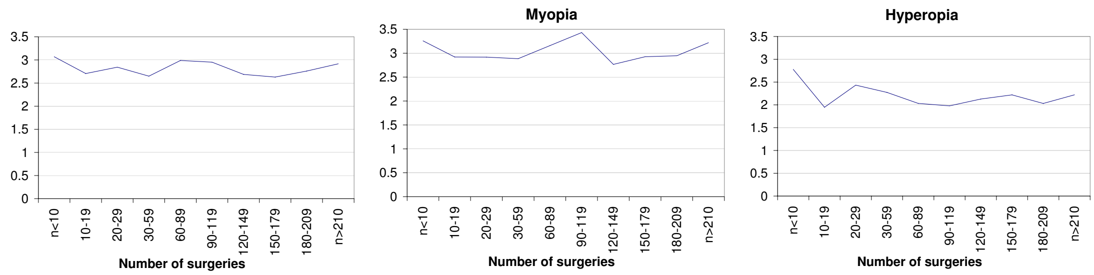
Figure 2.10: Absolute value of Initial Spherical Equivalent for All refractive Surgeries.



slope. We find the strongest evidence of learning by doing in the cases of: (1) bad outcomes for Lasik Surgeries, all cases and myopia, (2) the absolute value of achieved minus attempted correction for all refractive surgeries and all lasik cases, (3) percentage of patients needing a second Lasik surgery and (4) number of required follow up visits after Lasik surgery. In part, the lack of striking evidence in all reported cases and outcomes could be explained by the fact that at this point we are only looking at the raw data. The are many other factors that may affect outcomes that we are not controlling for, such compositional effects, doctors' individual skills or other environmental factors like humidity.

A potentially important confounding factor could be changes in the degree of severity in patients' pre-existing conditions over time. If the severity of patient cases is falling over time, then some of the trends we observe in the graphs may be due to surgeries becoming easier with time. In order to elucidate this point, figures 2.10 and 2.11 show the initial spherical equivalent of the average patient per group of surgeries. Fortunately, these figures do not exhibit a clear trend with respect to doctors' surgical experience.

Figure 2.11: Absolute value of Initial Spherical Equivalent for Lasik Surgeries.



2.3.2 Regression Results

Looking at the regressions in tables 2.3 through 2.6, the first thing to notice about the control variables is that the patient characteristic like age and pre-surgical spherical equivalent are very important for the outcome as well as the humidity of the room. The patient gender is only important in the cases of the post-surgical spherical equivalent and in the number of visits.

In the simplest case, regression 1, we get a statistically significant negative effect of the experience on the outcome in all outcome measures except in the multi-surgery measure, which suggests that the outcome improves with the doctors' experience. It is important to notice that the squared terms are also statistically significant. The evidence is much weaker in the case of the time trend alone (regression 3) since it is statistically significant only in the case of the good/bad outcome, even if the sign suggests learning in time in all but in the multi-surgery. The learning effect is much stronger both in terms of the statistically significance and magnitude of the coefficient in the case of nomogram change (regression 2). Again, there is no effect on the multi-surgery outcome measure. It is interesting that the only significant effect is that of the last nomogram, suggesting an effective learning in the clinic or surgical center in incorporating the environmental and machine setting conditions and translating the surgical plan into the desired eyesight correction. Taken together, these regressions suggest that there is a learning effect that may come from the experience, from the institutional learning or from the time learning.

Table 2.3: Good outcome if inside the window $[-0.5. + 0.5]$ Dioptries

	(1)	(2)	(3)	(5)	(4)	(7)	(6)	(8)	(10)	(9)	(11)	(12)	(13)
age	0.0062	0.0061	0.006	0.0061	0.0061	0.0061	0.0061	0.0062	0.0062	0.0062	0.0062	0.006	0.006
	(0.0011)**	(0.0011)**	(0.0011)**	(0.0011)**	(0.0011)**	(0.0011)**	(0.0011)**	(0.0011)**	(0.0011)**	(0.0011)**	(0.0010)**	(0.0011)**	(0.0011)**
sex	0.053	0.0501	0.0503	0.0523	0.05	0.048	0.0503	0.0485	0.0476	0.0455	0.0464	0.0476	0.0478
	(0.0305)+	-0.03	-0.0306	(0.0305)+	-0.0316	-0.0309	-0.0314	-0.0309	-0.0308	-0.0314	-0.0312	-0.0313	-0.0315
abspre	0.0267	0.026	0.0257	0.0263	0.0261	0.0259	0.0263	0.0258	0.0256	0.0254	0.0255	0.0265	0.0264
	(0.0062)**	(0.0061)**	(0.0061)**	(0.0061)**	(0.0061)**	(0.0060)**	(0.0060)**	(0.0061)**	(0.0060)**	(0.0059)**	(0.0059)**	(0.0060)**	(0.0061)**
hum	0.007	0.0053	0.0033	0.0056	0.0045	0.0047	0.005	0.0064	0.0054	0.0044	0.0047	0.0054	0.0055
	(0.0031)*	(0.0029)+	-0.0027	(0.0030)+	-0.0027	-0.0028	(0.0029)+	(0.0027)*	(0.0029)+	-0.0026	-0.0028	(0.0025)*	(0.0027)+
n	-0.0023			-0.001	-0.0003		-0.001						
	(0.0008)**			-0.0012	-0.0013		-0.0013						
n^2	8.41e-6			5.71e-6	4.47e-6		5.98e-6						
	(2.79e-6)**			(2.73e-6)*	3.40e-6		(2.86e-6)*						
t		-0.0163		-0.0112		0.0135	0.0194		-0.0129		0.0279		0.0083
		(0.0089)+		-0.013		-0.0286	-0.0307		-0.0123		-0.0357		-0.0296
t^2		0.0004		0.0001		-0.0001	-0.0005		0.0002		-0.0007		-0.0003
		-0.0004		-0.0004		-0.0009	-0.0009		-0.0004		-0.0011		-0.001
s_1												-0.1712	-0.1836
												-0.1243	-0.1438
s_2			-0.036		-0.0498	-0.1033	-0.1043			-0.0595	-0.1277	-0.1788	-0.2211
			-0.0387		-0.0518	-0.1065	-0.1082			-0.0529	-0.1216	-0.12	-0.214
s_3			-0.1357		-0.1852	-0.268	-0.2713			-0.1872	-0.2952	-0.3135	-0.3741
			(0.0406)**		(0.0900)*	-0.1586	-0.1608			(0.0792)*	(0.1682)+	(0.1219)*	-0.2851
$n*_1$								-0.0034	-0.0014	-0.001	-0.0027		
								(0.0014)*	-0.0016	-0.0015	-0.0018		
n_2^*								0.0017	0.0023	0.0027	0.0024		
								-0.0014	-0.0014	(0.0015)+	-0.0014		
n_3^*								-0.003	-0.0024	-0.0019	-0.0024		
								(0.0010)**	(0.0012)+	-0.0013	-0.0014		
n_4^*								0.0025	0.0029	0.0029	0.0026		
								(0.0007)**	(0.0009)**	(0.0006)**	(0.0008)**		
$s_1 * n_{1j}$												0.0018	0.0016
												-0.0013	-0.0015
$s_2 * n_{2j}$												0.0004	0.0001
												-0.0015	-0.0017
$s_3 * n_{3j}$												0.0016	0.0015
												-0.0011	-0.0014
Const	-0.1371	-0.063	-0.0008	-0.0715	-0.0587	-0.0972	-0.1061	-0.0815	-0.0391	-0.0266	-0.0697	0	0
	-0.1453	-0.1469	-0.1296	-0.1479	-0.133	-0.1521	-0.153	-0.1251	-0.1352	-0.1252	-0.1364	0	0
Obs	1598	1598	1598	1598	1598	1598	1598	1598	1598	1598	1598	1598	1598
R2	0.1	0.1	0.1	0.1	0.11	0.1	0.11	0.1	0.1	0.11	0.11	0.1	0.1

Standard Errors in parenthesis. + significant at 10%; significant at 5%; * significant at 1%
hum=humidity; abspre=pre-surgical spherical equivalent; n = number of surgeries; s_l=nomogram l=1 to 3; $n_m^* = m^{th}$ knot of the spline
n_{lj}: number of surgeries performed by surgeon j under nomogram l where $n_{1j} + n_{2j} + n_{2j} = n_j$

Table 2.4: Outcome measure: Absolute value of final spherical equivalent

	(1)	(2)	(3)	(5)	(4)	(7)	(6)	(8)	(10)	(9)	(11)	(12)	(13)
age	0.0094	0.0092	0.0092	0.0093	0.0093	0.0091	0.0092	0.0097	0.0095	0.0095	0.0094	0.0092	0.0089
	(0.0023)**	(0.0023)**	(0.0022)**	(0.0022)**	(0.0022)**	(0.0023)**	(0.0022)**	(0.0022)**	(0.0022)**	(0.0022)**	(0.0022)**	(0.0022)**	(0.0022)**
sex	0.1129	0.1117	0.1094	0.1099	0.1075	0.1109	0.1091	0.1	0.097	0.0949	0.0971	0.1056	0.1081
	(0.0565)+	(0.0567)+	(0.0562)+	(0.0559)+	(0.0559)+	(0.0569)+	(0.0563)+	(0.0559)+	(0.0556)+	(0.0552)+	(0.0558)+	(0.0560)+	(0.0556)+
abspre	0.0784	0.0769	0.0771	0.0771	0.0776	0.0769	0.077	0.0755	0.075	0.0752	0.0749	0.077	0.0766
	(0.0127)**	(0.0126)**	(0.0126)**	(0.0124)**	(0.0126)**	(0.0126)**	(0.0124)**	(0.0128)**	(0.0127)**	(0.0128)**	(0.0128)**	(0.0125)**	(0.0124)**
hum	0.0171	0.0114	0.0122	0.0121	0.014	0.0111	0.0117	0.0147	0.0112	0.0127	0.0109	0.0134	0.0104
	-0.0102	-0.0087	-0.0079	-0.0089	-0.0085	-0.0083	-0.0084	(0.0084)+	-0.0079	-0.0076	-0.0075	-0.0079	-0.0076
n	-0.0039			0.0016	0.0002		0.0015						
	(0.0018)*			-0.0037	-0.003		-0.0038						
n^2	1.30e-5			2.12e-6	4.44e-6		2.54e-6						
	(6.34e-6)*			9.21e-6	8.01e-6		9.37e-6						
t		-0.0275		-0.0479		0.0077	-0.0174		-0.0413		0.0079		-0.0254
		-0.0243		-0.0398		-0.0586	-0.0715		-0.042		-0.0844		-0.0602
t^2		0.0005		0.0006		-0.0005	-0.0002		0.0005		-0.0009		-0.0005
		-0.001		-0.0012		-0.002	-0.0022		-0.0013		-0.0026		-0.0021
s_1												-0.3073	-0.2158
												-0.3965	-0.386
s_2			-0.1295		-0.1678	-0.1428	-0.1138			-0.1569	-0.1834	-0.4978	-0.2728
			-0.0938		-0.1086	-0.1892	-0.2017			-0.1092	-0.2298	-0.4086	-0.4553
s_3			-0.2609		-0.3609	-0.2486	-0.2213			-0.3167	-0.2899	-0.6327	-0.1893
			(0.0874)**		(0.1909)+	-0.2877	-0.2953			(0.1666)+	-0.32	-0.3917	-0.5108
n_1^*								-0.0095	-0.0028	-0.0051	-0.0038		
								(0.0028)**	-0.0047	-0.003	-0.0054		
n_2^*								0.0072	0.009	0.0088	0.009		
								(0.0031)*	(0.0033)*	(0.0033)*	(0.0033)*		
n_3^*								-0.008	-0.0059	-0.0065	-0.0061		
								(0.0021)**	(0.0024)*	(0.0022)**	(0.0026)*		
n_4^*								0.0046	0.0061	0.0052	0.006		
								(0.0012)**	(0.0017)**	(0.0011)**	(0.0016)**		
$s_1 * n_{1j}$												-0.0005	0.0013
												-0.0022	-0.0024
$s_2 * n_{2j}$												0.0018	0.0045
												-0.0036	-0.0041
$s_3 * n_{3j}$												0.0017	0.0048
												-0.0016	(0.0027)+
Const	-0.423	-0.1347	-0.2162	-0.1639	-0.317	-0.1844	-0.2026	-0.1832	-0.0385	-0.1354	-0.093	0	0
	-0.4919	-0.4209	-0.3649	-0.4365	-0.439	-0.426	-0.439	-0.4089	-0.3862	-0.3926	-0.3826	0	0
Obs	1598	1598	1598	1598	1598	1598	1598	1598	1598	1598	1598	1598	1598
R2	0.11	0.11	0.11	0.11	0.11	0.11	0.11	0.12	0.12	0.12	0.12	0.11	0.11

Standard Errors in parenthesis. + significant at 10%; significant at 5%; * significant at 1%
hum=humidity; abspre=pre-surgical spherical equivalent; n = number of surgeries; s_l=nomogram l=1 to 3; $n_m^* = m^{th}$ knot of the spline
n_{lj}: number of surgeries performed by surgeon j under nomogram l where $n_{1j} + n_{2j} + n_{2j} = n_j$

Table 2.5: Outcome measure: Number of visits after surgery

	(1)	(2)	(3)	(5)	(4)	(7)	(6)	(8)	(10)	(9)	(11)	(12)	(13)
age	0.0131	0.0129	0.0132	0.013	0.0132	0.0128	0.013	0.0133	0.013	0.0133	0.013	0.0129	0.0125
	(0.0034)**	(0.0034)**	(0.0033)**	(0.0035)**	(0.0034)**	(0.0034)**	(0.0034)**	(0.0035)**	(0.0035)**	(0.0034)**	(0.0035)**	(0.0034)**	(0.0034)**
sex	0.164	0.1648	0.1569	0.1659	0.1608	0.1644	0.1657	0.1655	0.1678	0.1635	0.1676	0.1607	0.1649
	(0.0955)+	(0.0954)+	-0.0978	(0.0938)+	-0.0956	(0.0955)+	(0.0939)+	-0.0979	(0.0957)+	-0.0977	(0.0958)+	-0.0975	(0.0968)+
abspre	0.0455	0.0437	0.0443	0.0439	0.0447	0.0437	0.0439	0.0451	0.0441	0.0445	0.044	0.0459	0.0455
	(0.0201)*	(0.0195)*	(0.0199)*	(0.0197)*	(0.0200)*	(0.0195)*	(0.0197)*	(0.0203)*	(0.0199)*	(0.0202)*	(0.0199)*	(0.0193)*	(0.0195)*
hum	0.0125	-0.001	0.0066	-0.0007	0.0066	-0.0013	-0.001	0.0107	-0.0007	0.0052	-0.0011	0.0095	0.0019
	-0.0097	-0.0097	-0.0078	-0.0097	-0.0089	-0.0096	-0.0097	-0.0093	-0.0097	-0.0086	-0.0095	-0.0101	-0.0103
n	-0.0065			-0.0005	-0.0027		-0.0006						
	(0.0033)+			-0.0064	-0.0058		-0.0063						
n^2	1.60e-5			6.98e-6	8.73e-6		7.30e-6						
	(8.75e-6)+			1.37e-5	1.35e-5		1.34e-5						
t		-0.0195		-0.0222		0.0082	0.0039		-0.0227		0.0041		-0.046
		-0.0324		-0.0752		-0.0879	-0.0995		-0.0738		-0.108		-0.0952
t^2		-0.0011		-0.0014		-0.0019	-0.0021		-0.0014		-0.0021		-0.0014
		-0.0015		-0.0025		-0.0029	-0.0033		-0.0025		-0.0035		-0.0033
s_1												2.2653	2.5045
												(0.6690)**	(0.7109)**
s_2			-0.1739		-0.0998	-0.1114	-0.0977			-0.0582	-0.09	2.3231	2.8153
			-0.1505		-0.2688	-0.3636	-0.3481			-0.2574	-0.3659	(0.6190)**	(0.9055)**
s_3			-0.4873		-0.3814	-0.1996	-0.1874			-0.3343	-0.1869	1.9353	2.8806
			(0.1729)**		-0.327	-0.443	-0.4217			-0.3073	-0.4467	(0.5978)**	(1.0258)**
n_1^*								-0.009	0.0002	-0.0051	-0.0005		
								-0.0054	-0.0078	-0.0064	-0.0079		
n_2^*								-0.0025	-0.0001	-0.001	-0.0002		
								-0.0047	-0.0051	-0.0055	-0.0051		
n_3^*								-0.0013	0.0022	0.0009	0.0022		
								-0.0051	-0.0054	-0.0051	-0.0055		
n_4^*								-0.0012	0.002	-0.0004	0.0019		
								-0.0012	-0.0015	-0.0015	-0.0015		
$s_1 * n_{1j}$												0.0064	0.0097
												-0.0052	(0.0048)+
$s_2 * n_{2j}$												-0.003	0.0024
												-0.0034	-0.0034
$s_3 * n_{3j}$												0	0.0065
												-0.004	-0.0038
Const	2.3776	2.9038	2.5227	2.9052	2.5809	2.8668	2.8731	2.514	2.8946	2.68	2.8731	0	0
	(0.6191)**	(0.5744)**	(0.4242)**	(0.5714)**	(0.5718)**	(0.6182)**	(0.6046)**	(0.5859)**	(0.5804)**	(0.5562)**	(0.5959)**	0	0
Obs	2013	2013	2013	2013	2013	2013	2013	2013	2013	2013	2013	2013	2013
R2	0.31	0.32	0.32	0.32	0.32	0.32	0.32	0.31	0.32	0.32	0.32	0.32	0.32

Standard Errors in parenthesis. + significant at 10%; significant at 5%; * significant at 1%
hum=humidity; abspre=pre-surgical spherical equivalent; n = number of surgeries; s_l=nomogram l=1 to 3; $n_m^* = m^{th}$ knot of the spline
n_{lj}: number of surgeries performed by surgeon j under nomogram l where $n_{1j} + n_{2j} + n_{2j} = n_j$

Table 2.6: Outcome measure: If more than one surgery was needed

	(1)	(2)	(3)	(5)	(4)	(7)	(6)	(8)	(10)	(9)	(11)	(12)	(13)
age	0.0008	0.0007	0.0008	0.0008	0.0008	0.0007	0.0007	0.0008	0.0008	0.0008	0.0008	0.0008	0.0007
	(0.0005)+	-0.0005	-0.0005	-0.0005	(0.0005)+	-0.0005	-0.0004	(0.0005)+	(0.0005)+	(0.0005)+	-0.0005	(0.0005)+	-0.0005
sex	0.0172	0.0179	0.0177	0.0176	0.0168	0.0178	0.0176	0.0169	0.0176	0.0168	0.0176	0.0175	0.0184
	-0.0118	-0.0121	-0.012	-0.0121	-0.0119	-0.0121	-0.0121	-0.012	-0.0122	-0.0121	-0.0122	-0.0119	-0.012
abspre	0.0007	0.0006	0.0006	0.0005	0.0006	0.0006	0.0006	0.0006	0.0005	0.0005	0.0005	0.0005	0.0004
	-0.0026	-0.0026	-0.0026	-0.0026	-0.0026	-0.0027	-0.0026	-0.0026	-0.0026	-0.0026	-0.0026	-0.0026	-0.0027
hum	0.0028	0.0014	0.0016	0.0014	0.0021	0.0013	0.0014	0.0025	0.0013	0.0018	0.0012	0.0017	0.0012
	(0.0009)**	-0.0009	(0.0007)*	-0.0009	(0.0008)*	-0.0009	-0.0009	(0.0008)**	-0.0008	(0.0008)*	-0.0009	(0.0008)+	-0.0008
n	-0.0001			0.0003	0.0004		0.0002						
	-0.0002			-0.0005	-0.0004		-0.0004						
n^2	7.54e-7			4.77e-7	-7.13e-8		6.38e-7						
	6.57e-7			1.05e-6	8.89e-7		1.01e-6						
t		0.0056		0.0018		0.0179	0.0136		0.0046		0.0182		0.0288
		-0.0044		-0.006		-0.011	-0.0117		-0.0065		-0.0129		(0.0108)*
t^2		-0.0003		-0.0003		-0.0007	-0.0006		-0.0004		-0.0007		-0.0011
		-0.0002		-0.0002		(0.0004)+	-0.0004		-0.0002		(0.0004)+		(0.0004)**
s_1												-0.0693	-0.1024
												-0.0428	(0.0444)*
s_2			0.0087		-0.0103	-0.052	-0.0466			-0.002	-0.0504	-0.0757	-0.2062
			-0.0158		-0.0192	-0.0397	-0.0392			-0.02	-0.0393	(0.0372)+	(0.0695)**
s_3			-0.0066		-0.0447	-0.0806	-0.0751			-0.0334	-0.084	-0.095	-0.2613
			-0.0178		-0.0305	-0.0607	-0.0596			-0.0288	-0.0612	(0.0391)*	(0.0860)**
n_1^*								-0.0007	-0.0005	-0.0004	-0.0007		
								-0.0005	-0.0007	-0.0005	-0.0008		
n_2^*								0.0005	0.0006	0.0007	0.0006		
								-0.0004	-0.0005	-0.0005	-0.0005		
n_3^*								0.0001	0.0003	0.0003	0.0002		
								-0.0004	-0.0003	-0.0003	-0.0003		
n_4^*								0.0001	0.0003	0.0002	0.0003		
								-0.0002	(0.0002)+	-0.0002	-0.0002		
$s_1 * n_{1j}$												-0.0006	-0.0013
												-0.0004	(0.0005)*
$s_2 * n_{2j}$												0	-0.0004
												-0.0006	-0.0007
$s_3 * n_{3j}$												0.0002	0.0003
												-0.0002	-0.0003
Const	-0.1313	-0.0839	-0.0769	-0.0841	-0.1064	-0.1014	-0.0996	-0.1017	-0.0724	-0.0816	-0.0862	0	0
	(0.0447)**	(0.0448)+	(0.0341)*	(0.0417)+	(0.0376)**	(0.0512)+	(0.0479)*	(0.0432)*	(0.0395)+	(0.0377)*	(0.0456)+	0	0
Obs	2013	2013	2013	2013	2013	2013	2013	2013	2013	2013	2013	2013	2013
R2	0.04	0.04	0.04	0.05	0.04	0.04	0.05	0.04	0.05	0.05	0.05	0.04	0.05

Standard Errors in parenthesis. + significant at 10%; significant at 5%; * significant at 1%
hum=humidity; abspre=pre-surgical spherical equivalent; n = number of surgeries; s_l=nomogram l=1 to 3; $n_m^* = m^{th}$ knot of the spline
n_{lj}: number of surgeries performed by surgeon j under nomogram l where $n_{1j} + n_{2j} + n_{2j} = n_j$

In order to further investigate which is the relevant learning effect we regress different combinations of all three effects. When combined with the nomogram variable, the experience measure loses all the statistical significance and the nomogram measure is relevant only in the case of the good/bad outcome and in the final spherical equivalent outcome measure. When combined with the time trend, the experience measure also loses all the significance and the time trend is only relevant in the case of good/bad outcome. However, the quadratic term keeps the significance when using this outcome. If all the learning variables are put together, none of them has any statistical significance, but only the nomogram variable keeps always the right sign. As discussed before, it is hard to identify all these effects separately, but the institutional learning reflected in the nomogram is the hypothesis that is more supported by the data.

When investigating the existence of nonlinearities, the spline shows an important effect of the nomogram in the case of the first two outcome measures, and the overall joint significance of the different slopes in each group of surgeries is not important with some having opposite signs in some groups. If something, there is some significance in the slope reflecting learning by doing in the first 50 surgeries in the case of the good/bad outcome measure. The piecewise linear regression, which looks to determine the existence of different regimes and learning curves every time the clinic changes the nomogram, shows a similar story. The effect of the nomogram is consistently affecting the outcomes and the effect of the experience is weaker.

Summarizing the regressions results, the empirical evidence points towards a clinic or surgical center learning instead of learning by doing or learning in time. This comes from the facts that the strongest statistical evidence of the effect of learning on the outcomes comes from the changes in the nomogram, while there is no statistical evidence of an effect of learning in time and only weak statistical evidence of the effect of experience in Lasik outcomes.

2.4 Conclusions

In this paper, we examine the existence of learning by doing in Lasik and other types of refractive eye surgeries. We use a remarkable data set that allows us to observe the evolution of well defined outcomes for a group of doctors since they began performing laser surgeries in June 2003.

The distinguished feature of this paper, in comparison with previous studies, is the use of a longitudinal data set with good measures of doctors' experience and medical outcomes. Past studies have instead used cross sectional data linking volume with poorly defined measures of outcomes making it difficult to isolate the effect of learning by doing from other effects such as selective referral.

Although the main question of the paper is whether physicians' outcomes improve with their experience, we also allow for the possibility of learning coming from a time trend or from the accumulation of experience in the surgical center. We do find evidence of learning, although, it points towards an institutional learning reflected in the updates of the clinic nomogram used to translate the surgical plan into the desired eyesight correction.

As a future extension of this research, we plan to analyze the medical procedure in the context of a production technology for which the outcomes are the products while the technology, the nomogram and the accumulated skills of the doctors are the input factors.

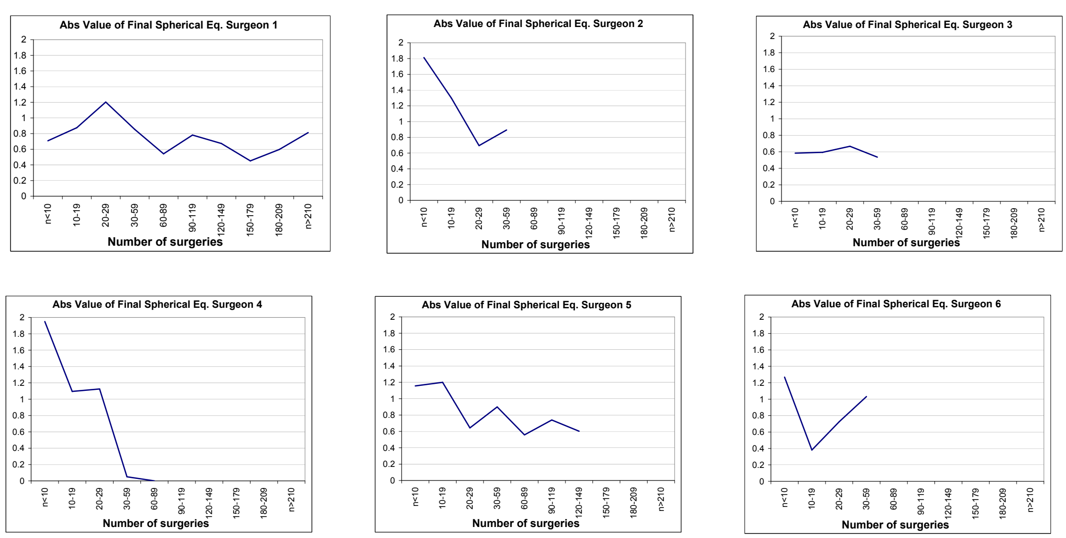
The empirical evidence provided here is potentially relevant to the policy debate about regionalized medical care since it investigates and suggests potential channels through which experience or learning can affect medical outcomes.

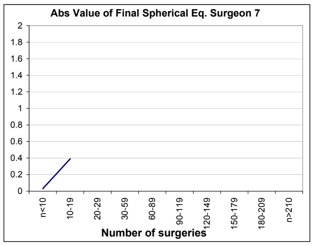
Appendix B

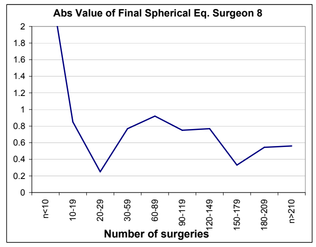
Appendix Part II

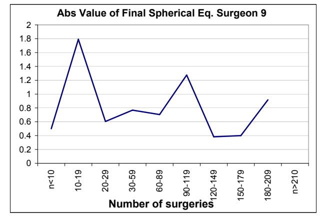
Figure B.1: Steps in Lasik procedure (Source: Allaboutvision.com)

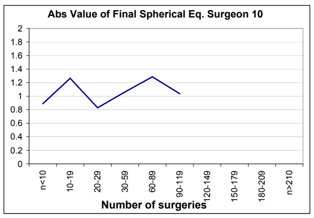
Figure B.2: Final Spherical Equivalent by Doctor, Lasik

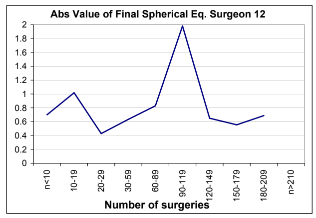


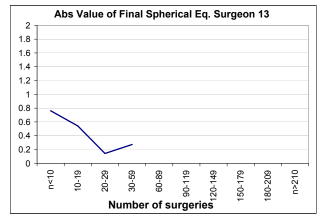

Abs Value of Final Spherical Eq. Surgeon 7
2 1.8 1.6 1.4 1.2 1 0.8 0.6 0.4 0.2 0
n<10 10-19 20-29 30-59 60-89 90-119 120-149 150-179 180-209 n>210
Number of surgeries

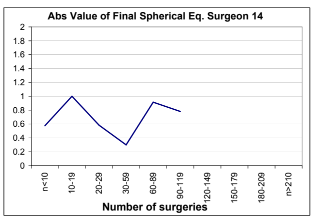

Abs Value of Final Spherical Eq. Surgeon 8
2 1.8 1.6 1.4 1.2 1 0.8 0.6 0.4 0.2 0
n<10 10-19 20-29 30-59 60-89 90-119 120-149 150-179 180-209 n>210
Number of surgeries

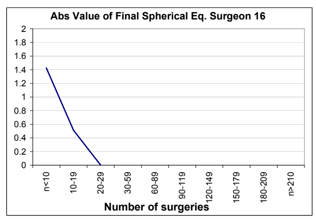

Abs Value of Final Spherical Eq. Surgeon 9
2 1.8 1.6 1.4 1.2 1 0.8 0.6 0.4 0.2 0
n<10 10-19 20-29 30-59 60-89 90-119 120-149 150-179 180-209 n>210
Number of surgeries

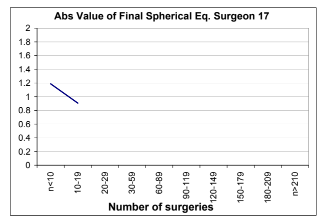

Abs Value of Final Spherical Eq. Surgeon 10
2 1.8 1.6 1.4 1.2 1 0.8 0.6 0.4 0.2 0
n<10 10-19 20-29 30-59 60-89 90-119 120-149 150-179 180-209 n>210
Number of surgeries

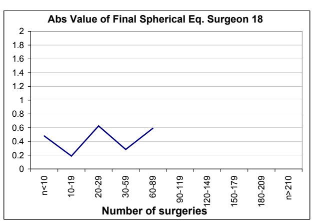

Abs Value of Final Spherical Eq. Surgeon 12
2 1.8 1.6 1.4 1.2 1 0.8 0.6 0.4 0.2 0
n<10 10-19 20-29 30-59 60-89 90-119 120-149 150-179 180-209 n>210
Number of surgeries

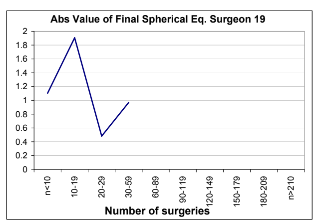

Abs Value of Final Spherical Eq. Surgeon 13
2 1.8 1.6 1.4 1.2 1 0.8 0.6 0.4 0.2 0
n<10 10-19 20-29 30-59 60-89 90-119 120-149 150-179 180-209 n>210
Number of surgeries

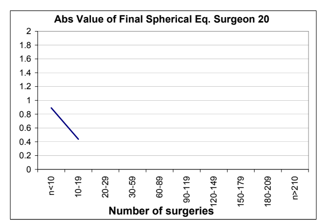

Abs Value of Final Spherical Eq. Surgeon 14
2 1.8 1.6 1.4 1.2 1 0.8 0.6 0.4 0.2 0
n<10 10-19 20-29 30-59 60-89 90-119 120-149 150-179 180-209 n>210
Number of surgeries

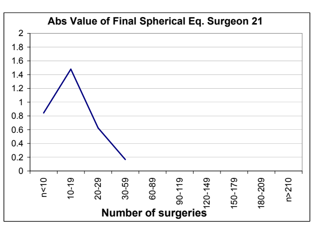

Abs Value of Final Spherical Eq. Surgeon 16
2 1.8 1.6 1.4 1.2 1 0.8 0.6 0.4 0.2 0
n<10 10-19 20-29 30-59 60-89 90-119 120-149 150-179 180-209 n>210
Number of surgeries

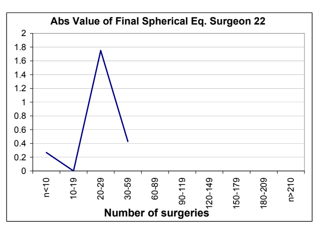

Abs Value of Final Spherical Eq. Surgeon 17
2 1.8 1.6 1.4 1.2 1 0.8 0.6 0.4 0.2 0
n<10 10-19 20-29 30-59 60-89 90-119 120-149 150-179 180-209 n>210
Number of surgeries

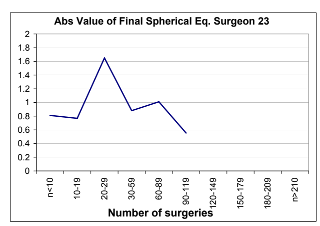

Abs Value of Final Spherical Eq. Surgeon 18
2 1.8 1.6 1.4 1.2 1 0.8 0.6 0.4 0.2 0
n<10 10-19 20-29 30-59 60-89 90-119 120-149 150-179 180-209 n>210
Number of surgeries

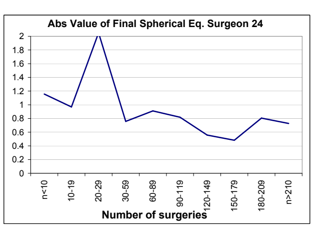

Abs Value of Final Spherical Eq. Surgeon 19
2 1.8 1.6 1.4 1.2 1 0.8 0.6 0.4 0.2 0
n<10 10-19 20-29 30-59 60-89 90-119 120-149 150-179 180-209 n>210
Number of surgeries

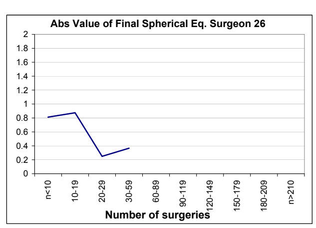

Abs Value of Final Spherical Eq. Surgeon 20
2 1.8 1.6 1.4 1.2 1 0.8 0.6 0.4 0.2 0
n<10 10-19 20-29 30-59 60-89 90-119 120-149 150-179 180-209 n>210
Number of surgeries

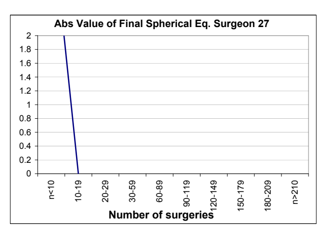

Abs Value of Final Spherical Eq. Surgeon 21
2 1.8 1.6 1.4 1.2 1 0.8 0.6 0.4 0.2 0
n<10 10-19 20-29 30-59 60-89 90-119 120-149 150-179 180-209 n>210
Number of surgeries


Abs Value of Final Spherical Eq. Surgeon 22
2 1.8 1.6 1.4 1.2 1 0.8 0.6 0.4 0.2 0
n<10 10-19 20-29 30-59 60-89 90-119 120-149 150-179 180-209 n>210
Number of surgeries


Abs Value of Final Spherical Eq. Surgeon 23
2 1.8 1.6 1.4 1.2 1 0.8 0.6 0.4 0.2 0
n<10 10-19 20-29 30-59 60-89 90-119 120-149 150-179 180-209 n>210
Number of surgeries


Abs Value of Final Spherical Eq. Surgeon 24
2 1.8 1.6 1.4 1.2 1 0.8 0.6 0.4 0.2 0
n<10 10-19 20-29 30-59 60-89 90-119 120-149 150-179 180-209 n>210
Number of surgeries


Abs Value of Final Spherical Eq. Surgeon 26
2 1.8 1.6 1.4 1.2 1 0.8 0.6 0.4 0.2 0
n<10 10-19 20-29 30-59 60-89 90-119 120-149 150-179 180-209 n>210
Number of surgeries


Abs Value of Final Spherical Eq. Surgeon 27
2 1.8 1.6 1.4 1.2 1 0.8 0.6 0.4 0.2 0
n<10 10-19 20-29 30-59 60-89 90-119 120-149 150-179 180-209 n>210
Number of surgeries

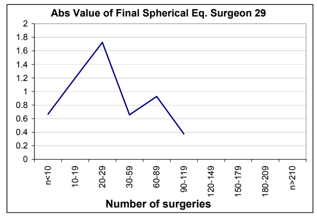
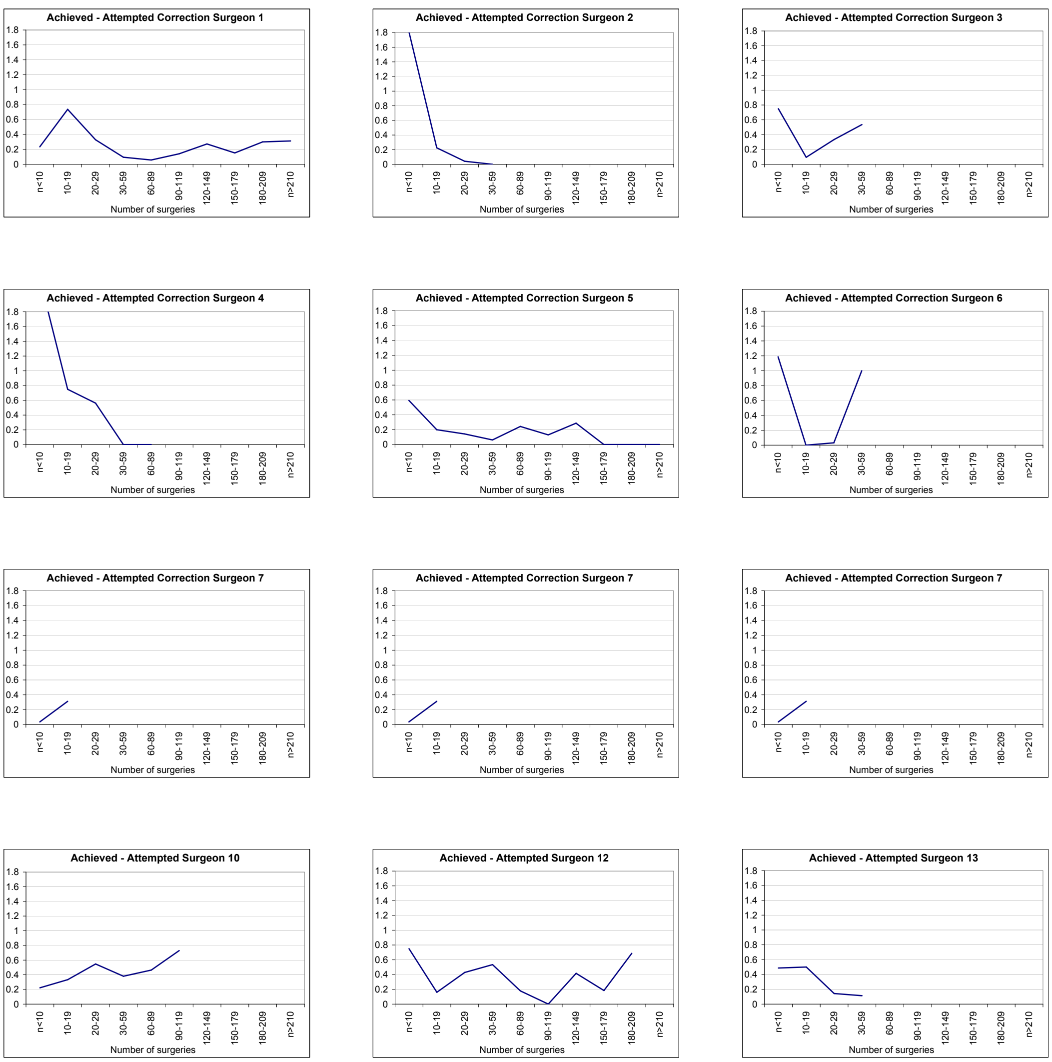
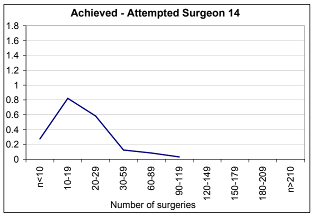
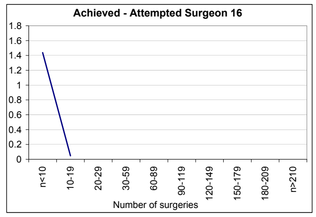
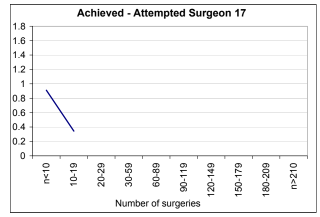


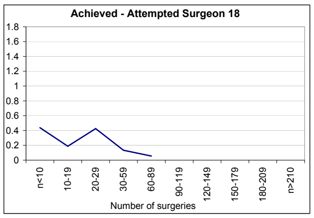
Figure B.3: Absolute Value of Achieved-Attempted Correction by Doctor, Lasik

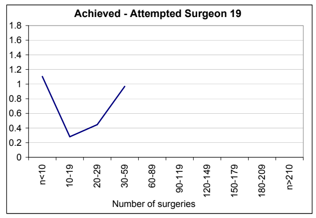


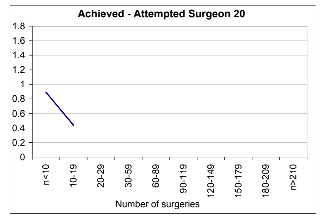

Achieved - Attempted Surgeon 14
1.8
1.6
1.4
1.2
1
0.8
0.6
0.4
0.2
0
n<10
10-19
20-29
30-59
60-89
90-119
120-149
150-179
180-209
n>210
Number of surgeries

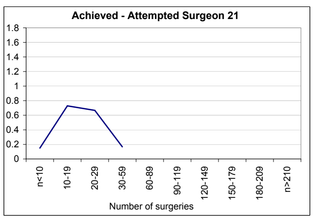

Achieved - Attempted Surgeon 16
1.8
1.6
1.4
1.2
1
0.8
0.6
0.4
0.2
0
n<10
10-19
20-29
30-59
60-89
90-119
120-149
150-179
180-209
n>210
Number of surgeries

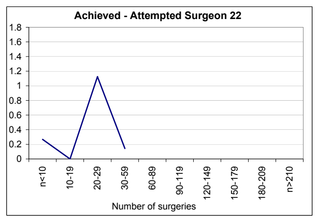

Achieved - Attempted Surgeon 17
1.8
1.6
1.4
1.2
1
0.8
0.6
0.4
0.2
0
n<10
10-19
20-29
30-59
60-89
90-119
120-149
150-179
180-209
n>210
Number of surgeries

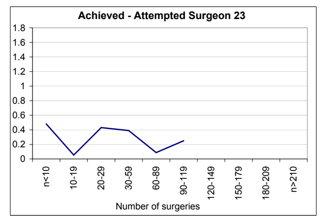

Achieved - Attempted Surgeon 18
1.8
1.6
1.4
1.2
1
0.8
0.6
0.4
0.2
0
n<10
10-19
20-29
30-59
60-89
90-119
120-149
150-179
180-209
n>210
Number of surgeries


Achieved - Attempted Surgeon 19
1.8
1.6
1.4
1.2
1
0.8
0.6
0.4
0.2
0
n<10
10-19
20-29
30-59
60-89
90-119
120-149
150-179
180-209
n>210
Number of surgeries


Achieved - Attempted Surgeon 20
1.8
1.6
1.4
1.2
1
0.8
0.6
0.4
0.2
0
n<10
10-19
20-29
30-59
60-89
90-119
120-149
150-179
180-209
n>210
Number of surgeries


Achieved - Attempted Surgeon 21
1.8
1.6
1.4
1.2
1
0.8
0.6
0.4
0.2
0
n<10
10-19
20-29
30-59
60-89
90-119
120-149
150-179
180-209
n>210
Number of surgeries


Achieved - Attempted Surgeon 22
1.8
1.6
1.4
1.2
1
0.8
0.6
0.4
0.2
0
n<10
10-19
20-29
30-59
60-89
90-119
120-149
150-179
180-209
n>210
Number of surgeries


Achieved - Attempted Surgeon 23
1.8
1.6
1.4
1.2
1
0.8
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0.4
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0
n<10
10-19
20-29
30-59
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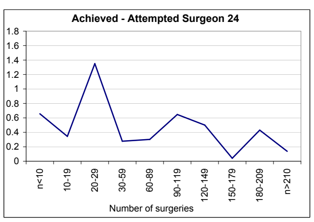
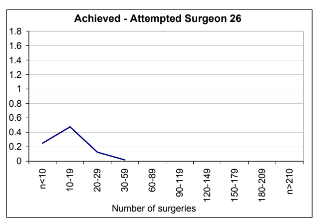
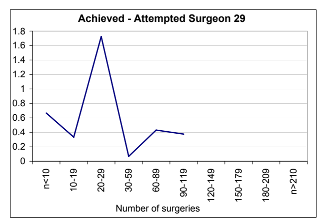
90-119
120-149
150-179
180-209
n>210
Number of surgeries


Achieved - Attempted Surgeon 24
1.8
1.6
1.4
1.2
1
0.8
0.6
0.4
0.2
0
n<10
10-19
20-29
30-59
60-89
90-119
120-149
150-179
180-209
n>210
Number of surgeries


Achieved - Attempted Surgeon 26
1.8
1.6
1.4
1.2
1
0.8
0.6
0.4
0.2
0
n<10
10-19
20-29
30-59
60-89
90-119
120-149
150-179
180-209
n>210
Number of surgeries


Achieved - Attempted Surgeon 29
1.8
1.6
1.4
1.2
1
0.8
0.6
0.4
0.2
0
n<10
10-19
20-29
30-59
60-89
90-119
120-149
150-179
180-209
n>210
Number of surgeries

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