Family Formation and Equilibrium Influences

by

Andrew Beauchamp

Department of Economics
Duke University

Date: ______________________

Approved:

____
Peter Arcidiacono, Advisor

____
V. Joseph Hotz

____
Paul Ellickson

____
Shakeeb Khan

Dissertation submitted in partial fulfillment of the requirements for the degree of
Doctor of Philosophy in the Department of Economics
in the Graduate School of Duke University
2009

Abstract

(Economics)

Family Formation and Equilibrium Influences

by

Andrew Beauchamp

Department of Economics
Duke University

Date: ____________________

Approved:

____
Peter Arcidiacono, Advisor

____
V. Joseph Hotz

____
Paul Ellickson

____
Shakeeb Khan

An abstract of a dissertation submitted in partial fulfillment of the requirements for the degree of Doctor of Philosophy in the Department of Economics in the Graduate School of Duke University
2009

Abstract

This dissertation considers incentives arising from equilibrium influences that affect the sequence of decisions that lead to family formation. The first chapter examines how state regulations directly aimed at abortion providers affect the market for abortion in the United States. Estimates from a dynamic model of competition among abortion providers show that regulations' main impact is on the fixed costs of entry for providers. Simulations indicate that the removal of regulations would promote entry and competition among abortion providers, and because abortions are found to be price sensitive, this would lead to increases in the number of abortions observed. The second chapter tests if an important negative externality of abortion access exists, namely whether abortion access makes prospective fathers more likely to leave pregnant women. Designing a number of empirical tests, I confirm that in some areas where abortion is more accessible women who give birth are more likely to be single mothers, rather than sharing parental responsibility with the biological father. The final chapter, which is joint work with Peter Arcidiacono and Marjorie McElroy, examines how gender ratios influence bargaining power in romantic relationships between men and women. Gender ratios, by influencing the prospects of matching, allow us to estimate preferences for various match characteristics and activities. We find men prefer sexual relationships more than women at high school ages, and that men and women trade off their preferred partner for an increased chance of matching.

Contents

Abstract **iv**

List of Tables **viii**

List of Figures **x**

Acknowledgements **xi**

1 Abortion Supplier Dynamics **1**

1.1 Introduction 1

1.2 Abortion Markets 6

1.3 Data 11

1.3.1 Abortion Providers 11

1.3.2 State Laws 14

1.3.3 Policy Endogeneity and Reduced Forms 16

1.4 Model 18

1.4.1 Production 19

1.4.2 Entry and Exit 21

1.4.3 State Space and Equilibrium 24

1.4.4 Non-Profit Activity 26

1.5 Estimation and Results 27

1.5.1 Recovering First-Stage Parameters 27

1.5.2 Recovering Production Costs 31

1.5.3 Recovering Entry Costs and Exit Payoffs 33
1.5.4 Including Unobserved Heterogeneity 38
1.6 Simulations 40
1.7 Conclusion 43
1.8 Tables and Figures 45
2 Testing Theories of Out-of-Wedlock Childbearing 57
2.1 Introduction 57
2.2 Explaining Out-of-Wedlock Childbearing in Economics 61
2.3 Data 65
2.3.1 Abortion Reporting 65
2.3.2 Sample 66
2.4 Empirical Methodology 68
2.4.1 Capturing the Effect 68
2.4.2 OLS Estimates with Linear Sample Selection 72
2.4.3 A Non-Linear Model with Selection 74
2.4.4 Bias and Instrumenting 76
2.4.5 Miscarriage, IV and Bounding 79
2.4.6 Checks on the Results 82
2.5 Conclusion 83
2.6 Tables and Figures 83
3 Competing For The Opposite Sex: An Equilibrium Model of High School Sex and Dating 91
3.1 Introduction 91
3.2 Review 94
3.3 Model and Estimation 97

3.3.1 Individuals . . . 98
3.3.2 Matching . . . 99
3.3.3 Equilibrium . . . 102
3.3.4 Estimation . . . 102
3.4 Data and Descriptive Characteristics . . . 103
3.4.1 Preferences for Sex Behavior . . . 105
3.4.2 Grade Profile of Matching . . . 106
3.4.3 Cross-Race Matching Patterns . . . 107
3.4.4 Gender Ratio Variation . . . 108
3.4.5 From the data to the model . . . 109
3.5 Results . . . 110
3.6 Conclusion . . . 111
3.7 Tables and Figures . . . 111
Appendix **114**
Bibliography **121**
Biography **122**

List of Tables

1.1 Percent Abortions by Gestation, Procedure 46
1.2 Auxiliary Data Sources 47
1.3 Descriptive Statistics 48
1.4 State Law Implementation Years 49
1.5 Lagged Abortions Predicting Policy Enactment 50
1.6 Log Abortions on Policies 51
1.7 Reduced Form: Prices 51
1.8 Entry and Exit Probit 52
1.9 Elasticity Estimates 53
1.10 Marginal Cost Estimates 54
1.11 Fixed Cost Estimates 55
1.12 Firms, All Regulations Off at 1991 55
1.13 All Regulations Off at 1991 56
1.14 Marginal Cost Effects 56
2.1 Implications of a Decrease in Abortion Costs 84
2.2 Add Health Pregnancies 84
2.3 Add Health: Estimation Sample* 85
2.4 Distribution of Abortion Providers 85
2.5 Probability of Separation Beyond Preg., Selected LPM Coefficients . 86

2.6 Pairwise Smooth Maximum Score Estimates 87
2.7 Pairwise Smooth Maximum Score Estimates, Core Sample 88
2.8 Probability of Separation by Post-Pregnancy, Selected IV Estimates . 89
2.9 County Descriptive Statistics 89
2.10 Probability of Separation, W/ Non-marital Fertility 90
3.1 Preferences and Participation 111
3.2 Cross-Grade Matching Distribution 112
3.3 Cross-Race Matching Distribution 112
3.4 Gender Ratio Variation 112
3.5 Model Estimates 113

List of Figures

1.1 Procedures and Firms 45

1.2 Regulation Changes Over Time 46

1.3 Simulated Number of Firms, Remove Regulations at 1991 47

Acknowledgements

This dissertation has benefitted greatly from frequent discussions with my advisor Peter Aricidacono and with Joe Hotz. Special thanks are due to Paul Ellickson, Shakeeb Khan, Marjorie McElroy, Pat Bayer, Andrew Sweeting and Jason Blevins for all their comments, insights and support.

1

Abortion Supplier Dynamics

1.1 Introduction

The debate over abortion rights in the United States has continued unabated since the landmark decisions of *Roe vs. Wade* and *Doe vs. Bolton* in 1973. Together, these two cases established a framework of competing rights between a state's interest in protecting potential or prenatal life and a woman's right to privacy, life and health. Perhaps not surprisingly, despite important rulings from the U.S. Supreme Court,[1] much of the debate to protect and restrict abortion rights has occurred at the state level. By one estimate the period of 1995-2007 saw 557 separate state laws enacted in attempts to restrict access to and provision of abortion services.[2] In addition to restrictions, some states have acted to enshrine the concepts and rights of *Roe vs. Wade* in their laws and constitutions, with 16 states establishing such protections as of 2008. In recent years, federal legislation has also been proposed, namely the

[1] Since *Roe vs. Wade* a series of decisions have clarified and further defined the rights of individuals and states; these include *Webster v. Reproductive Health Services*, 1989, *Planned Parenthood vs. Casey* 1992, and *Gonzales v. Carhart* 2007.

[2] NARAL Pro-Choice America, In Your State.

"Freedom of Choice Act"(FOCA), in an effort to overrule state regulations. Although a number of studies have addressed the impact of policies like public funding and parental consent laws on abortion incidence, very little is known about the effects of direct regulations of abortion providers.[3]

Abortions in the United States are supplied by three types of organizations: hospitals, non-specialized providers such as private physicians' offices or health clinics, and more specialized abortion or reproductive health clinics. Over time, the composition of these three types of firms has changed. The number of abortions in the U.S. has been falling since around 1990, as can be seen in the upper line in the left hand side of Figure 1.8.[4] [5] There has also been an increase in the number of procedures per firm, depicted by the lower line, which includes all firms, for the varying demand conditions over the period my data span. This increase could be the result of changing marginal costs, shifts in demand to larger firms, or both. However, in the right hand panel of Figure 1.8, the difference between the top and middle lines represents the number of hospital providers which declined from the early 1980's onward, reflecting a shift from hospitals serving as a major provider of all types of abortions in the early 1970's to hospitals playing a much more specialized role after the early 1980's.[6]

[3] More recently Haas-Wilson (1996), Levine, Trainor, and Zimmerman (1996), Blank, George, and London (1996), Bitler and Zavodny (2001), and Levine (2003) all measure the impact of state laws on abortion demand. Results vary depending on the fixed effects models estimated and the years used for estimation, and Medoff (2007) contains a review. In general findings are consistent with theory: public funding increases abortion ratios, restrictions such as parental consent reduce them. Studies such as Haas-Wilson (1996) examine impacts separately for minors, where she finds more pronounced effects. By "direct regulations" I refer to those policies which aim specifically at changing provider behavior, they are outlined in greater detail in Section 1.3.

[4] The abortion rate(abortions over women aged 15-44) and ratio(abortions over pregnancies) have seen very similar declines, and the number of live births was 4,179,000 in 1990 and 4,138,349 in 2005(National Center for Health Statistics). The birth rate declined from 16.7 births per 1000 population in 1990 to 14.2 in 2007, and teen birth rate saw steeper declines.

[5] The decline in abortion likely has many explanations including better contraception, acceptance of single motherhood, and a lack of abortion access.

[6] Hospital abortions accounted for 46% in 1973, declining to 18% by 1982, 7.3% in 1991 and 4.8% in 2005.

Physicians' offices and other non-specialized providers offering abortion services are represented by the difference between the middle line and the bottom line in Figure 1.8. Like hospitals, they have become increasingly rare since the late 1980's, while abortion clinics have increased in size and their numbers have remained steady. The figure indicates that the cost structures of firms must have changed. If this phenomenon was simply demand driven all firms might have seen a downward shift in the number of abortions provided, with little change in the number of firms. The shift in the number of firms is suggestive of changing fixed costs. So is the fact that the firms who exited(hospitals and non-specialized providers) probably substituted toward other services, leaving larger and more specialized producers operating in the market, characteristic of markets with fixed costs. However, the decline does not rule out changing marginal costs among the different types of providers as another explanation. For example production-cost increases across different times and locations could be responsible for the observed decline in firms. In either of these cases, whether fixed or marginal costs were changing, an open question is to what extent state level regulations lead to cost increases.

In this paper, I focus on the question of how state level regulations influenced abortion providers' entry and exit decisions by estimating a dynamic model of entry, exit and differentiated services competition between providers. This strategy allows me to estimate how regulations changed the costs of production, the fixed entry and fixed operation costs which firms face, as well as allowing me to estimate heterogeneous effects for different types of firms. This is especially relevant to understanding abortion markets since increasing the fixed costs of entry may significantly alter the set of providers, given the dynamic nature of the firm or organizations' problem. The policy functions I estimate allow me to simulate the distribution of abortion providers in the U.S. resulting from regulation changes. In particular, I look at the impact, if any, of removing relevant direct regulations on the composition of firms and the resulting equilibrium number of abortions.[7]

To estimate a model which incorporates some of the market dynamics, I use data drawn from the most comprehensive database on abortion providers: The Alan Guttmacher Institute's(AGI) Periodic Survey of Abortion Providers. Combining this data with recent innovations in the literature on estimating dynamic games, I recover the structural parameters of abortion providers' profit functions via a two-step procedure.[8] My approach follows the literature that has evolved on estimating dynamic games of imperfect information, notably Bajari, Benkard, and Levin (2007), Aguirregabiria and Mira (2007) and Pakes, Ostrovsky, and Berry (2004). In the model firms engage in services competition in spatially separated metro-area markets in each period, optimizing their production choices independently across periods. The result is a Markov-perfect Nash Equilibrium(MPNE), consistent with the framework put forward by Ericson and Pakes (1995)[9] for studying industry dynamics. In the first stage of estimation, state level regulations on abortion providers over the time period of 1973-2005 interact with health care market fundamentals to provide plausibly exogenous supply side instruments, which identify the price elasticities of demand. Because I only observe total procedures by the type of firm in each market, I use firm type to proxy for the differentiation among services available which appears to characterize this market. Using the demand parameters, I then estimate the marginal costs of the stage game, paying attention to how regulations influence marginal costs. Finally, to estimate the fixed costs I use methods first introduced in Hotz and Miller (1993) namely a conditional choice probability (CCP) estimator which exploits the structure

[7] The simulations will address possible impacts of FOCA and are discussed in more detail in Section 1.6.

[8] The impact of some firms operating as non-profits is addressed in Section 1.4.

[9] Prior research does show some evidence of overlapping of abortion markets at least on the demand side. The issue is discussed further in Section 1.2.

of the model more fully than prior methods, allowing for faster estimation under the assumption that exit provides an absorbing state. The eased computational burden allows for estimation of the model using the methods of Arcidiacono and Miller (2008) to deal with market level unobserved heterogeneity.

The results indicate that regulation of abortion providers played an important role in the industry dynamics observed. Simulations of the dynamic model with all regulations removed show less centralized markets for abortion services with increases in the number of hospitals and smaller providers operating. Simulating the removal of all regulations from 1991-2005 shows an increase in the total number of abortions observed by an average of 3.2% per year, resulting from increased entry and competition among providers. One reason put forward for removing regulations is access, generally measured as locations with providers. Simulations indicate metro-areas with providers increase by an average of 4.1% per year from 1991 to 2005 when regulations are removed. Therefore much of the effect of regulation appears to be limiting competition in markets with providers. The simulated overall increases in abortion and observed declines in national birthrates suggest that these state policies had the consequence of reducing the number of unintended pregnancies.

The rest of the paper proceeds as follows. Section 1.2 discusses in further detail abortion markets in United States from the early 1970's onward and how I deal with modeling this complicated market. Section 1.3 covers the data used here, the market level information on firms and quantities, and the state level restrictions over the period of interest. Section 1.4 presents the dynamic model of differentiated Cournot services competition, while Section 1.5 focuses on the estimation procedure and results. Finally Section 1.6 covers the policy simulations and Section 1.7 concludes.

1.2 Abortion Markets

What we know about abortion markets in the U.S. comes from two data sources: Centers for Disease Control(CDC) compilations of (most) state health department records and the Alan Guttmacher Institute's(AGI) periodic Survey of Abortion providers.[10] As stated above there are essentially three types of providers and they usually maintain different gestational limits on the procedures they will perform. The differences in services by the type of provider is addressed in Henshaw and Finer (2003), who found that in 2001 specialized clinics were the most likely to offer services until 17 weeks of gestation, while the majority of non-specialized offices and clinics cease providing services after 12 weeks. After 17 weeks, hospitals are most likely to provide services, especially when there are health risks or fetal abnormalities.[11] At the same time, over 90% of hospital providers, 70% non-specialized clinics and all specialized clinics provided services at 12 weeks of gestation. Reports from the early 1980's show gestational limits for the different providers to be more similar. Abortions in the first trimester were frequently performed within hospitals.[12] However, Table 1.1 contains data drawn from various CDC *Abortion Surveillance* reports from 1972-2004 and shows that the percent of all abortions performed prior to 12 weeks has remained near 90% over those 32 years. The predominant method used during this period has been curettage across all gestations.[13] Only in 2004 do the reports pick up increases in the number of medical abortions.[14] It appears the technologies used and the

[10] CDC has incomplete information since many states no longer require abortion reporting to state health agencies.

[11] These cases are often covered by State Medicaid programs.

[12] Henshaw, Forrest, and Baine (1984). Data show hospital abortions accounted for 46% in 1973, declining to 18% by 1982, 7.3% in 1991 and 4.8% in 2005.

[13] While other methods are used more frequently in later term abortions, curettage is still by far the most practiced method, accounting for 87% of procedures after 21 weeks of gestation in 2004.

[14] The term medical groups a number of procedures including hysterectomies, but the recent rise comes from the impact of RU-486 on the market. RU-486 was approved by the FDA in 2000. CDC

gestation-specific demand as a fraction of total abortions have been fairly constant over time despite changes in the composition of firms. Technology or productivity differences do not appear to explain the changes in industry structure. Both the early and more recent reports contain some information on prices and find that on average smaller providers and hospitals charge higher prices than large clinics, with a difference around $200 in 2005 constant dollars.[15] The desired data for understanding how services competition changed over time would be gestation and provider specific quantity and price data over time. This would allow a straightforward modeling of differentiated services. Unfortunately this series of data lays directly between AGI and CDC data and is therefore unavailable.

However, even with the data available, it appears that the market for abortions in U.S. has undergone a series of changes over time. Most notably, hospitals and non-specialized clinics played an important role early in the period of study, but large clinics have served much more of the demand in the past 15-20 years. Given the current gestation-structure of the market and the higher prices of hospitals and smaller providers, this market appears to be characterized by differentiated services providers. The differentiation is along at least two dimensions: the gestational age of the fetus, and factors associated with the type of provider. Provider characteristics such as proximity, familiarity and the availability of non-surgical abortion, help explain demand for higher priced private offices. Some hospitals' requirement of admission helps explain the falling hospital provision of early term abortions and hospitals' role in providing abortions when a woman's health is in danger. Given that these two dimensions of differentiation are correlated and the lack of information in the data on gestation, I proceed in Section 1.4 to model the differentiation across the type

data do not delineate consistently between surgical curettage and vacuum aspiration or suction curettage.

[15] See Table 1.3 for an estimate of the difference between smaller and larger clinic prices.

of provider, paying attention in the estimation section to differences in demand over time, which should pick up the changing nature of substitution as the market evolves.

Market overlap is a characteristic of abortion markets pointed out in recent research, notably Kane and Staiger (1996) and Blank, George, and London (1996). This arises when individuals living in one location consider other markets when making abortion-related choices. Blank, George, and London (1996) highlights neighboring state policies and finds no impact of minor restrictions, but does find that as the number of providers in a state increases, so too does the number of abortions performed on out-of-state residents. These results are hindered by the geographic specificity of the data since cross-state travel in a many locations is also within-metro area travel.[16] With the greater geographic detail here, I use a Metro-Micro Statistical Area market definition to alleviate much of this concern. The work of Kane and Staiger (1996) addresses how the distance to the nearest provider affects abortion choices. Consistent with an endogenous pregnancy model, they find that as the distance increases birth rates fall. This highlights that some individuals may look to substitute toward abortion providers in nearby markets, while some may opt to avoid pregnancy altogether in the absence of conveniently available services. Unfortunately, the endogeneity of pregnancy is beyond the scope of this paper but the elasticity estimates presented will be a reduced form combining all the channels of substitution: away from pregnancy, toward other markets, and toward other types of providers within the same market.[17]

There are a number of concerns when using the observed abortion prices, especially the possibility of discounted prices being charged from insurance or subsidies. The AGI database also contains information on the methods of payment for abortion

[16] CDC data show that Washington D.C. has generally been the leader in the fraction of abortions obtained by out of state residents.

[17] The extent to which abortion markets overlap, and the substitution across markets, seems like a promising avenue for future research given the great geographical specificity of the data used here.

services to non-hospital providers. Although I do not have direct access to such data, a summary of 2001 data is presented in Henshaw and Finer (2003). They found a sample 637 non-hospital providers reporting an average of 62% of patients paying full price out-of-pocket, 13% having the procedure billed directly to their private insurance company and another 13% having the procedure funded through state medicaid agencies. Additionally, 12% paid an out-of-pocket reduced fee with the help of one of the charitable funds providing financial assistance for abortions for women who could not otherwise afford the procedure. Some unknown fraction of those paying out-of-pocket received reimbursements from insurers. And a portion of those with direct billing had to pay a fraction to their insurer, meaning both groups may appear to be price sensitive on average. These results are surprising and given the historically slow rate at which private insurers adopt abortion into their coverage, it is likely that the percent paid out of pocket was higher in the past. Additionally, large populations within the U.S. are expressly prohibited from having abortions paid for by insurance, including all federal employees, military members and state employees in 12 states as of 2008. Another 5 states expressly prohibit all private insurers from covering abortion.[18] The Kaiser Foundation estimates from 2003 show that only one third of employees at firms with less than 200 workers have insurance coverage for abortion and two thirds of employees at firms larger than 200 workers carry the coverage.[19] Finally, there are factors within households that can make insurance coverage of abortion undesirable.[20] For example, women insured through spousal or parental coverage who desire to terminate their pregnancy without family members knowing must often avoid insurance coverage and pay out-of-pocket.[21] Despite all

[18] Insurance policies covering abortion must be purchased with an additional rider and payment of an extra premium in these states. Guttmacher Institute, State Polices in Brief

[19] Census data from 2004 show between 42-51% of the paid workforce worked at the smaller firms.

[20] This topic arises in the debates surrounding minors' access to abortion services.

[21] CDC data show that between 18-23% of women obtaining abortions were married and between

these factors, price discounting still occurs and in an effort to mitigate the impact these discounts may have on elasticity estimates, I include proxies for the extent of discounting.

How prices influence the quantity of abortions performed has been addressed before, notably in Medoff (1988) and Medoff (2007), [22] and elasticity estimates in various studies generally fall between -0.7 and -1.0. There are however some important problems with prior estimates. Prior studies of direct prices have generally estimated models with the abortion rate defined as the percent of pregnancies[23] ending in abortion over the number of women aged 15 to 44 years old. This rate is then regressed on prices, usually instrumenting for prices. The price variation comes from differences across states and over time. A number of issues arise in this context, firstly the use of the abortion rate as defined above, which is a combination of the abortion rate(abortions over population) and the abortion ratio(abortions over pregnancies). The work of Kane and Staiger (1996) highlights the endogeneity of pregnancy with respect to the abortion services, in particular the number of clinics. The elasticity estimated via this empirical strategy is something like a net of both changes in births and changes in abortions, rather than solely changes in abortion due to price.[24] In a related problem, most studies use the number of abortion clinics in the state as one of the instruments. However, given the evidence in Kane and Staiger (1996), abortion clinics have an independent impact on birth rates, the effect does not work solely through prices. The number of providers is itself related to market specific characteristics as the results from entry and exit decisions presented below will show. To obtain better elasticity estimates, I use an instrumenting strategy based on the

52-65% were under the age of 25 for most of the sample period.

[22] See Medoff (2007) for a review.

[23] Pregnancies in these studies is given by abortions plus births.

[24] Abortion price changes could increase births and/or reduce pregnancies.

interaction of state level regulations and the number of physicians and hospitals per capita. Despite the issues with prior estimates, they still appear reasonable but are generally smaller than the two demand elasticities I estimate.

1.3 Data

The data I use consists of county level quantity, price, and the number of firms aggregated to a metro-area, data on state laws including the timing of their implementation, as well as other data sources which will be used to capture differences in demand across markets. The quantity, price and firm data are reviewed in more detail below, followed by the state laws. The final subsection deals with concerns surrounding policy endogeneity. The other data and their sources can be found in Table 1.2 in the Appendix.

1.3.1 Abortion Providers

The data are drawn from the Alan Guttmacher Institute(AGI) Survey of Abortion Providers, a periodic survey of all known abortion providers in the United States which began in 1973.[25] The survey began as an annual survey through 1988, with missing years in 1983 and 1986, and was conducted less frequently after 1988.[26] This survey constitutes the best estimates available for the incidence of abortion in the

[25] The best description of the survey can be found in Henshaw and Van Vort (1994). To gather data AGI contacts all known providers from prior surveys, dropping those who closed or no longer offered abortion services, and includes questions about other providers in the local area and well as conducting phone book searches. Other listings used include the National Abortion Federation(NAF), Planned Parenthood and The National Abortion Rights Action League(NARAL), a national newspaper clipping service, and Internet listings in later years. Beginning in 1992 AGI purchased commercial mailing listings relevant to abortion providers to expand their efforts to include all providers. Establishments not responding were followed up with phone calls, up to a dozen times in some cases. Some state health departments also keep records on establishments which were used for non-responders when available. Henshaw and Van Vort (1994) estimate they recorded at least 97% of the abortions conducted in 1992, with the potential missing abortions occurring at physicians offices and hospitals who provided very small numbers of abortions.

[26] After 1988 the survey was conducted annually for 2 consecutive years, followed by 2 years without a survey, so data exist for years 1991-92, 1995-96, 1999-00, and 2004-05.

U.S. over the period of time[27] and the only panel data on abortion markets.

I use an extract of the file in this paper which includes information on the total number of providers and procedures by the type of provider along with some price data. The three types of providers established in the survey are hospital abortion providers(hereafter referenced as H), non-hospital providers who provided more than 400 procedures(L), and non-hospital providers performing fewer than 400 procedures(S) in one calendar year. The group of larger clinics includes but is not limited to Planned Parenthood affiliated clinics. The smaller providers include both physicians offices and non-specialized clinics which were known to provide abortions. I observe the number of firms in each category, along with the total number of abortions performed by all of the firms in a category. I do not observe firm specific quantities.[28] The number of procedures includes all abortions at all gestations performed in each calendar year by the provider.

Price data are less frequent than the quantity data, with questions about patient charges included every 3-5 years beginning in 1981 and only observed for non-hospital abortion providers.[29] The price observed most frequently is the mean county charge for a non-hospital procedure at 10 weeks gestation with local anesthesia. This price is intended to capture the cost anywhere during the first trimester, the time during which almost 90% of abortions were preformed.[30] Also observed is the standard deviation within county and the number of respondents to the pricing questions[31].

[27] The Centers for Disease Control maintain information on the number of abortions by state but data are provided voluntarily by states and after 1997, not all 50 states provide data. Mentioned in Henshaw and Van Vort (1994), the largest difference between AGI and CDC data was in 1977 and 1978 when CDC reported 22% fewer abortions. In 1992 that figure was 12%.

[28] For counties with fewer than 4 total providers the number for firms is censored, but the number of abortions by each type is observed.

[29] Price data years are 1981, 1984, 1987, 1991,1996, 2000, and 2005.

[30] See Table 1.1.

[31] This is the number of non-hospital respondents, this number does not delineate between small and large providers

Since the reports published by AGI for the length of the period showed that smaller clinics charged higher prices, I assume that within each county there is a mixture of distributions of prices of both types of providers present. With these assumptions and the information on the mean, standard deviation, the number of respondents and knowledge of the fraction of large providers from the firm data, I back out two observed prices for each county. These two prices serve as estimates of the mean of a low price and a high price distribution. I use these two prices as a clinic and non-clinic price respectively, given the absence of information on hospital prices and the similarity between private physicians offices and outpatient hospital procedures.[32] The details of the procedure used are explained in the Appendix.

Sample statistics of the data are described in more detail in Table 1.3. The observations in each are metropolitan and micro-politan statistical areas(M/MSA's) as defined by the Office of Budget and Management.[33] In 2005 there were 935 such M/MSA's. If I remove observations with missing data, 865 such locations remained; there were on average fewer than 4000 per year abortions reported in the areas I drop, on average accounting for 0.29% of the abortions preformed per year.[34] The top panel shows the trends in the overall entry and exit within the metro and micro statistical areas. Entry occurred en mass among all the types of firms during the 1970's, but as outlined before, hospitals generally exited first, followed by a wave of exit among smaller providers. The share of total procedures shows that the occurrences of exits

[32] Although this assumption is less than ideal, reports from the 1970's through the early 1980's did show rising rates of outpatient procedures for hospital abortions, with outpatient procedures being in the majority by the early 1980's. Hospital prices especially later in the period will be measured with error, especially for more complicated procedures, but it is also the case that the inputs and to non-hospital and hospital abortions are very similar, and the procedure used(curettage) is the same in both, even in after 21 weeks of gestation.

[33] If Metropolitan Areas grow over time, I include all counties which were ever part of the MSA in the market definition

[34] BEA income and other data sources(especially health services sector) had missing information for small micro-politan areas in the 1970's and early 1980's.

coincided with a concentration of services at larger providers and as mentioned in the introduction, the smaller and hospital providers were likely providing more differentiated services by the end of the period. Also presented in the final panel are the prices, observed and imputed, over time in 2005 constant dollars. Again, consistent with exiting smaller providers, we see prices rose over time while essentially staying constant for the large providers.[35]

1.3.2 State Laws

State level regulations from 1973-2005 have taken a variety of forms. Most recently, regulations termed TRAP(Targeted Regulation of Abortion Providers) laws have been passed. Along with TRAP laws many states have physician and license requirements, as well as regulations of later term procedures requiring they be performed in or around hospitals. While the text of these laws varies from state to state, I have categorized these state regulations into six major divisions, restricting attention to those laws which are effective (i.e. not subject to permanent judicial stay or overrule), or those which if overturned or stayed, were in effect for at least one year. The primary source for these regulations are the National Abortion Rights Action League (NARAL) state report cards, which generally include the legislative codes and relevant judicial histories. Some dates of enactment or revision were unclear and so I followed up on these cases by examining the state legislation or health code as necessary. The results are compiled into Table 1.4 which excludes the seven states and Washington DC which had no such regulations over the time period, although these ares are included in estimation.

[35] Though there is an increase in large provider prices by 2005, the 2000 prices not shown here are similar to 1996 and 1984, suggesting the rise is due to the presence of medical abortion being included in the reported data. Medical abortion can cost more since it usually requires multiple visits, and can require follow-up surgical procedures in some cases. Another argument is that large providers achieved scale economies in surgical abortions, and introducing the new technology lead to higher prices charged by large providers.

States often impose license requirements on abortion providers in two forms. The first column denoted “License” refers to the state requirement that any organization performing abortions must be licensed by that state in order to do so and generally must pay an accompanying annual fee. The fee charged for obtaining a license varies from state to state but was unobserved for many states and so is not used in the analysis.[36] In some cases, the license requires facilities to meet the license requirements of an outpatient surgical facility. The second column of Table 1.4 contains the dates of enactment of laws restricting the performing of abortions to only those physicians who are licensed to practice medicine within the state. Again, there may be some difference in the law between states since some laws reference medical licenses within the state directly and other laws are ambiguous as to the state of medical license.[37] Combined in the physician laws are restrictions on nurse practitioners and physicians' assistants performing abortions, an issue that when combined with the introduction of non-surgical abortion appears to have been a factor leading to the reversal of these laws in two states.

Provider regulations that involve various hospital requirements have also been enacted. In columns 3-5 of Table 1.4, these restrictions are grouped together. The requirement that second trimester abortions be performed in hospitals has been rejected as unconstitutional and many states have passed laws to move the requirement beyond the 12 week hurdle determining the trimester. Included in this group are laws which specifically require those facilities who perform second trimester abortions(beyond some specified point) to be licensed as free standing ambulatory surgical centers. The hospital location and agreement laws require that either an abortion

[36] The nominal fee is likely just one part of economic costs which providers must pay to obtain the license, such as record keeping and filling out applications, (which is often specifically mentioned in the statutes).

[37] Especially in states with non-reciprocal medical license these laws may represent large fixed costs to entry or exit.

provider be located within a certain distance or travel-minute radius of a hospital, or that the provider have a written agreement with the hospital specifying the care to be provided by the hospital on the occasion that emergency care is necessary for the providers' patients.

The final group of restrictions I have termed "Physical and Administrative." These restrictions take a variety of forms but generally require providers to make some explicit capital or labor expenditure. This can take the form of ultra-sound machine requirements or regulations of the size of the procedure room, facility, hallways, parking lot and/or waste disposal(e.g. AK, SC). Another element of these laws involves the hiring of certain staff: medical directors for each facility who have a certain level of experience and maintain OB/GYN board certification(e.g. AL) and counselors or social workers with graduate degrees in certain subfields(e.g. CT). Some laws also allow for unannounced inspections by state officials and fines for non-compliances.[38] These laws have generated the most controversy and publicity, as they place clear burdens on providers and may play an important role in altering the fixed costs of entry and operation.

1.3.3 Policy Endogeneity and Reduced Forms

A major concern in understanding the role that state level policies played in the determining the costs of firms and the observed industry structure is that policies may not be exogenous. If for instance, unobservable resentment or disapproval of abortion in society were declining prior to a policy being enacted, one would worry that an observed effect of the policy on the abortion market is due to the unobserved resentment and not the policy. To verify that the policy changes are not being driven by changing unobservables, I regress the enactment of each of the policies

[38] The Missouri law has had the elements relating to unannounced inspections placed under injunction.

on the full state vector and the log of lagged total abortions in markets where there were any abortions prior to a policy change. The results are presented in Table 1.5. The results indicate that without controlling for the vector of market specific information license laws, requirements on second trimester procedures, and physical or administrative requirements are all predicted by abortions in the prior period, suggesting that enactment is a policy response to increases abortion. Waiting period and public funding laws show a similar relationship to lagged procedures. However, controlling for the state vector all the policy coefficients shrink to some extent and none remain significant. This means the state vector, which includes state specific trends, at least by this measure controls for much of the unobserved sentiment or policy response.

Table 1.6 contains coefficients from the policy impact on the log of abortions for different types of providers. I included in this sample all market-years who had all types of providers. The results suggest the importance of examining not just the response of total abortions to policy changes but also the impact for different types of firms. The different signs for some policies in columns 2-4 suggest the importance of understanding how firms interact in these markets. For example, the policy on providers maintaining agreements with hospitals, titled "Agreement with Hospital" appears to increase demand for hospitals, with negative and significant effects for small non-hospital providers. This finding is consistent with shifts in the provision of later term abortions to hospitals where and when this regulation is in place. To capture total effects requires an understanding of the marginal and fixed costs, and related prices, all of which may be different for small providers and hospitals. A number of the policies show significant negative effects on the type-specific quantities. However, these regressions focus on policy influences in markets with all types of providers, not on the number of establishments in the market. To help separate out effects, I estimate the effects on prices as well as entry and exit likelihoods in Tables 1.7 and 1.8 respectively. Table 1.7 uses the two prices discussed above, one for small providers and another for larger clinics. When I include state and MSA-level fixed effects the results still show that a number of the policies positively affected both observed prices.[39] Table 1.8 also displays evidence that policies influenced firm decisions about entry and exit. I estimate probit models of the likelihood of market-years seeing entry and exit, which importantly does not deal with the intensive margin of entry and exit, the complications of which are delayed until I discuss the formal model.[40] The top panel shows that small providers especially appear to be influenced by changes in policy and the bottom panel indicates that the tightening of license regulations leads to an increased likelihood of smaller firms exiting the market.

Overall, it appears that policies had an impact on both prices and therefore marginal costs, and on entry. Evidence indicates that these impacts are distinct from the preexisting trends in the number of abortions. The fact that policies shift prices will be exploited as an instrument to improve on prior estimates of the price elasticity of abortion. The model put forward in the following section will allow us to separate the impacts of policies on the costs and entry, exit and production, and to deal with the number of entering and exiting firms.

1.4 Model

My motivation for the model proposed here is mainly empirical: understanding how fixed and marginal costs are influenced by regulation. To do so I adopt the framework of Ericson and Pakes (1995) which has been studied in detail, meaning we know what

[39] The fact that hospital agreements appears to have lowered large clinic prices is consistent with the shifting of later term, higher cost, procedures to hospitals in presence of this policy.

[40] Count data models of the number of firms showed similar policy effects, but differences in costs between entrants and incumbents motivates focusing on entry and exit.

conditions are required for equilibrium to exist in pure strategies and that the model is tractable enough to estimate. This strategy entails breaking apart the static decisions from dynamic decisions to aide in estimation. Here I assume production occurs in a static game, meaning I abstract away from investment and capacity, an assumption made more plausible by there nature of this services sector. The production game is assumed to be in quantities because of the lack of price data discussed above. For the same reason I assume firms engage in Cournot competition; another reason for this assumption is that the model must explain behavior in markets with many firms and few firms. With better data on prices one could gain better estimates of markups, and a better understanding of how competitive this market is; without such data, the focus is on how regulation affects costs as identified by the data available. In the first stage marginal costs of the model will be identified by variation in the quantity of abortions and in the cost vector (which includes regulations) over market-years. Fixed costs are identified from changes in the number of firms of each type, controlling for the first stage estimates of profits today and in the future.

1.4.1 Production

To capture some of the differences in the types of producers I assume firms compete in Cournot quantities in a differentiated services market.[41] In the demand side of the model large(L) providers consists of non-hospital providers who perform more than 400 procedures and small(S) providers are both smaller non-hospital clinics or offices and hospital providers. Within a particular market j, firms in the two groups face a

[41] Firms, providers, and establishments all used through refer to establishments, or singe physical locations at which abortions take place. Large providers and non-profits and their networks are discussed in more detail later in this section.

demand system of the following form: [42]

$$\log(Q_j^s) = a_j^s - b^s \cdot \log(P_j^s) - b^l \cdot \log(P_j^l)$$
$$\log(Q_j^l) = a_j^l - c^s \cdot \log(P_j^s) - c^l \cdot \log(P_j^l) \tag{1.1}$$

where (a_j^s, a_j^l) are market specific factors accounting for differences in the demand for abortion from the two groups of providers. The parameters (b^s, c^l) are the own-price elasticities providers face, and (b^l, c^s) capture the effect of other group-prices on provider demand. Here I assume hospitals and small non-hospital providers receive the same price and combine to determine the quantity $Q_j^s = Q_j^S + Q_j^H$.[43] Assuming that firms engage in Cournot competition for abortion services in each market, profits for firm i of type k take the following form:

$$\pi_{ij}^k = q_{ij}\left(P_j^k(Q_j^k, Q_j^{-k}) - MC_j^k + \varepsilon_j^k\right), \tag{1.2}$$

where type takes on three values (L, S, H) corresponding to large non-hospital providers, small non-hospital providers, and Hospital providers. Observed marginal costs differ across markets and types within a market and ε_j^k is a market-type specific productivity shock the log of which distributed $N(0, \sigma_k)$.

Taking the first order conditions for the case of a small provider above gives rise to the following:[44]

$$P_s - \frac{q_{ij}}{b_s}\frac{\partial P_s}{\partial q_{ij}} = MC_j^t - \varepsilon_j^t \tag{1.3}$$

[42] Markets with only one group present(g=s,l) are assumed to have demand: $\log(Q_j^g) = a_j^g - b^g \cdot \log(P_j^g)$. An indicator for belonging to such a market is included in the a_j^g term during estimation

[43] As noted in the data section hospital fees are unobserved, but in surveys containing information on all charges(Jones et al (2008)), these are generally similar to smaller provider charges. One could reinterpret the composite good as a more medically sophisticated or differentiated service than what a larger clinic generally provides.

[44] An analogous set of equations holds for the other types $t = L, H$, and a simplified pricing equation is substituted for markets with only one group: $P_s = e^{a_s/b_s} Q_s^{-1/b_s}$ and $P_l = e^{a_l/c_l} Q_l^{-1/c_l}$.

where the price P_s received is a function of their own and rival production and is given by:

$$P_s = \left(e^{a_s/b_s} Q_s^{-\frac{1}{b_s}} (e^{a_l/c_l} Q_l^{-\frac{1}{c_l}})^{-\frac{b^l}{b^s}}\right)^{\frac{b^l c^s}{b^l c^s - b^s c^l}} \tag{1.4}$$

where

$$\begin{aligned} Q_s &= q_{ij} + \sum_{k \neq i}^{N^H + N^S - 1} E(q_{kj}) \\ Q_l &= \sum_{k=0}^{N^L} E(q_{kj}). \end{aligned} \tag{1.5}$$

Given the lack of information on firm identity, I am unable to link quantities with firms. Therefore I adopt a symmetric equilibrium within each market-type. Under this assumption the symmetric Cournot expectations are simplified to:

$$\begin{aligned} Q_s &= q_j^s N^S + E(q_j^h) N^H \\ Q_l &= E(q_j^l) N^L. \end{aligned} \tag{1.6}$$

where the expectation is removed before production choices are made, under the assumption that ε_t is common information for all firms within the market.

1.4.2 Entry and Exit

In this stage of the model, an incumbent firm i makes exit and production decisions(denoted $d_{i,t}$) each period to maximize the discounted sum of future profits give by(suppressing firm-type and market subscripts):

$$\begin{aligned} &\max_{d_{it}} \;\; \pi(q_{it}, s_t) - FC_t + \eta_{it}^d + \\ &\quad + E\left(\sum_{\tau=t+1}^{T} \beta^{\tau - t} (\pi(q_{i\tau}, s_\tau) - FC\tau + \eta_{i\tau}^d) p(s_\tau | s_{\tau-1}, exit_{i\tau-1} = 0) \right) \end{aligned} \tag{1.7}$$

where the value from exiting in each period is $\pi(q_t, s_t) - FC_t + \eta_{it}^{d_1}$ and $p(s_\tau | s_{\tau-1}, exit_{i\tau-1} = 0)$ the probability of transition to each state s_τ conditional on the firm deciding to stay in period t. Profits accrue to firms operating and they also must pay a fixed cost to operating in each period denoted FC_t. Unobserved profits in each period are denoted by $(\eta_{it}^{d_0}, \eta_{it}^{d_1})$ which are distributed i.i.d. Type I Extreme Value. The state vector s_t captures the demand and other firm behavior in period t. Given the assumptions outlined in Rust (1987) of additive separability and additionally the conditional independence of s_t and η_{it}^d, the firm problem can be re-written via the Bellman equation:

$$V_t(s_t, \eta_{it}^d) = \max_{d_{it}}(v_t(s_t, d_{it}) + \eta_{it}^d) \tag{1.8}$$

where the choice specific value function takes the form:

$$v_t(s_t, d_{it}) = u(s_t, d_{it}) + \beta \int \int_{s_{t+1}} V_{t+1}(s_{t+1}, \eta_{it+1}^d) p(s_{t+1}|s_t, d_{it}) dF(\eta_{it+1}^d). \tag{1.9}$$

Given the generalized extreme value(GEV) structure of the error terms, one can substitute a closed form for the expected value of facing the choice set in the future:

$$\begin{aligned} &\int \int_{s_{t+1}} V_{t+1}(s_{t+1}, \eta_{it+1}^d) p(s_{t+1}|s_t, d_{it}) dF(\eta_{i,t+1}^d) = \\ &\int_{s_{t+1}} \log\left(\sum_{d=0}^{1} e^{v_{t+1}(s_{t+1})}\right) p(s_{t+1}|s_t, d_{it}) + \gamma \end{aligned} \tag{1.10}$$

With this substitution, one can re-write the firm problem as a simple binary decision in each period with firms deciding to exit($d_t = 1$) by comparing the following payoffs:

$$\begin{aligned} V(s_t, d_t = 0) &= \pi(s_t) - FC_t + \eta_t^{d_0} + \\ &\beta\left(\int \log\left(\sum_{d_{t+1}=0}^{1} e^{v_{t+1}(s_{t+1}, q_{t+1}, d_{t+1})}\right) p(s_{t+1}|s_t, d_t = 0) + \gamma\right) \end{aligned} \tag{1.11}$$

$$V(s_t, d_t = 1) = \pi(s_t) - FC_t + \eta_t^{d_1}$$

where γ is Euler's constant and the CCP substitution will eliminate the recursion in (1.11) and further simplify the estimation. I outline that substitution in Section 1.5.

The inclusion of the fixed costs of operation in the model is important in this particular context. A maintained assumption throughout the discussion thus far is the separability of abortion services and any other (unobserved to the econometrician) services in the firms' profit functions. These services clearly exist for hospital and non-specialized providers, but may also exist for specialized clinics, who often provide birth control and other family planning services alongside abortion services.[45] As abortion services may be subject to particular opposition, it seems clear that abortion procedures while providing a direct source of revenue, may also cause controversy, leading to possible picketing or boycotts. It is conceivable then for certain firms in certain places to gain from leaving the abortion market and avoiding any negative effects such activities might have on demand for other services. These gains will be captured in the estimates in FC being positive. The gains from providing abortion services beyond direct revenue impacts would be reflected in FC being negative.

The problem for potential entrants is very similar to that for incumbents outlined above. The only major differences are that entering firms pay a different fixed cost in the entry period and do not engage in production until the following period. This structures gives rise to potential entrants facing the following two payoffs when considering whether or not to enter:

$$\begin{aligned}
&V(s_t, e_t = 0) = \eta_t^{e0} \\
&V(s_t, e_t = 1) = \\
&= FCE_t + \eta_t^{e_1} + \beta\left(\int \log\left(\sum_{d_{t+1}=0}^{1} e^{v_{t+1}(s_{t+1}, q_{t+1}, e_{t+1})}\right) p(s_{t+1}|s_t, e_t = 1) + \gamma\right)
\end{aligned} \tag{1.12}$$

[45] The Planned Parenthood Federation of America 2006-2007 Annual Report outlines the services distribution.

where FCE captures the fixed costs of entry associated with beginning the provision of abortion services. How FCE varies with supply side regulations is a key parameter vector of interest.

1.4.3 State Space and Equilibrium

Equilibrium strategies for firms consist of production, entry, and exit choices in a given period. Following the work of Bajari, Benkard, and Levin (2007), I assume firms play Markov-perfect pure strategies, which are also symmetric and anonymous.[46] Formally the strategy σ_i for a firm is a function $\sigma_i : S \times E \mapsto (q_i, enter_i, exit_i)$, where S is the current state, E is the vector of current shocks, and $(q_i, enter_i, exit_i)$ are the quantity, entry and exit decisions in the current period. The existence of private information shocks in the model, the η terms in the entry and exit equations, is shown in Doraszelski and Satterthwaite (2007) to be necessary to ensure the existence of a pure strategy MPE in a dynamic model of entry and exit with investment.[47] Aguirregabiria and Mira (2007) set forth the assumptions which identify the model in the presence of multiple equilibria, which do exist even in simple models as shown in Doraszelski and Satterthwaite (2007). I maintain the Aguirregabiria and Mira (2007) assumption, that the same equilibrium is played in all markets.[48]

The state space discussed throughout includes the number of firms of each type of provider within the market, along with a set of observable market level characteristics including total population, density, income, and the variables measuring the religious composition of the population. Also included in the state space are the state in which the provider operates and the calendar year. The observable market characteristics are

[46] Symmetry here is within each type of firm. Although this enlarges the state space considerably, the distinction between firm types is essential for describing abortion providers' behavior.

[47] Without the inclusion of private information, scrap values and setup costs, firms are induced to play mixed strategies when the equilibrium exits.

[48] In order to relax this assumption in estimation one is required to know which equilibria are played in each market.

especially relevant given the large variation in demand for abortion across markets. Due to the size of the state space, these observable variables' transitions are be assumed known by providers from one period to the next.[49]

Finally the timing of decisions in the model follows Doraszelski and Satterthwaite (2007) and Ryan (2005) fairly closely.

- Each incumbent and potential entrant receives a set of private information draws, η. Firms observe the current number of firms of the three types operating in the market. Incumbents and entrants make simultaneous choices over entry and exit.

- Firms receive their type-specific productivity shocks and engage in simultaneous quantity competition.

- Incumbent firms exiting leave the market, potential entrants entering join the market.

- The state vector adjusts to reflect any (net) differences in the number of competitors from entry and exit.

So firms leaving the market still produce in the current period and exit only after production, while entering firms sit out the current period and enter after production. Firms here are making production choices without knowledge of their competitors of different types. Since the productivity shocks are independent firms do not attempt to learn about rivals' productivity from one period to the next.

[49] The one period ahead assumption is all that is required given the absorbing state assumption. Another alternative is to collapse these demand shifters into a single demand index using the coefficients from the first stage regressions.

1.4.4 Non-Profit Activity

Although I do not observe non-profit/for-profit status in the data, it is nonetheless an important consideration in understanding the results. I use the framework put forward in Lakdawalla and Philipson (1998) to understand non-profit and for-profit interactions. Although there are many ways to model non-profit behavior, a straightforward approach is to view non-profit producers as maximizing a combination of profits and quantities. This stems from the notion that (1) non-profits are interested in providing the service for its own value, or some non-monetary value, and (2) the decision to operate as a non-profit is itself a strategic one, induced by different tax status, which requires profits be directed in a certain matter, not that profits cannot be earned. Such a setup is straightforward given the quantity stage game already outlined. A non-profit firm will maximize the following:

$$U_{ij}^k = \alpha q_{ij} + (1-\alpha) q_{ij} \left(P_j^k(Q_j^k, Q_j^{-k}) - MC_j^k + \varepsilon_j^k \right), \tag{1.13}$$

where α is the parameter of non-profit interest in providing services for their non-monetary value, U is the organizations' utility function. Note that utility can be rescaled by $(1-\alpha)$, therefore this formulation implies the non-profit first order condition takes the form of:

$$P_s - \frac{q_{ij}}{b_s} \frac{\partial P_s}{\partial q_{ij}} = MC_j^k - \frac{\alpha}{1-\alpha} - \varepsilon_j^k \tag{1.14}$$

Importantly this means that under the assumed utility function, most of the non-profit marginal cost parameters are still identified by variation in the marginal cost shifters, but the intercept in the MC vector will be biased. All the MC parameters will be biased only if the degree of non-profit concern(α) varies with quantities or the marginal cost shifters.

For the problem at hand, it is important to note that only the large type firms contain significant numbers of non-profit producers. While certainly hospitals in the data file tax status as non-profits, the relevant dimension here is whether they provide services and continue to do so in excess of marginal costs. Give the industry dynamics showing so many hospitals leaving the market, this seems unlikely. The major concern in the estimation then is the intercept for large providers.[50] Another issue is whether national organizations like Planned Parenthood engage in profit sharing among their affiliates, which would influence the relationships assumed in the model between producing and the costs of doing so. Recent annual reports from Planned Parenthood indicate this is not the case, with revenue flowing the opposite direction and the national organization providing some services to local affiliates.[51]

1.5 Estimation and Results

1.5.1 Recovering First-Stage Parameters

The first parameters necessary in the estimation of production parameters are the demand elasticities. As outlined above there has been variation across time and locations in abortion prices, but a major concern with OLS regressions is simultaneity resulting from equilibrium in the market. For this reason I instrument for prices in the following system:

$$\begin{aligned}\log(Q_j^s) &= b^s \cdot \log(P_j^s) + b^l \cdot \log(P_j^l) + X_j^s \beta_s + \nu_j^s \\ \log(Q_j^l) &= c^s \cdot \log(P_j^s) + c^l \cdot \log(P_j^l) + X_j^l \beta_l + \nu_j^l\end{aligned} \tag{1.15}$$

where the price elasticities and demand indices β are the parameters of interest. The the set of instruments will include the interaction of various supply side regulations

[50] The estimates of marginal costs appear to confirm this prediction: the large provider mean MC is very small relative to other providers. It seems unlikely that economies of scale account for all of this difference.

[51] Based on calculations from Planned Parenthood balance sheets in 2007, affiliates(as distinct from the national organization which performs no abortions) received only 19.1% of their income from donations.

with state level physicians and hospitals per capita and the ratio of physicians to hospitals. Controlling for other market specific demand shifters, the X_s, X_l will be important in reducing the bias present in the elasticity estimates, these terms include state fixed effects to help deal with unobserved market characteristics.

The results are presented in Table 1.9, estimated with instrumental variables and standard errors clustered at the state level.[52] The sample consists of MSA-level prices for seven years beginning in 1981 and ending in 2005.[53] The estimates presented are larger than the prior work on price elasticities (around -1.0) which were estimated with the data aggregated to the state level and used clinics in the state as an instrument. The data here essentially allow for estimation of clinic and non-clinic elasticities which proves to be informative.[54] The own price elasticities are similar and the cross price elasticities are not significantly different from zero. The two prices are highly correlated and the inclusion of other prices in markets with more than one price is import for the results. This is consistent with what we know about how the firms operate, employing essentially the same inputs to perform procedures at different gestations.[55] The fact that the cross-price elasticity is negative for small providers is

[52] The IV estimator is used to obtain estimates of the state fixed effects. I use Two-step Generalized Method of Moments(the most efficient estimator) for model selection and specification testing, but two-step GMM estimation requires partialling out the fixed effects to estimate the optimal weighting matrix. The two methods yielded similar results.

[53] Markets with only one price are included in the analysis and an indicator for these markets is included to help deal with the bias created by this approach. Experimenting with dividing the sample showed there are two few single-price markets to precisely estimate different sets of elasticities.

[54] Proxying for clinics with large non-hospital providers and non-clinic prices with small non-hospital prices.

[55] I also estimated different elasticities after 1990 to test whether elasticities have changed over time. The later period interactions were insignificant and the point estimates presented essentially stayed the same. To be clear, elasticities may have changed, but with instruments available there is not evidence for this. On a related note, if regulations changed the actual service being provided, say by making it safer, we would expect possibly different elasticities in areas with certain regulations. I estimated these models and again they did not show any significant differences in the elasticity estimates. However instrument strength is a major concern when estimating one regulation interacted with price on other regulations interacted with health care market characteristics. There is likely simply not enough information in these price data to meaningfully distinguish the extent of

consistent with women demanding services at these providers making choices based on the average price observed in the market. The included and excluded instrument sets differ slightly given the different geographic characteristics of locations with the two types, the list is included in the footnote of Table 1.9.

In addition to the log-price coefficients, Table 1.9 reports the estimates of the impact of demand-aimed restrictions on the log-quantity of abortions. Interestingly the only regulation that appears to change quantities are parental consent laws, which I distinguish from parental notification laws. The null result for the other laws is consistent with the literature addressing the policy effects which are summarized in Medoff (2007). Indeed the only policy effects confirmed by the literature are on minors' abortion ratios. However the insignificance in prior studies generally appears when adding state-specific trends to regressions with state fixed effects, where the unit of observation is at the state level. In contrast, the quantity-price regressions in Table 1.9 find insignificant coefficients with only state fixed effects, a large vector of controls, and MSA-level data. This result suggests that the inclusion of detailed ethnic and religious composition variables is important to finding policy effects[56] and confirms from a different source of variation (across-MSA) the null result in the prior literature.[57]

An important concern here is the strength of the instruments used. Evaluating the strength of instruments in the presence of multiple endogenous variables is still an important active area of research. Following the work of Stock, Wright, and Yogo (2002) as well as Kleibergen and Paap (2006), I have reported Kleibergen-Paap Wald statistics in the table which are computed when errors violate the i.i.d. assumption.

differentiation of the service induced by the regulations.

[56] Table 1.9 does not include state trends because the instrument variation, hospitals and physicians per state, are imputed for missing years with state linear-trends.

[57] This result persists even when I drop prices from the regressions, which expands the sample since price data limit the number of observations.

Unfortunately the limiting distribution of this statistic is not easily computed, but as a guide the table includes the critical values from the Craig-Donald Wald statistic (computed under i.i.d. errors). The values are near the rule of thumb of ten proposed by Staiger and Stock (1997), but in general the inclusion of state fixed effects creates a trade off for small providers, between the strength of the instruments and desire to deal with state specific unobserved demand. This arises because the instruments are measured only at the state level. To help mitigate the worry that the elasticities contain a significant amount of weak instrument bias, I also estimated models with only region fixed effects. The elasticity estimates for smaller providers were quite similar across both specifications, but the own price elasticity for large providers was larger with region fixed effects, highlighting the importance of the unobserved state specific factors in estimating the elasticities for larger providers. Accordingly, I use the state fixed effects models going forward in estimating per period profits and the entry and exit costs.

Another issue in estimating the elasticities is whether the presence of price discounting affects the elasticity estimates. I include factors d_{jst} as discount proxies which are related to the likely discount occurring in the market. Another set of series occasionally published in AGI reviews are the level of state expenditures on abortions and family planning services respectively. Additionally, Kaiser Foundation reviews indicate that the likelihood of private insurance coverage is strongly related to firm size. Firms with greater than 200 employees are twice as likely to have insurance policies which cover abortion in some cases. Included in Table 1.9 are regressions of the model with the added discount proxies. It appears that family planning expenditures influence the extent to which abortion occurs at small providers, consistent with other forms of birth control being one dimension of substitution. Although not shown here, the first stage showed the ratio of abortions funded by the state to the MSA estimate of the population was negatively (although only significant at the 10% level) related to prices at non-clinic providers and positively and significantly related to clinic prices. This result is consistent with clinics making pricing decisions strategically. The elasticity estimates do not change significantly in the presence of the proxies, lending support to the notion that those receiving full subsidies are the infra-marginal consumers.[58]

1.5.2 Recovering Production Costs

The next step in estimation is to manipulate the first order conditions of the firms' problem to estimate the marginal costs of production. In a market with both types of producers, the first order conditions take the following form for small providers and hospitals:

$$P_s - \frac{\partial P_s}{\partial Q_s} q_t = MC^k - \varepsilon^k \tag{1.16}$$

where

$$\frac{\partial P_s}{\partial Q_s} = -\frac{K}{b_s}[e^{a_s/b_s}(e^{a_l/c_l}(Q_l)^{-1/c_l})^{-b_l/b_s}]^{K-1} Q_s^{-1/b_s - 1} \tag{1.17}$$

where $K = \frac{b_l c_s}{b_l c_s - b_s c_l}$, q_t is the observed (symmetric) number of services performed by producers of type t, and $E(Q_l)$ is the expected number of services performed by large providers. With the parameters on the left side of equation (1.16) already estimated, one can redefine the left hand side as known transformation of the observed equilibrium quantities for providers of each type. The left hand side of (1.16) is the marginal revenue. Therefore, given that ε^t is log-normally distributed, the log of marginal revenues can be regressed on the marginal cost vector to recover the parameters. The results of this estimation are presented in Table 1.10.

[58] Unfortunately the data on the family planning funding proxies does not exist prior to 1980, so I proceed without these series, using the elasticity estimates from the left side of Table 1.9.

The upper panel of Table 1.10 captures the impact of state regulations on abortion providers which can be distinguished from state specific trends in the marginal revenues from abortion services. For small providers, only license requirements positively and significantly increased marginal costs, while administrative requirements appear to have decreased marginal costs, consistent with the substitution toward smaller providers. For larger providers marginal costs were largely unaffected, with the exception of second trimester hospitalization laws reducing costs, consistent a shift toward hospital provision of later term abortions. Finally, hospitals' marginal costs were increased by the requirement that after some point in the second trimester, all procedures must be performed within a hospital. The laws which specifically mention a gestation week were included in this group and these laws often include other clauses such as a double diagnosis from two different physicians or a required ultrasound and review of the results.

The most important cost shifter included is an indicator that the year is greater than 1999, when medical (prescription) abortion became available in the U.S. This significantly reduced marginal costs of service provision for hospitals and small providers and raised marginal costs for large providers.[59] This result could be due to large providers attaining scale economies in surgical abortions, and after 1999 having to provide abortions which although lower cost than other providers, are still high relative to their specialization. Note the mean marginal cost is lowest for large providers in the final row of Table 1.10. The state level medical market variables, hospitals and physicians, strongly influence marginal costs in expected ways: when the physician pool is larger we see lower prices, as the number of hospitals increases this likely pulls physicians out of abortion provision, raising marginal costs. The large city indicator is for metro areas with more than 3.5 million people and suggests the difficulty larger

[59] This indicator produces a biased toward zero estimate of true impact of medical abortion on marginal costs given the rising costs of health care after 1999.

providers being able to meet their labor input needs in cities smaller than this size.

1.5.3 Recovering Entry Costs and Exit Payoffs

To estimate the parameters of the entry and exits costs, I begin by estimating a reduced form of the probability of entry among potential entrants and exit for incumbent firms. Given the structure of the data, these two probabilities combine to create the observed number of firms and so the likelihood expression takes a fairly complicated form. This results from a lack of observation of firm identity, so I cannot know from observing the total number of firms which firms are new entrants and which have been operating in the market. However the probability of entry (potential entrants) and staying in the market (incumbents) is identified from variation in markets with the same current number of firms and different number of firms in the preceding and proceeding periods. Reduced forms take the following form:

$$\begin{aligned} Entry_i &= 1(X\zeta_E + \epsilon_i^E) \\ Exit_i &= 1 - 1(X\zeta_I + \epsilon_i^I) \end{aligned} \tag{1.18}$$

where $(\epsilon_i^E, \epsilon_i^I)$ are firm level unobservables distributed i.i.d. logistic. For each market there are a set of possible entrants and incumbents who combine to determine the number of firms in the next period. The pool of potential entrants is scaled to the population size since the data encompass large markets with many entrants as well as smaller markets with local monopolies.

The likelihood of observing a particular number of firms of each type is given by a logit mixture distribution, which is limited in each particular market by either the number of potential entrants or the number of incumbent firms, depending on the prior state of the market. The log-likelihood takes the following basic form (suppressing market and type subscripts):

$$\begin{aligned}
&\sum_{j=0}^{Max}\binom{N_{t-1}}{\min(N_t,N_{t-1})-j}\binom{N_p}{\max(N_t,N_{t-1})-\min(N_t,N_{t-1})+j}\cdot\\
&\quad\ldots\cdot(1-P_I)^{\max(N_t,N_{t-1})-\min(N_t,N_{t-1})+j}P_I^{\min(N_t,N_{t-1})-j}\cdot\\
&\quad\ldots\cdot(1-P_E)^{N_p-\max(N_t,N_{t-1})-\min(N_t,N_{t-1})-j}P_E^{\max(N_t,N_{t-1})-\min(N_t,N_{t-1})+j}
\end{aligned} \tag{1.19}$$

where N_p is the number of potential entrants, P_I and P_E are respectively the probabilities of an incumbent staying and an entrant entering, and N_t is the number of firms in the market at time t. The term Max takes on different values depending on whether the market is in one of four states: (1) the number of firms today and yesterday is the same and less than the number of potential entrants, (2) the number is the same and greater than the number of potential entrants, (3) the number of firms today is greater than yesterday and (4) the number of firms yesterday is greater than today. The likelihood takes this complex form because the number of entrants can be greater than one.[60]

Given the estimates of ζ which come from maximizing (1.19), one can compute the transition probabilities $p(s'|s)$ mentioned above as well as the one-step ahead probability of exiting which can be exploited to simplify the future value terms in (1.11) and (1.12). Under any generalized extreme value (GEV) error distribution there exits an equivalence between the expected value of making a choice in the future and the probability of exit. To see this, note that the probability of exiting is given by:

$$P(d=0)=\frac{e^{V_0(s)}}{\sum_{k=0}^{N_d}e^{V_k(s)}}. \tag{1.20}$$

[60] This formulation of the likelihood, although apparently complicated can be estimated fairly easily given the case-structure. Many studies of industry dynamics focus on the number of competing firms being quite small, generally less than five. This likelihood formulation on the other hand, along with some restriction on the pool of entrants, can allow a general number of firms.

Taking the natural log of both sides yields the following:

$$\log \sum_{k=0}^{N_d} e^{V_k(s)} = V_0(s) - \log P_0(s) \tag{1.21}$$

where $V_0(s)$ is the value from exiting at state s. Given the timing outlined above, $V_0(s) = \pi(s) + FC$. Substituting in, the relative value for incumbents staying in the market relative to exit is given by:

$$V(s_t, d_t = 0) - V(s_t, d_t = 1) =$$
$$= \tilde{\eta}_t + \beta\left(\int (\pi(s_{t+1}, q_{t+1}) + FC_{t+1} - \log(P_1(s_{t+1})))p(s_{t+1}|t+1, d_t = 0) + \gamma \right)$$

where FC' is the values of exiting in the following period and $\tilde{\eta}_i^d$ is the logistic error. To study how regulations alter the value of leaving the market, I assume $FC = R_t\theta$ where R_t is the regulatory environment faced at time t. I assume firms know one-period in advance of any coming regulations, an assumption consistent with the lagged nature of legislation and regulation, and the active efforts by groups such as NARAL to alert the public to proposed legislation and regulation.[61] The savings from this substitution is not having to solve a recursive equation such as Equation (1.11) for each value of parameters during the maximization but rather plugging the reduced form estimates $\hat{P}_1(s_{t+1})$ into (1.22). This exploits the notion that firm behavior in the next period contains valuable information on the profitability of the market in the periods beyond, as put forward in Hotz and Miller (1993).

In a similar fashion, the potential entrants' problem can be rewritten as the fol-

[61] Viewing regulations as part of the state space, what is required for this formulation to correctly measure profits is that the regulation evolutions, say $q(R'|R)$ be conditionally independent of the private information profits η. So the extent to which individuals forecast ahead more than one period the regulatory environment in the future is accounted for in the reduced form probability of exiting in the next period. In estimating these reduced forms I include the regulations as well as the entire state space.

lowing value for entering relative to not entering:

$$V(s_t, e_t = 1) - V(s_t, e_t = 0) =$$

$$= \tilde{\eta}_t + FCE_t + \beta FC_{t+1} + \beta\bigg(\int (\pi(s_{t+1}, q_{t+1}) - \log(P_1(s_{t+1})))p(s_{t+1}|s_t, e_t = 0) + \gamma \bigg)$$

Note that the fixed costs of entry and operation are independent of the state s_{t+1}, allowing them to be factored out of the integrals in (1.22) and (1.22). Given that profit parameters, the marginal cost vector and demand elasticities have been already been estimated along with the transition probabilities which can be used to compute the one-step ahead probabilities. Estimating the parameter vectors (FC, FCE) can be accomplished by maximizing 1.19 where P_I and P_E are the choice probabilities from (1.22) and (1.22).

Given that some markets contain many firms, even capping the number of hospital firms at one hundred leads to just over 29 million different states. Rather than keeping track of that number of probabilities for use as weights in calculating the integrals in (1.22) and (1.22), I follow a different method for calculating future values presented in Bajari, Benkard, and Levin (2007), and used in Bishop (2007). Since I have already estimated reduced forms on the probability of entry and exit for incumbent firms and potential entrants, I simulate states from these probabilities and take an average of the resulting one-step ahead values:

$$\sum_{s_{t+1}} (\pi(s_{t+1}, q_{t+1}) - \log(P_0(s_{t+1})))q(s_{t+1}|s_t, d_t = 0) \approx$$

$$\frac{1}{N_s} \sum_{sim_s=1}^{N_s} \pi(sim_s, q_{sim_s}) - \log(P_0(sim_s))$$

the simulated states sim_s probabilistically include the states which are most likely to be seen next period and as the number of simulations increases, the simulated sum will converge the sum over all the possible states.[62] Bajari, Benkard, and Levin (2007) proposed this simulation method to calculate future values for many periods into the future; the insight here is that with a one-step ahead problem, one needs only to simulate the next period future value term.

The results of the maximum likelihood estimation are presented in Table 1.11. These estimates include state fixed effects and state specific linear trends and even controlling for these, a number of regulations appear to significantly alter the entry costs firms face. Entering firms, both small providers and hospitals, had their entry costs raised by restrictions on physicians providing abortion services. These laws generally require that a physician certified as an OB/GYN in that state perform abortions. This may highlight the fact that these providers are not necessarily specialized in abortion services and therefore may not maintain the same certification as more specialized clinics, for whom the law appears not to have had a significant impact. The requirement that hospital facilities provide abortions after some point in the second trimester increased the fixed cost of entry for larger providers; these laws generally require facilities to obtain certification similar to outpatient care facilities. The marginal cost estimates discussed above, and entry costs shown in Table 1.11 are consistent with the two responses of larger providers to these laws: existing providers refer later term abortions to hospitals, and incoming providers must invest in facilities in order to continue providing these services. Finally provider license requirements actually decreased the costs of entry for larger providers, which could be picking up a shift in demand toward larger providers not discernible in the noisy price data. Recall this same regulation increased marginal costs for small providers and hospitals, implying higher prices for non-clinic abortions in these markets.

The estimates also show the average fixed cost of operation to be negative, im-

[62] The state space must be discretized so the integral becomes a sum.

plying that the value of providing abortion services is not completely explained by my estimate of the resulting profits. The ordering of these average costs accords with what we know: large providers, hospitals and small providers. Large providers which includes non-profit firms has the highest non-revenue benefit, followed by hospitals, for whom I have the worst measure of profits, and finally smaller private clinics who are for-profit producers for whom we have the best measure of prices and relevant costs. These intercepts can also be interpreted as evidence there are interactions in the profit function from providing abortion services and other health services which I cannot capture directly. Finally, the intercepts may be the result of market level unobservables, which can to some extent be alleviated by the introduction of unobserved heterogeneity.

1.5.4 Including Unobserved Heterogeneity

In order to the relax the assumption of independence over time in the unobservables η, I incorporate unobserved heterogeneity into the model. Heckman and Singer (1984) proposed approximating a continuous unobserved distribution (essentially of the intercept term) by using a discrete approximation. I adopt the work of Arcidiacono and Miller (2008) and Arcidiacono and Jones (2003) by using their adaptations of the Expected-Maximization (EM) algorithm. Here I assume that each market belongs to one of K types, while K is known, the type of each market k is unobserved to the econometrician. In such a setting, the unconditional likelihood takes the following form:

$$l(d_{nt}|x_{nt},\theta,p) = \sum_k p_k f(d_{nt}|x_{nt},\theta,k) \tag{1.22}$$

where p_k is the unconditional probability of a market being type k and p is the vector of these probabilities. Here, f is the likelihood conditional on being type k, and d_{nt} and x_{nt} are the observed number of firms and other state variables respectively. I assume unobserved heterogeneity is permanent and therefore the log-likelihood takes the following form for the sample:

$$\log(\ell) = \sum_{n=1}^{N} \log\left(\sum_{k=1}^{K}\prod_{t=1}^{T} p_k L(d_{nt}|x_{nt},\theta,\pi,k)\right) \tag{1.23}$$

To estimate such a likelihood, I adopt the methods put forward in Arcidiacono and Miller (2008) and rather than directly maximize (1.23), I instead iteratively maximize the expected log likelihood function. This function takes the following form:

$$\sum_{n=1}^{N}\sum_{k=1}^{K}\sum_{t=1}^{T} q_{nk}^{(m)} f(d_{nt}|x_{nt},\theta,\pi^{(m)},k) \tag{1.24}$$

where m is the iteration and $q_{nk}^{(m)}$ is the probability of market n being in unobserved state k at iteration m, conditional on the last iteration parameter estimates and all the data on market n. The procedure can most easily be explained with a four step iterative approach:

1. With an initial guess at parameters θ, including the value of being in state k, evaluate the unconditional likelihood function. The result is an NXT matrix of conditional likelihoods for each state k.

2. Using these likelihoods and Bayes Rule, one can calculate the conditional probability of being in each unobserved state k for each market $n = 1, ...N$.

3. Using these conditional probabilities as weights, $q_{nk}^{(m)}$ above, maximize the expected log-likelihood as though the unobserved states were observed.

4. Simulate future value terms conditional on the new likelihood of being in each state. With the resulting future value terms and parameter estimates from step 3, return to Step 1.

Given that the unobserved heterogeneity here is of a permanent type, the conditional probability of being type k(from Step 2) is given by:

$$q_{nk}^{(m)} = \frac{\pi_k \prod_t l(d_{nt}|x_{nt}, \theta^{(m)}, k)}{\sum_{\tilde{k}} \pi_{\tilde{k}} \prod_t l(d_{nt}|x_{nt}, \theta^{(m)}, \tilde{k})} \tag{1.25}$$

where π_k is the initial probability of being in state k.

1.6 Simulations

The simulations presented here serve to clarify how regulations impact the market for abortion services and how those markets would function in the absence of regulations. I focus as well on the Freedom of Choice Act, a recent proposal in the U.S. Senate which would arguably remove many state regulations placed on abortion providers. As discussed above, many of these laws and regulations have been subject to judicial and constitutional challenges and there is no reason to think the Freedom of Choice Act would not create legal challenges as well. However, to gain a first understanding of the role which regulations play, I focus on simulating one potential interpretation, which allows a straightforward comparison to demand effects.

First proposed on January 22, 2004, the language of the Act which was is quite broad, and contains the following relevant subsection under Section 4:[63]

(b) PROHIBITION OF INTERFERENCE- A government may not–

(1) deny or interfere with a woman's right to choose–

(A) to bear a child;

(B) to terminate a pregnancy prior to viability; or

(C) to terminate a pregnancy after viability where termination is necessary to protect the life or health of the woman; or

[63] This draft is taken from the Library of Congress, http://thomas.loc.gov/cgi-bin/query/z?c108:S.2020:

(2) discriminate against the exercise of the rights set forth in paragraph (1) in the regulation or provision of benefits, facilities, services, or information.

Therein, the government refers especially to state governments and particularly relevant is subsection (b)(2), suggesting that state level regulations of benefits, facilities, services and information could violate the FOCA.[64] With the exception of physician requirement laws, the other five groups of regulations discussed above would likely be subject to challenge or direct overturning. These regulations generally deal specifically with and apply only to providers of abortions. However, many advocates contend that, especially given the advent of medical abortion, physicians' assistants and possibly nurse practitioners should be able to prescribe medical abortion,[65] providing a basis for considering the overturning of even the physician restrictions. As a first step the simulations take the form of simulating the model removing all restrictions.

The simulated number of firms arising in the counter factual world, where all regulations were eliminated during the year 1991, are presented in Table 1.12. The major trends can be seen in Figure 1.3 as well. In that figure, lines without markers represent the baseline model simulations, and lines with markers represent the model with all regulations turned off("R=0"). The simulations show that over the 15 year time horizon the changes in the composition of abortion providers in the U.S. is significant. The number of large providers essentially remains the same and smaller and hospital providers increase their presence. The trend among small providers toward exiting the market is slowed, leading to around a 11% increase in the number of small providers relative to the model with regulations. The declines among hospital providers were also slowed, leading to around a 13% increase in the number of hospital

[64] The first section of the article, Section 1(14) establishes as a basis for the law Congress' ability enact legislation to secure statutory rights.

[65] CT and WA overturned their physician restrictions voluntarily after medical abortion was FDA approved.

providers relative to the model with regulations. How these changes in firm dynamics influences the total quantity of abortions observed in the U.S. can be seen in Table 1.13. The average increase in abortions over the columns in Table 1.13 is 6.62% per year. The data indicate that comparing 1991 to 2005 there was a decline in the total number of abortions in the United States of 317,900 procedures, a 20.9% decline. The model captures most of this decline, predicting a 23.62% decline over the same period. Removing regulations from the model and simulating entry, exit, and service provision shows a decline of only 18.51%, attributing 22% of the decline to the impact of state level regulations. The rest of the observed decline presumably resulted from increased use of contraception and increases in desired pregnancy and a corresponding decrease in unintended pregnancy.

These increases result from two effects of removing regulations. One effect is increasing entry in areas with pre-existing providers, which lowers prices. Another effect is increasing entry into new markets.[66] The model predicts that removing all regulations, by 2005 the number of small provider monopoly markets increased to 88 from a baseline of 67 markets in the same year. This result means that most entry is occurring in pre-exiting markets. Indeed, removing restrictions in 1991 only results in an increase of markets which have any provider from 294 to 306 M/MSA's in 2005. The percent of M/MSA's with providers increases from 34% to 35.4% of the 865 M/MSA's in my panel in 2005. This last point illustrates the important issue of access. Indeed Section I of the FOCA, mentions that 87% of U.S. counties have no abortion provider, and many have argued this is due to state regulation. However these results indicate that removing regulations would have a moderate impact on access, and that access declines are occurring primarily due to shifts in demand.

[66] Although a spatial model of competition is beyond the scope of this paper, this seems like an area for future research: quantifying the different effects of price vs. presence in a market, and especially how these influence pregnancy avoidance behavior as shown in Kane and Staiger (1996) who focus in presence and distance.

Another way to decompose the increases resulting from removing the policies is to separate their marginal and fixed cost components. Table 1.14 contains the results from simulating the production side of the model with the observed number of firms. The simulation column shows the total abortions resulting from using the observed distribution of firms and removing the effects of regulations on marginal costs. As can be seen from the final two columns, this exercise shows that most of the increases beyond the first few years are due to the presence of more firms, not more productive firms. This is related to some stated reasons for the regulations being enacted, namely that they may be altering quality. These estimates suggest that this is not the primary effect of regulations. [67]

1.7 Conclusion

An accurate understanding of how government regulation influences abortion markets has suffered from both a lack of data and little understanding of how firms interact. This paper argues that indeed the interactions of firms prove to be consequential in addressing to what extent state policies have been responsible for the recent declines in abortion observed in the United States. By estimating a dynamic model of competition among firms who provide abortion in the U.S., we gain a greater understanding of how regulations affect different firms and in-turn consumers. State regulations have increased the costs of entry for both hospitals and smaller providers of abortion. These regulations have played an important role, contributing to observed increases in the concentration of services at large providers. With fewer providers, market prices for abortion have increased and this has reinforced the declines in abortion.

By estimating a model which allows for counter factual simulation, this paper provides the first estimate of the impact of regulations which specifically target abor-

[67] To test this notion more formally, one would need better instruments in order to test for regulations' impact on the price elasticities as well as marginal costs.

tion providers, showing that around 22% of the decline in total abortions from 1991 onward can be attributed to the increased regulation of state governments. Also, in percentage terms these restrictions appear to play at least as important a role as restrictions aimed at demand. My demand-side estimates show parental consent laws were responsible for an average annual decline of 2.5% in the total number of abortions, while the supply side restrictions were responsible for a 3.2% average-annual decline.[68] This is partially due to the dynamic nature of the firms' problem. Policy today influences the composition of the market far into the future. With fairly large estimates of the fixed costs of entry, the model implies that once firms exit, especially in periods of already declining demand like the 1990's, the number of firms will not increase. This appears to have been the case for both hospitals and smaller providers. Given these new insights into the market for abortion services, it follows that removing these regulations of abortion providers as proposed in Freedom of Choice Act would have an important impact on the number and types of providers. In particular, it would allow greater entry, increasing competition and, as in most other markets, increasing quantities. Given that the number of live births remained relatively constant over the period, while birth rates declined, these results suggest that state policies restricting abortion providers had the consequence of reducing abortions by reducing pregnancies. This final point seems to be a promising area for further research with more detailed data on abortion demand.

[68] The review of Medoff (2007) shows that state funding increases abortion rates from between 0-3% controlling for preexisting state trends, and minor restriction impacts are between 0% for all women, and -15% for the smaller group of minors(who make up about 20% of abortion demand) yielding another 3% decline.

1.8 Tables and Figures

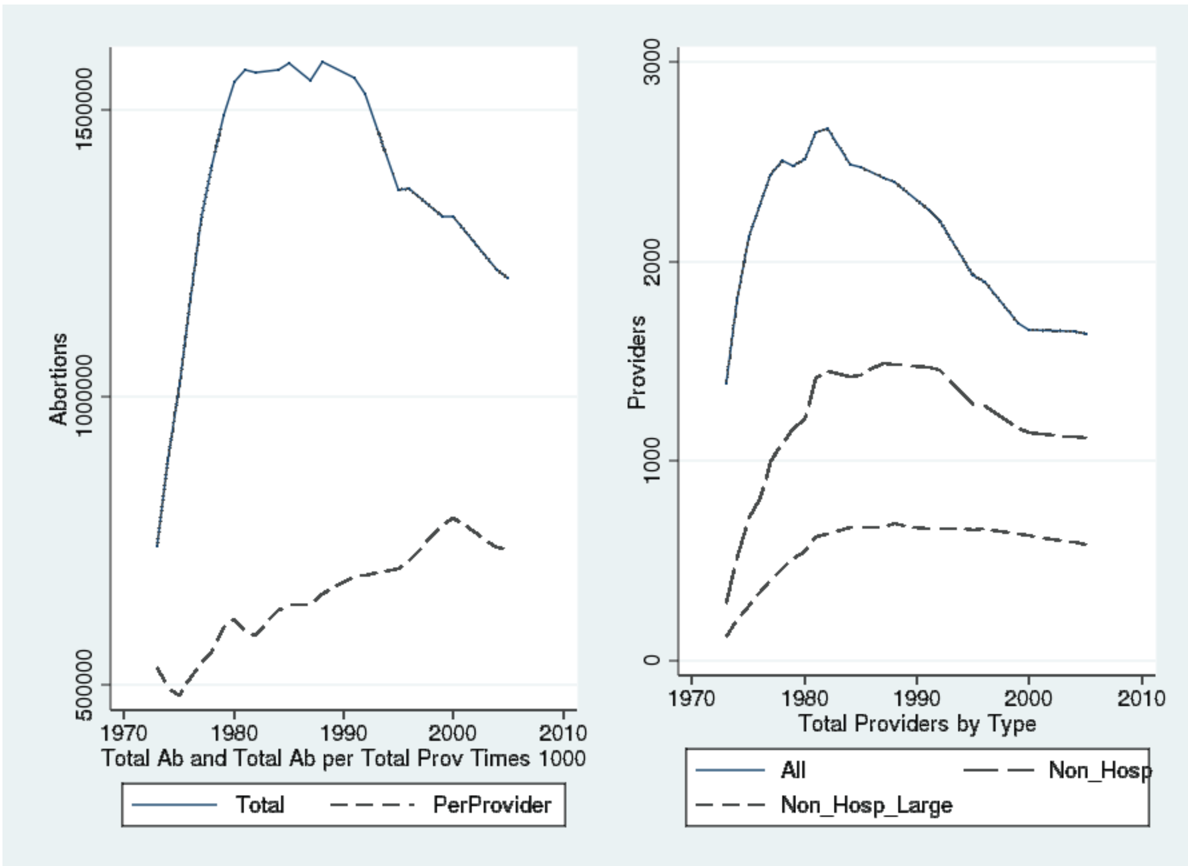

FIGURE 1.1: Procedures and Firms

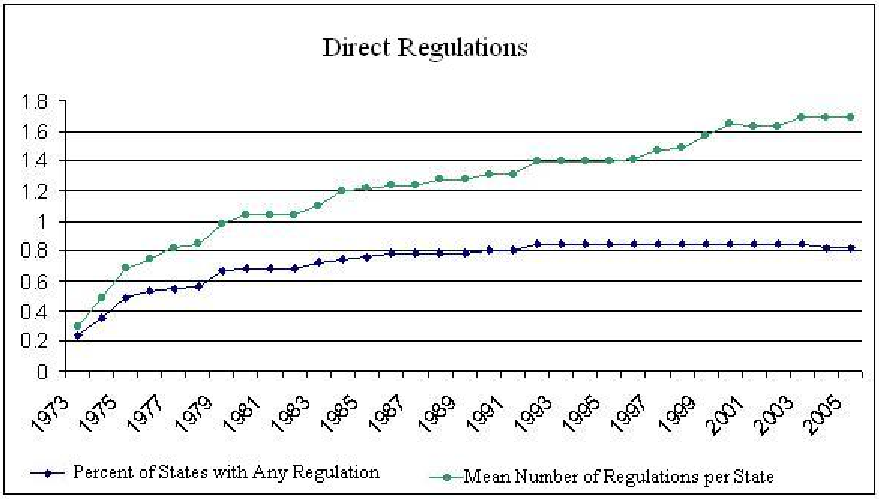

FIGURE 1.2: Regulation Changes Over Time

Table 1.1: Percent Abortions by Gestation, Procedure

	Gestation[a]			Procedure	
	$\leq$ 12 Weeks	13-20 Weeks	$\geq$ 21 Weeks	Curettage	Medical
1972	82.2	16.6	1.2	88.6	1.0
1976	89.5	9.6	0.9	92.8	1.2
1980	90.1	9.0	0.9	95.5	1.4
1985	89.4	9.8	0.8	97.5	0.8
1990	88.6	10.4	1.0	98.9	0.3
1995	88.0	10.6	1.4	98.9	0.6
1999	88.0	10.5	1.5	98.2	1.6
2004	87.0	10.1	1.3	88.5	11.5

[a] Source: Centers for Disease Control summary of Abortion Surveillance reports.

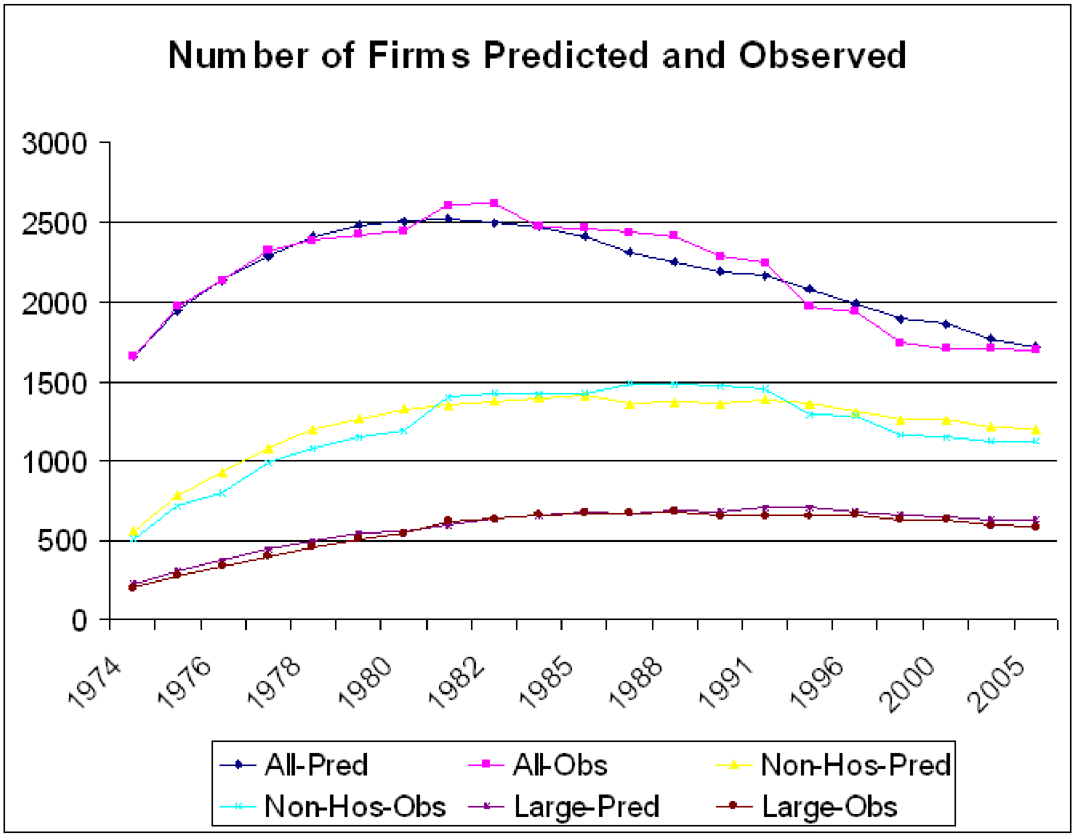

FIGURE 1.3: Simulated Number of Firms, Remove Regulations at 1991

Table 1.2: Auxiliary Data Sources

Data	Source
Census Population Estimates by Age, Race, Gender	Census population estimates, county level, http://www.census.gov/popest/archives/
Per Capita Income	BEA Local Area Personal Income File
Population Density	Land measures from Census 2000
Health Services Employment, Payroll, Establishments	County Level Business Patterns U.S. Census
Number of Physicians and Hospitals per State	Statistical Abstract of The United States, 1970, '75, '80, '85,'90,'95,2002-'05, missing years interpolated.
State Level Expenditures on Family Planning	Alan Guttmacher Institute, Public Funding for Family Planning, Sterilization and Abortion Services, FY 19802006.
Religious Populations	Church and Church Membership Survey, various years, intercensal values interpolated.

Table 1.3: Descriptive Statistics

Number of M/MSA's with Firms	1975	1985	1995	2005
Small	132	206	156	119
Large	113	193	186	193
Hospital	367	289	195	154
Number of Firms $\|N_f > 0$				
Mean				
Small	3.25	3.59	4.02	4.49
Large	2.45	3.44	3.52	3
Hospital	3.69	3.66	3.51	3.71
$N_f = 1$				
Small	78	122	94	67
Large	67	93	93	117
Hospital	262	179	124	95
Percent of Total Services				
Small	4.57	5.5	4.78	4.06
Large	55.46	81.37	88.18	91.94
Hospital	39.97	13.13	7.03	4.64
Price for 10 Week Procedure	1974	1984	1996	2005
Observed Mean	-	459.64	457.39	468.28
Imputed Small, Mean	-	548.85	576.96	613.84
Imputed Large, Mean	-	360.98	357.5	399.23
σ Across	-	105.32	106.41	164.29
σ Within	-	108.97	106.18	114.61

Table 1.4: State Law Implementation Years

State	License	Only Phys.	2nd Trim. Hosp.	Hosp. Location	Hosp. Agreement	Phys./Admin.
AL	1982	2002				2002
AK	1970(r 1981)	1970				
AZ	1999	1984				1999
AR	1983	1983	1999			1999
CO		1967				
CT	1983	1974(r 2001)				1995
DE		1969				
FL	1978	1979	2005			
GA		1968	1974			
HI		1970				
ID		1973				
IL	1973	1979				
IN	2005	1959	1973			
IA		1976				
KY	1982	1974			1998	
LA	2001	1978				2003
ME		1979				
MD		1991				
MA		1974				
MI	1978	1973				
MN	1974	1974				
MS	1991	1953	1996			1991
MO	1987	1974		2005		1987
NE		1978				
NV		1973	1973			
NJ		1978	1978			
NM		1969				
NY		1965				
NC	1967	1967	1967			1976
ND		1975				
OH		1974			1996	
OK		1978				
PA	2002	1982			1983	1983
RI	1973	1973	1973			
SC	1995	1974	1974			1996
SD	2006	1973	2006			
TN	1998(r 2001)	1989				
TX	1989	1985				1997
UT	1981	1973		1998	1998	
VA		1975	1975			
WA		1991(r 2004)				
WI		1956		1976	1976	
WY		1977				

Table 1.5: Lagged Abortions Predicting Policy Enactment

Direct Regulations[a]	No Regressors	State Variables
Abortion Provider License	0.01391*	-0.00522
	0.00541	0.00472
2nd Trimester Hospitalization	0.01220*	-0.00231
	0.00607	0.00357
Physician Restriction	0.01301	-0.00460
	0.01054	0.00581
Physical/Administrative Requirements	0.00752**	-0.00009
	0.00275	0.00202
Locate Near Hospital	0.00264	-0.00101
	0.00290	0.00218
Agreement with Hospital	0.00670	0.00002
	0.00356	0.00217
Demand Restrictions		
Parental Consent	0.00184	0.00082
	0.00092	0.00075
Parental Notification	0.00071	-0.00140
	0.00093	0.00086
Waiting Period	0.00234**	0.00053
	0.00541	0.00470
Public Funding	-0.00194*	-0.00022
	0.00093	0.00086
Fixed Effects	None	State
Trend	None	State-Linear
State Variables[b]	None	All

[a] Observations are market-years, standard errors are clustered at the state level, and the dependent variable is the log of total abortions in the period prior(or closest) to enactment.

[b] State Variables are listed in the footnote of Table 1.9

Table 1.6: Log Abortions on Policies

	Abortions			
Policies[a]	Log(total)	Log(large)	Log(small)	log(hospital)
Abortion Provider License	-0.1396	-0.1471	-0.5794*	-0.1262
	0.0947	0.1105	0.192	0.2116
2nd Trimester Hospitalization	-0.5266	-0.6285	-1.6357*	0.8789
	0.534	0.6969	0.7182	0.6398
Physician Restriction	0.0706	0.1312	-0.0627	-0.3589*
	0.0727	0.0897	0.1359	0.1758
Physical/Administrative Req.	-0.2302	-0.3331	1.1473*	-0.0962
	0.1659	0.1808	0.403	0.2195
Locate Near Hospital	0.2397	0.2566	1.8255*	-1.2051*
	0.2598	0.2724	0.3779	0.2832
Agreement with Hospital	-0.059	-0.0322	-1.5284*	0.6867*
	0.2415	0.2522	0.3009	0.2334
Parental Notification	0.0170	0.0033	0.2166	0.5164
	0.0537	0.0638	0.4074	0.1638
Parental Consent	-0.1694	-0.1686	-0.0912	-0.3691
	0.1209	0.1407	0.3100	0.2812
Waiting Period	-0.1869*	-0.1724*	-0.0683	-0.0746
	0.0658	0.0854	0.2581	0.2834
Public Funding	0.0329	0.0987	0.2904*	-0.1148
	0.0515	0.0835	0.1441	0.1569
N	1925	1925	1925	1925
R^2	0.8745	0.8274	0.5192	0.7707
Fixed Effects	State	State	State	State
Trend	State-Linear	State-Linear	State-Linear	State-Linear
State Variables	All	All	All	All

[a] Observations are market-years, standard errors clustered at the state level.

Table 1.7: Reduced Form: Prices

Prices[a]	Small	Large	Small	Large
Abortion Provider License	-0.023	-0.042	0.022	-0.041
	(0.068)	(0.046)	(0.071)	(0.057)
2nd Trimester Hospitalization	0.225**	-0.004	0.251**	0.061
	(0.075)	(0.108)	(0.087)	(0.070)
Physician Restriction	0.072*	-0.017	0.057	-0.010
	(0.033)	(0.028)	(0.062)	(0.033)
Physical/Administrative Req.	0.072	0.145**	0.059	0.155**
	(0.057)	(0.043)	(0.099)	(0.057)
Locate Near Hospital	-	0.290***	-	0.240***
		(0.059)		(0.069)
Agreement with Hospital	-0.050	-0.223***	-0.154	-0.172***
	(0.072)	(0.046)	(0.145)	(0.049)
R^2	0.460	0.274	0.659	0.519
N	652	816	652	816
Fixed Effects	State	State	MSA	MSA
Trend	State-Linear	State-Linear	State-Linear	State-Linear

[a] Observations are market years and exit is conditional on firms present in the prior period. Standard errors are clustered at the state level.

Table 1.8: Entry and Exit Probit

Entry[a]	Small	Large	Hospital
Abortion Provider License	0.0878	0.3559	-0.0533
	(0.119)	(0.128)	(0.144)
2nd Trimester Hospitalization	-1.2205*	-1.4958*	-1.119*
	(0.157)	(0.173)	(0.152)
Physician Restriction	-0.5654*	-0.4955*	-0.490*
	(0.078)	(0.090)	(0.099)
Physical/Administrative Req.	-0.0068	0.1482	0.0664
	(0.165)	(0.177)	(0.208)
Locate Near Hospital	-1.4144	-0.8959	-1.2828*
	(0.407)	(0.454)	(0.488)
Agreement with Hospital	0.8976*	0.9577*	1.2086*
	(0.307)	(0.339)	(0.400)
N	19030	19030	19030
Pseudo R^2	0.3065	0.3456	0.3689
Exit	Small	Hospital	Large
Abortion Provider License	0.3403*	0.0188	0.1894
	(0.157)	(0.175)	(0.141)
2nd Trimester Hospitalization	0.2126	0.2377	0.1507
	(0.453)	(0.488)	(0.326)
Physician Restriction	-0.2580	-0.1027	0.1593
	(0.140)	(0.167)	(0.118)
Physical/Administrative Req.	-0.4629	0.0791	0.0741
	(0.256)	(0.238)	(0.179)
Locate Near Hospital	-1.0802	-0.583	0.2729
	(0.709)	(0.714)	(0.559)
Agreement with Hospital	0.6982	-0.1103	0.0794
	(0.409)	(0.391)	(0.307)
N	3495	6011	3449
Pseudo R^2	0.0694	0.0902	0.0988
Fixed Effects	State	State	State
Trend	State-Linear	State-Linear	State-Linear

[a] Observations are market years and exit is conditional on firms present in the prior period. Standard errors are clustered at the state level.

Table 1.9: Elasticity Estimates

	Dependent	Variable[a]		
	$\log(Q_s)$	$\log(Q_l)$	$\log(Q_s)$	$\log(Q_l)$
$\log(P_{small})$	-1.7053*	0.1983	-1.6449*	0.1456
	0.649	0.4392	0.6619	0.4625
$\log(P_{large})$	-0.3845	-1.6761*	-0.4035	-1.4061*
	0.6535	0.5574	0.6569	0.5584
Family Planning/Total Poverty			0.0066	-0.0489*
			0.0268	0.0087
Percent Small Business			-0.4311*	-0.3092
			0.2115	0.2113
Public Funding/Total Poverty			-0.303*	-0.0398
			0.0869	0.0532
Waiting Period	0.1134	-0.1095	0.052	-0.1216
	0.2526	0.076	0.2397	0.0774
Parental Consent	-0.3579	-0.2151*	-0.34	-0.207*
	0.2439	0.0885	0.2339	0.089
Parental Notification	0.0254	-0.0261	0.0423	-0.0251
	0.2581	0.078	0.2369	0.0839
Public Funding	-0.1865	0.0917	-0.2158	0.1034
	0.2325	0.077	0.2296	0.0712
N	652	816	652	816
R^2	0.6145	0.791	0.6291	0.8204
Fixed Effects	State	State	State	State
Discount Terms	No	No	Yes	Yes
Weak Instrument Tests				
KP rank F Wald	29.53	13.95	17.44	13.87
CD-Critical Value 10% Relative Bias	10.69	9.92	10.69	9.92
CD-Critical Value 10% Size	31.11	23.72	31.11	23.72
CD-Critical Value 15% Size	17.06	13.34	17.06	13.34

[a] Dependent variable is log of the quantity of total procedures by all firms of each type; observations are market-years.

Table 1.10: Marginal Cost Estimates

Regulations[a]	Small Provider Coeff.	s.e.	Large Provider Coeff.	s.e.	Hospital Coeff.	s.e.
Physical/Admin. Req's	-0.2838*	0.094	-0.053	0.0544	0.0912	0.0745
Provider License	0.1253*	0.0571	0.0536	0.0386	0.1229*	0.0626
2nd Trimester Hosp.	0.1527	0.1477	-0.3657*	0.1019	0.2107*	0.1001
Physician Restriction	0.0884	0.0499	0.0563	0.0349	-0.0622	0.0524
Locate Near Hosp.	0.4333	0.3057	0.2587	0.1764	0.3697	0.266
Agreement with Hosp.	0.1377	0.152	-0.0336	0.0972	0.0876	0.1569
MC Shifters						
Constant	6.0942	0.2822	7.2072	0.3134	8.1343	0.2678
Hospitals per Capita	0.1245	0.0163	0.0669	0.0142	0.1087	0.0245
Physicians per Capita	-117.07	19.69	-20.25	18.55	-67.03	22.39
Physicians per Hosp.	-0.0015	0.0004	0.0003	0.0004	-0.001	0.0005
Physicians per Capita^2	2.005	0.4302	0.4686	0.5402	4.2787	0.4775
Health Services Emp.	0.0065	0.0009	-0.0031	0.0006	0.0044	0.001
Health Services Emp.^{2}	-0.0046	0.0007	0.0019	0.0005	-0.0048	0.0008
Health Services Wage	-0.065	0.0297	-0.1943	0.0342	-0.2173	0.0263
Health Services Wage^2	0.002	0.0009	0.0053	0.001	0.0056	0.0008
Medical Abortion	-0.1083	0.0439	0.0671	0.0286	-0.2034	0.0513
Population	-0.0362	0.0033	0.013	0.0024	-0.0714	0.0037
Population^2	0.0163	0.0013	-0.0036	0.001	0.0368	0.0016
Large City	0.2925	0.0769	0.1345	0.0553	1.1927	0.0953
Fixed Effects	State		State		State	
Trend	State-Linear		State-Linear		State-Linear	
N	3543		3654		5974	
R^2	0.3799		0.266		0.3802	
Mean MC	448.3839		302.023		801.4583	

[a] Dependent variable is log of marginal revenue for firms for each type; observations are market-years. Three states, Delaware, North Dakota and Wyoming, did not have enough observations to estimate state fixed effects and/or state specific trends; these states are included in the "No State" indicator.

Table 1.11: Fixed Cost Estimates

	Small Provider		Hospital		Large Provider	
Fixed Cost of Entry[a]	Coeff.	s.e.	Coeff.	s.e.	Coeff.	s.e.
Constant	5.9528*	0.4047	6.1029*	0.3943	7.6589*	0.5428
Physical/Admin. Req's	0.0913	0.365	0.3479	0.4359	-0.4693	0.3991
Provider License	-0.0986	0.2124	0.1682	0.2598	-0.4916*	0.2433
2nd Trimester Hosp.	-2.2301*	0.5665	-0.2768	0.3158	0.8111*	0.4042
Physician Restriction	0.4974*	0.1485	0.0142	0.1858	0.0392	0.1993
Locate Near Hosp.	1.8557	1.0834	-1.034	1.1661	-0.8841	1.1537
Agreement with Hosp.	-0.3957	0.6849	-0.095	0.6701	0.2433	0.7934
Fixed Cost of Operation						
Constant	-1.5816*	0.3558	-2.5642*	0.3055	-3.3085*	0.5289
Physical/Admin. Req's	-0.0275	0.2616	-0.1363	0.2491	0.1131	0.2795
Provider License	0.2424	0.1451	-0.01	0.1492	-0.0606	0.1859
2nd Trimester Hosp.	0.7375	0.4008	0.0774	0.2629	-0.6963	0.3897
Physician Restriction	-0.1169	0.1112	0.1771	0.115	0.1172	0.165
Locate Near Hosp.	-1.2369	0.6765	0.2087	0.7454	-0.5965	0.856
Agreement with Hosp.	0.4167	0.4119	0.069	0.339	0.0708	0.4565
N	865		865		865	
T	22		22		22	
Fixed Effect	State		State		State	
Trend	State-Linear		State-Linear		State-Linear	
-LL	6954.4		6454.0		4061.2	

[a] * indicates significance at least the 5% level. Observations are market-years.

Table 1.12: Firms, All Regulations Off at 1991

	Small[a]			Hospital			Large		
Year	Sim	Base	Observed	Sim	Base	Observed	Sim	Base	Observed
1992	804	777	792	791	777	790	653	655	658
1995	795	720	633	773	715	682	639	645	657
1996	796	682	620	732	675	653	630	633	663
1999	757	655	535	700	623	572	610	620	632
2000	718	643	517	684	602	566	596	629	627
2004	682	607	533	638	560	587	580	602	592
2005	642	577	538	620	537	577	581	589	583

[a] Average for 100 simulations.

Table 1.13: All Regulations Off at 1991

	Total Abortions[a]		
Year	Sim	Base	Observed
1992	1.5412	1.5363	1.5214
1995	1.3744	1.3748	1.3556
1996	1.4480	1.4456	1.3600
1999	1.3826	1.3224	1.3126
2000	1.3803	1.3227	1.3106
2004	1.2828	1.2098	1.2196
2005	1.2560	1.1735	1.2035

[a] Numbers in millions, average for 100 simulations.

Table 1.14: Marginal Cost Effects

Year	Total Change[a]	MC-Induced	MC Proportion Of Change
1992	4953	2534	0.51
1995	391	1752	4.48
1996	2340	1637	0.70
1999	60121	2058	0.03
2000	57625	2585	0.05
2004	73017	1780	0.02
2005	82502	1536	0.01

[a] Average for 100 simulations.

2

Testing Theories of Out-of-Wedlock Childbearing

2.1 Introduction

The availability of legalized induced abortion in the United States has been hailed by many as an indispensable option in the reproductive lives of women. Availability is often viewed as means of empowering women. By eliminating unwanted childbearing, reducing teen motherhood rates, and bettering the environment in which children are raised, both women and society as a whole are viewed as benefiting directly from greater availability. [1]

However, some have suggested that abortion availability may have negative welfare consequences for women through indirect effects. The work of Akerlof, Yellen, and Katz (1996) points out one possible negative externality of greater abortion availabil-

[1] Donohue and Levitt (2003) and Joyce (2004), are two important articles in the growing debate over whether legalized abortion decreased crime by decreasing the potential criminal population. Joyce (2004) acknowledges the large set of decisions which this link encompasses, and this paper provides at least one explanation for Joyce's finding: lower abortion costs may also lead to more single parent families and a "repopulating" of potential criminals. Also Gruber, Levine, and Staiger (1999) to measure government savings from abortion through reduced social expenditures on the "marginal child," who could be replaced if lower abortion costs make separation more likely for parents.

ity. If women value both having children and continuing a relationship with the father, greater access to abortion may reduce the chances of keeping a relationship by severing the bundling between relationships and children. Under such assumptions greater abortion availability is responsible for declines in "shotgun" marriages(marriage as a response to pregnancy) and therefore increases in out-of-wedlock births. Discussed in more detail below, such a result arises in model a where the fractions of men and women preferring not to marry in the event of a pregnancy are high enough. Falling abortion costs induce men who do not want children to leave women who prefer both children and marriage, while equilibrium in the marriage market forces these women to accept relationships with these men despite the risk of them leaving. The two types of women are in competition due abortion availability. If such an effect exists it provides an important complication to the notion that abortion availability is unambiguously beneficial for women. Indeed, such a scenario lends support to a contrary claim: that one primary beneficiary of abortion access are single men, who can find it easier to escape parenting responsibilities.

In this paper I test whether lower abortion costs increase the likelihood of births being out-of-wedlock using data from the National Longitudinal Study of Adolescent Health (Add Health). The data provide information on relationships, pregnancies, and partners of a nationally representative sample of young people, along with some information on county level abortion access. Importantly the data include abortions with a relatively high reporting rate, which is necessary to accurately measure transitions into parenthood and out of relationships and has been a concern in prior studies. [2] I begin by estimating a baseline linear probability model of separation between un-

[2] Lundberg and Plotnick (1995) and Lundberg and Plotnick (1990) are able to study abortion choices and relationship status, but do so using NLSY79 data. As they discuss, these data have reporting rates for whites around 60%, and for blacks reporting rates are lower than 20%. In contrast, the Add Health used here show an age-weighted reporting rate of around 90%, and a black reporting rate near 60%. There are likely many reasons for this difference. The information in Add Health was elicited in the context a relationship history, beginning first with partners, followed by pregnancies,

married biological parents following pregnancy. I find support for the AYK hypothesis namely that increased abortion access leads to higher probabilities of a breakup occurring if the woman gives birth. The results are robust to the sequential addition of individual level characteristics, county level controls for population and relevant characteristics, and the inclusion of state fixed effects. To deal with the endogeneity of birth and selection into miscarriage I exploit arguably exogenous various in biological fertility events. Firstly, miscarriage can provide a natural experiment to identify the effect of giving birth on separation in lower cost environments. Intuitively, if pregnancies only ended in live births or random miscarriages, then miscarriages would serve as the ideal natural experiment to measure the exogenous effect of giving birth on separation. Although this is not that case, I implement the estimator outlined in Hotz, McElroy, and Sanders (2005), who point out that as long as miscarriage is random, correctly reported and has the same impact as abortion on the outcome of interest, one can still identify the causal effect of giving birth on the outcome of interest. An adaptation of the bounding strategy of Hotz, Mullin, and Sanders (1997) allows me to partially identify the effect under even less stringent assumptions about the randomness and reporting of miscarriage. Secondly, I include selection correction terms in all linear specifications, and relax the linearity assumption by estimating a non-linear binary choice selection correction model adapted from Abrevaya, Hausman, and Khan (2007). I use factors related to fecundity, age at menarche and teenage menstrual problems as exclusions restrictions in the selection correction models. The baseline results are robust to controlling for selection into pregnancy and instrumenting for birth. The estimates from the natural experiment and their related worst

and then pregnancy outcomes, all via an anonymous computer aided system. In contrast the NLSY79 administered questions related to pregnancy termination with in person written surveys and phone interviews for most of the relevant years. This fact coupled with a decrease in stigma surrounding abortion over the 15-20 years separating the surveys are likely responsible for the more accurate data used here.

case bounds both confirm that for changes from no access to small scale physician provided abortion access increases the likelihood of separation following birth from between 13-17%.

The results here indicate that abortion costs do play a role in determining whether couples remain together following pregnancy, providing evidence in favor of the theory of Akerlof, Yellen, and Katz (1996). If mothers value joint parenthood with the father, the effect studied here implies these women suffer in welfare terms from decreases in abortion costs. This evidence is found with only cross sectional variation in access to abortion, and importantly is relevant when moving from no access to the smallest and generally first available form of access, physicians offices or small providers. It appears from my results that some women with moderate levels access are getting pregnant and, if giving birth, suffering from the negative externality. Although the welfare effects here are the result of lowering abortion costs, there are both winners and losers from that change, so increasing abortion costs would similarly have ambiguous effects.[3] Alternatively the results here indicate that an increase in the cost of leaving a partner who gives birth, for example through strengthening child support requirements, could help correct for the negative externality.

The rest of the paper proceeds as follows: Section 2 reviews recent theoretical work on out-of-wedlock childbearing and abortion costs, with attention paid to the comparative statics of falling abortion costs. Section 3 discusses the relatively new data set and the sample drawn from it. Section 4 presents my empirical strategy for identifying the effect interest from the observed data along with the estimation results and Section 5 concludes.

[3] This claim abstracts away from the endogeneity of pregnancy and the possibility of moral hazard effects.

2.2 Explaining Out-of-Wedlock Childbearing in Economics

The 1990's saw three seminal papers addressing economic theories of out of wedlock childbearing and its rise in many western countries in recent decades. The work of Kane and Staiger (1996)(hereafter KS) and Akerlof, Yellen, and Katz (1996) provide the guidance for the estimation strategy here, and their models and implications are dramatically simplified and summarized in what follows; I also comment on the work of Willis (1999) as it relates to the outcomes of interest.

The model presented in KS is a simple model of out-of-wedlock childbearing decisions that captures the insurance value of abortion in the choice process. Importantly, attention is paid to both small and large changes in abortion costs and their impact on both the entry into pregnancy and the choices occurring conditional on pregnancy. In their model there is information revealed after pregnancy has occurred, interpreted as the whether or not the birth would be "legitimated", i.e. whether marriage would occur(presumably the choice of the man) following the pregnancy or not. If not, and the woman would prefer to remain childless rather than become a single mother, abortion insures against the lowest utility state for the woman, single motherhood. In the model small decreases in abortion costs are decreases in the price of insurance, and induce more pregnancies, some of which end in abortion, and others which end in in-wedlock births. For large decreases in abortion costs(necessarily from much higher absolute cost levels, such as one imagines is the case going from illegal to legal abortion regimes), the effects are different. Here women who would have been forced to have a child out-of-wedlock now exercise the insurance option of abortion, reducing the number of births and changing the composition towards in-wedlock births.

These impacts of a decrease in abortion costs are cataloged in the "KS" rows of Table 2.1. Importantly one should view both of these effects as being operable in a set of observed women, since heterogeneity in characteristics may lead what is a small change for one woman, to be a large change in cost for a different woman. Note the final column in the Table shows that "insurance" effect on the fraction of births occurring out-of-wedlock are both negative.

In contrast to an insurance model, the idea that abortion costs reductions drove changes in female family headship and created female welfare losses are implications of theoretical models put forth in Akerlof, Yellen, and Katz (1996) . They propose a strategic model between men and women where private information on both the male dis-utility of marriage and female dis-utility of being a single mother are inferred from actions. In addition to the models AYK presents a set a descriptive statistics documenting the dramatic rise in out-of-wedlock childbearing in the United States over the period 1964-1989. The time series indicate that much of the rise in out-of-wedlock childbearing is due to the disappearance of the custom of "shotgun marriage," or marriage following an out-of-wedlock pregnancy which will lead to birth. The theoretical models explain the decline in shotgun marriage as resulting from the equilibrium responses of men to the fertility control cost shocks of widespread access to abortion and contraception.

The logic of the two AYK models are as follow. When abortion costs drop, the women who adopt abortion in the event of a pregnancy do not make marriage in the event of a pregnancy a precondition for sex. Because of this, abortion adopting women essentially sever the bundling of pregnancy and marriage for all women in equilibrium. One interpretation is that if the fraction of abortion adopting women is high enough, women who want both a partner and a child will not demand a marriage commitment prior to sex. Doing so would expose them to an increased risk of being left for a woman who does not want children, who are now in greater supply. The second model generates similar implications from different assumptions. As abortion costs fall, men value their partners altruistically, but lower cost abortions mean that those who do not obtain abortions have a lower dis-utility of being a single parent than those who do obtain abortions. The drop in abortion cost lowers the mean dis-utility of single mothers. A man's probability of marriage is an increasing function of this dis-utility, so as it falls, so does the likelihood that marriage will occur. Both AYK models generate the set of implications in Row 3 of Table 2.1, where the key difference from the KS insurance model is the increase in fraction out-of-wedlock. In addition to altering outcomes for those having sex, the models of AYK should generate incentives for some women to stop and start having sex. Some women will now no longer risk becoming single mothers("stoppers"), and some who can now afford an abortion in the event of a pregnancy("starters"). These implications are cataloged in the final two columns of Table 2.1.

Both the KS and AYK models are accurate descriptions of the incentives at work, KS abstract away from strategic choices by men varying systematically with abortion costs, and AYK abstract away from the insurance value of abortion. The goal of this paper is to test if there is any empirical evidence in favor the model of AYK with individual level data; do abortion cost declines generate strategic interactions which increase the likelihood of out-of-wedlock birth? With reference to Table 2.1, this question is whether the cost decrease alters the fraction out-of-wedlock births not just by reducing births among those that would have been in-wedlock births(Row 3, Column 5), but by increasing the likelihood of separation among those who do give birth (Row 3, Column 6). This situation, outlined in AYK, is one of important interest since there is then evidence of a clearly negative externality of lowering abortion costs on the welfare of some single mothers. Given that insurance effects go in the opposite direction, a finding that abortion cost decreases do increase the likelihood of births being out-of-wedlock can be viewed as evidence that the implications of AYK cannot be rejected. Establishing the effect is a significant issue given the likely important role of unobservables, and not just the incentives outlined, in driving observed outcomes.

Another major theoretical contribution, Willis (1999), focuses on more traditional Beckerian marriage market fundamentals such as the resource distribution between men and women and the sex ratio. Willis (1999) proposes a model to explain the recent increases in out-of-wedlock childbearing. In the model, marriage market equilibria can arise among low income households in which men shift the cost of child-rearing to single women. This equilibrium arises due to a skewed sex ratio (relative scarcity of men) and the fact that women at the low end of the income distribution have more resources relative to men. While this model no doubt gives a convincing explanation for part of the increase in out-of-wedlock childbearing in the last half century, it does rest on an assumption of perfect fertility control. Women above an income threshold have a positive demand for children. This setup is useful for understanding the post-birth contribution game that arises, but abstracts away from heterogeneous abortion costs since all women are assumed to not have children if their income is below the threshold. Ultimately the work here complements Willis (1999), my aim being to relax the perfect control assumption, studying the extent to which female demand for children is affected, not by income, but by uncertainty about future relationship status and abortion access.[4] I emphasize the models do not conflict, and may indeed reinforce each other: as abortions costs fall, a key sex ratio of interest, the ratio of men to *childless* women increases. One could argue this sex ratio shift feeds into the Willis (1999) model, leading to less male attachment to a particular family.

[4] If one could observe data on partner income and child support payment systems the games of Willis (1999) and Akerlof, Yellen, and Katz (1996) could be estimated together since they occur at different points along the sequence of childbearing and child-rearing decisions. Observing both income and representative abortion data is a key limitation however. Add Health contains very good abortion data by panel data standards, but has much less information about partner income.

2.3 Data

The data set used for estimation is The National Longitudinal Study of Adolescent Health, a large longitudinal data set consisting of three waves of interviews. The design was a stratified random sample of U.S. high schools and associated middle schools, Wave I was conducted between 1994-1995, Wave II in 1995-96, and Wave II in 2000-2001. Wave I surveyed approximately 90,000 middle and high school students, and from this sample around 20,000 individuals were selected for a more detailed In-Home survey. This smaller sample was then followed up at Waves II and II. Wave II collected retrospective information on key variables both for individuals in the original sample, and for an additional 1500 observations added for a sample of current partners.

2.3.1 Abortion Reporting

To estimate the model specified in Section 2.4 I use a subset of the Add Health data collected at Wave II, which contains a retrospective history of all relationships occurring after, or before if ongoing during, the summer of 1995. Partner characteristics were recorded for each relationship, as well as a detailed survey about each pregnancy that occurred with that partner. Breakdown of the Add Health pregnancies are given in Table 2.2.

An important problem with studies that include pregnancy termination decisions is the underreporting of abortions. Lundberg and Plotnick (1995) document the underreporting problems in the NLSY79. To check for reporting problems Table 2.2 allows one to compute the abortion ratio, that is the ratio of abortions per 1,000 live births. For Table 2.2 the abortion ratio across all races is 294.118, which is comparable to a 6 year mean over 1995-2000 period using medical records data: 252.5 and 267 from Finer and Henshaw (2006) and CDC respectively. The higher abortion ratio here no doubt reflects the age of the sample, and so I construct an age weighted mean abortion ratio taking as weights the age distribution of the sample, and the abortion ratio from CDC 2000 data.[5] The abortion ratio we would observe with perfect reporting from this portion of the age distribution is 330.531, in contrast the age weighted abortion ratio observed in Add Health data is 295.312. On average 89% of abortions in the data are reported.[6]

Racial differences in underreporting appear in this data as they do in the NLSY79, but are much less severe. The abortion ratio for Blacks in Table 2.2 is 320.399, compared to CDC data for 2000 which showed a ratio of 530. Even given this large underreporting, we still have around 60% of Black abortions reported,[7] near the two-thirds fraction of white reporting used in Lundberg and Plotnick (1995). All together, the Add Health data, while still suffering from underreporting problems, contain far more information about the population of pregnant women than any other panel data source known to the author.

2.3.2 Sample

Given the original design at Wave I, which included unrepresentative ethnic over samples, and the addition of individuals at Wave II in a couples sample, sampling weights are essential for the generalized validity of the results. All estimations use cross sectional probability weighting from Wave II, when all information was gathered. Table 2.3 gives summary statistics for the Add Health data at Wave II.

The sample used for estimation consists of only female respondents. Variables regarding the length of each pregnancy were only collected for women in the sam-

[5] $\mu_{ageweighted} = \Sigma_a \%Age_a \cdot Ratio_a$ where a denotes the 4 age groupings: < 15,15-19,20-24,25-29.

[6] This discrepancy is almost entirely drive by women in the age 20-24 bracket, who differ from the average of 300 abortions per 1000 live births by around 70 births. In contrast the sample of age 15-19 women match the population ratio almost exactly at 361.

[7] National aggregates are available only for race or age, but not both. Given the younger sample observed here, 60% serves a rough estimate of the percent of abortions recorded.

ple, and since this information is key to the timing of post-pregnancy relationship status I was forced to drop men from the analysis. Individuals who marry prior to pregnancy likely differ dramatically from those who do not marry, in unobservable ways regarding separation and abortion choices. Accordingly the sample includes only those women who were unmarried at the time of conception. Finally attention is restricted only to first pregnancies to avoid the complicated issues surround how preexisting family structure influence birth and separation choices. Together these restrictions: female reported first pregnancies(2903), less unmarried status(360), less stillbirths(206) result in a sample of 2337 pregnancies, which is further reduced by missing data. Missing probability weights and geographic identifiers(143) and non-response (148) limit the final sample size to 2046 pregnancies.[8]

The variables used to measure environmental factors like the abortion availability in the county, were drawn from Wave I of Add Health's Contextual Data. They are measured between 1990 (Census data) and 1995, depending on the data source. Because of the sensitive nature of Add Health data, I am unable to connect individuals with the county of residence at the time of pregnancy, but only at the time of the Wave I interview. The distribution is summarized in Table 2.4. It is likely that these variables are serving as good proxies for the environment where the pregnancy was resolved. The education distribution at the time of pregnancy is almost entirely concentrated at the below high school graduate and high school graduate levels (see Table 2.3). As such most of these pregnancies are occurring before any mass exodus to college, or among individuals who did not attend college. For individuals who did move, the extent that the old environmental variables might be picking up background demographics like the religiosity of the neighborhood they grew up in is addressed

[8] Wherever possible, indicators were included for non-response regarding partner characteristics, which may be particularly relevant. Most non-response problems come from linking the 2001 relationship roster data with early adolescent data on puberty, and from smoking or drinking during pregnancy questions.

below, by controlling for the observed county level correlates of abortion provider status.

2.4 Empirical Methodology

2.4.1 Capturing the Effect

This section provides a guide through an empirical strategy for testing whether the negative externality outlined above is present in data on women who experienced an out-of-wedlock pregnancy. For exposition I begin under the most stringent set of assumptions, and sequentially relax a number of assumptions. Given the age of respondents outlined above we will only partially observe the marriage market outcomes of each individual. For this reason the focus is only on the immediate post-pregnancy separation between the biological parents as a test of the theoretical implications.[9][10]

The major equation of interest is the (initially) linear probability model of the binary outcome of separation following a pregnancy out-of-wedlock. The indicator S_i will be one if there is a separation either between conception and resolution, or between resolution and some fixed time after pregnancy, which will vary to trace out possibly varying time effects.[11] The major equation of interest is parameterized as:

$$\begin{aligned} E(S_i|X) + \varepsilon_i = P(Separate_i|X) + \varepsilon_i =& \beta_0 + \beta_1 Birth_i \times LowCost_L + \beta_2 LowCost_L + \\ & \beta_3 Birth_i + \beta_I' X_i + \beta_P' X_p + \beta_z' X_L + \varepsilon_i \end{aligned} \tag{2.1}$$

[9] Ginther and Pollack (2004) point out that the major division in educational attainment by family structure is precisely those with both biological parents and those without both.

[10] The survey design asks respondents to combine any periods of on-off relationships into one relationship, so a separation will be the end of the final period of intercourse.

[11] The inclusion of those who separate between conception and resolution is important because as time passes selection may be responsible for the estimate on the sample who separated later.

where the first equality follows from the binary outcome, and various sets of assumptions will restrict who enters the estimation. The variable $LowCost_L$ will be a vector of indicators of the types of abortion access available at the county level. The vectors X_i, X_p and X_L will capture individual, partner, and location specific characteristics.[12]

Under a strict set of assumptions, one can interpret tests for a positive sign on the coefficient β_1 in (2.1) as evidence in favor of the implication that giving birth in low cost abortion environments increases the likelihood of separation. These assumptions are:

1. Pregnancy is exogenous.
2. $\text{Cov}(birth_i \times LowCost_L, \varepsilon_i) = 0$.
3. Miscarriage is conditionally random.[13]
4. Full disclosure of pregnancy type between partners.

Under these assumptions one can estimate (2.1) on the set of all observed women who experienced an out-of-wedlock pregnancy: those who gave birth, had an abortion, or miscarried.[14] The interaction terms capture the impact of giving birth in lower cost

[12] Pregnancies ending in birth, abortion, and sometimes miscarriage will all be combined in the estimation of (2.1). This is essentially a limitation of the data, as the abortion cost shifters do not vary enough within states to allow for separate regressions conditional on the three outcomes. The IV strategy employed later will deal to some extent with unobserved correlation between errors and the pregnancy outcome. With regard to miscarriages' possible correlation with the errors, the bounding strategy employed allows for a specified fraction of miscarriages to be non-random, a form of unobserved heterogeneity.

[13] The phrase "conditionally random" means that behaviors leading to miscarriage, notably smoking and drinking, are controlled for in (2.1)

[14] When the term miscarriage is used throughout, it is with reference to pregnancies ending before the 20 weeks of gestation, in line with the medical definition. One reason for this is because abortion prices increase dramatically after this point,(see Jones, Zolna, Henshaw, , and Finer (2008)) so pregnancies ending after this point were arguably attempts to carry the pregnancy to term. Results were largely insensitive to the cutoff for the length of miscarried pregnancy, with the exception of miscarriages occurring after 30 weeks of gestation. Also important is the emotional trauma involved in such events(pointed out in Hotz, Mullin, and Sanders (1997)) which likely has an independent effect on separation.

abortion areas on the separation likelihood, relative to those who did not give birth, either because an abortion was obtained or a miscarriage occurred. Assumptions (3) and (4), that the man knew of the pregnancy and the woman's decision, together allow one to interpret the separation as response to the pregnancy outcome.

To understand what I term "pregnancy types" and how miscarriages fit into the framework, assume each women who becomes pregnant has a latent type $\tilde{B}$ or $\tilde{A}$ corresponding to her expected utility from having a child or not.[15] For women who give birth or obtain an abortion we observe the latent type as B or A, but for women who miscarry we do not. Separations occurring before or after a birth or abortion can be viewed a response to this latent status, which has been disclosed by the woman to her partner. This amounts to assuming the game of KS and AYK are being played: conditional on pregnancy the woman makes the pregnancy resolution choice with uncertainty about the separation, which then occurs or does not.[16] Separations occurring after a miscarriage can be viewed as a response to the random event of not having a child, a switch to A. Finally then only separations occurring before a miscarriage are responses to an unobserved(to the econometrician) latent type. Under the assumption of fully random miscarriage this group could be excluded from estimation, with only efficiency losses. Leaving this group in the estimation sample creates a conceptual problem since some where latent type $\tilde{B}$ and others where type

[15] This expectation is taken mainly with respect to separation uncertainty.

[16] Empirically two problems may arise from this structure. Firstly the pregnancy could be terminated before the man knows of it. In this first case, I simply interpret these women has having very high dis-utilities of being mothers, a state likely to be observable to the man. Separations in this instance are still responses to the "no-child" state; the man knowing or not knowing about a pregnancy is assumed to have no effect on separation. Secondly the separation could occur before the man knows of the pregnancy, which appears to switch the ordering of the game from "pregnancy choice-separation" to "separation-pregnancy choice." However assuming the man has rational beliefs about the probability of pregnancy means the separation decisions are still partially a response to the (potential) pregnancy outcomes. These two groups, aborting before telling the man, and separation before telling the man make up 3.5% and 7.7% of pregnancies in the sample respectively, suggesting the games of KS and AYK describe the vast majority of cases.

$\tilde{A}$. In practice however, this group is very small, and since throughout use will be made of the assumption of conditionally random miscarriage(rather than fully random miscarriage), this small fraction (less than 10%) of miscarriages which saw early separations are left in the estimation sample.[17] This issue can also be dealt with clearly and explicitly in terms of calculating bounds on the effect, which is done below.

The four assumptions above will be relaxed in the following ways. The endogeneity of pregnancy will be dealt with via selection correction models, which correct for different unobserved conditional means in the likelihood of being pregnant in the linear selection equation, and control for the pregnancy-separation error correlation in non-linear selection models. The second assumption can be relaxed in the presence of an instrument for the birth-abortion access interaction; (assumed) conditionally random miscarriage interacted with the (1) the abortion access vector and (2) the partner staying until the (random) time of miscarriage, provides the instrument. And assumption (3) can be relaxed by calculating bounds on the IV effect in the event that miscarriages are not conditionally random. These bounds will explicitly take into account both (1) the fact that some unknown disproportionate fraction of miscarriages are latent abortion types (2) partners who leave miscarrying women prior to the miscarriage alter the estimate of the effect. Assumption (4) as discussed above, is in line with the models of AYK and KS; it appears to hold in the vast majority of cases.[18]

[17] In the results which follow, excluding early leaving miscarriages had no qualitative impact on the results.

[18] Excluding the groups who violate assumption four, those who separate or abort without telling their partner or the pregnancy, strengthened the results. However selection may be driving those estimates, so the groups are left in the estimation sample.

2.4.2 OLS Estimates with Linear Sample Selection

The problem associated the endogeneity of pregnancy is whether an estimated effect is only relevant for pregnant women, who may differ from the general population of women in their separation patterns or match quality in unobservable ways. In order the relax the assumption that pregnancy is exogenous, selection correction terms will be included in the estimations which follow. A semi-parametric version of the original Heckman (1979) selection correction procedure, appropriate for binary outcomes, will eventually be estimated. The advantage of this selection correction approach is that firstly it does not impose a parametric form on the selection equation,[19] and secondly allows an IV approach to be nested within the selection correction procedure, producing estimates dealing with both general forms of selection and the endogeneity of birth. As with any sample selection model, the pivotal assumption will be the exclusion of some variable in the selection equation from the outcome equation. The age at which a women begins puberty(age of menarche) contains a component which, conditional on a set behaviors, is plausibly random.[20] It is associated with pregnancy because it may be correlated with pregnancy through a longer sexual history but also through biological fecundity (e.g. the likelihood of ovulation or a fertilized embryo succeeding in implantation). To deal with the behavioral component age at sex at its square will be included, implicitly controlling for the years since menarche. In addition the age at menarche, the Add Health survey distinguishes whether women have recently been prescribed birth control pills to deal with irregular or painful menstruation, and/or for contraceptive purposes. These data are combined with age, race,

[19] Estimates of the specification under Bivariate normality were not robust, and failed tests for normality put forth in Pagan and Vella (1989).

[20] The medical and adolescent health literatures have established a set of behaviors correlated with later ages of menarche, especially weight or BMI (body mass index) related factors, but there is consensus that some component is due to genetic variation. Riley (1994) contains a review and Welch (2005) points out that race is the most salient factor in the U.S.

and exercise intensity information from Wave I in the selection equation. The set of instruments identifying the selection correction terms will be the age at menarche interacted with race, along with an indicator of whether the women experienced irregular menstruations during adolescence(a sign of lower fecundity).[21]

All the selection correction terms applied in estimation will arise from the following simple model:

$$
\begin{aligned}
P_i^* &= \delta_0 + Z_i^{'}\delta + u_i \\
S_i^* &= \beta_0 + X_{ip}^{\prime}\beta_p + Z_{2i}^{'}\beta_z + E(u_i|u > -Z'\delta) + \tilde{\varepsilon}_i, \text{ if } P_i^* > 0
\end{aligned}
\tag{2.2}
$$

where S_i^* is the separation index in the event of pregnancy, and its indicator of being positive S_i, is only observed for pregnant women. The variables affecting pregnancy $Z = [Z_1\ Z_2]$ are partitioned into biological factors labeled Z_1 and behavioral factors Z_2. The linear specifications which follow all include a linear approximation to the omitted conditional mean in (2.2). Newey (1999) showed that assuming the true selection process is linear in Z allows one to estimate a first-stage probit or logit on the selection equation even if this is a mis-specification, and the inclusion of resulting index $Z'\hat{\delta}$ still yields consistent estimates of β except for an invalid intercept estimate.

The first set of estimates of Equation (2.1) are presented in Table 2.5. Estimations include the selection index and the behavioral factors outlined above that affect selection into pregnancy, as well as indicators of smoking or drinking during pregnancy in accord with assumption that miscarriage is conditionally random. The upper panel in Table 2.5 control for only female and partner characteristics, outlined in detail in the appendix, they include age and education at the beginning of the pregnancy as well as religious attendance race indicators. The results indicate that the presence of an abortion clinic within the county during the first year after pregnancy resolution

[21] The F statistic on the excluded instruments was 16.93 pregnancy equation, larger than the rule of thumb suggested in Staiger and Stock (1997) for weak instrument testing.

has dramatically different effects on separation depending on whether or not a birth occurred. For those who did not give birth, the clinical availability was related to a 12% decline in the likelihood of separation, a result consistent with the match quality impact of abortion access. Meanwhile for those who did give birth, the total effect of clinical abortion availability erases the negative impact and is between a 1.8%-2.5% increase in the likelihood of separation. Note as well the effects of hospital and physician provided services are insignificant and generally the birth relative to no birth magnitudes offset one another.

The lower panel of Table 2.5 includes the entire set of controls in the data, again outlined in the appendix in full, they include female labor market information, county level observables on religiosity and political affiliation, income, population, urbanicity and state fixed effects. Inclusion of this set of controls reduces the magnitude and significance of the impact of clinical availability on those to who do not give birth to below a 5% significance level, for all but one time horizon. In contrast the positive impact of clinical access on those who do give birth remains positive. In all regressions the selection correction index coefficients were positive and insignificant, a failure to reject the null that selection bias is present in the separation equation. The impact of clinical abortion access for those who give birth relative to those who do not is positive and significant, in the range of a 13%-18% increase in the relative likelihood of separation.

2.4.3 A Non-Linear Model with Selection

While the OLS estimates above include linear selection correction terms, as a check on the results we can go further by estimating a semi-parametric outcome equation that allows for more general non-linear selection, applying the estimator outlined in Abrevaya, Hausman, and Khan (2007). One particular worry in this setting will be that birth control intensities are chosen to avoid pregnancies which are more likely to induce separation. This will be modeled as a correlation between unobservables in the separation and pregnancy equations, which although not estimated, is controlled for in the following model. The first step estimation of the probability of pregnancy will be estimated as a logit on the excluded variables(age at menarche, menstrual problems) and characteristics; the second step probability of separation will use a Pairwise Smooth Maximum Score estimator, including characteristics and background controls to economize on parameters. With a first-step estimate of $Z_i'\hat{\delta}$ in hand, the estimator takes the following form:

$$\beta_{PSMS} = \arg\max_{\beta} \binom{N}{2}^{-1} \sum_{i}^{N} \sum_{j,i\neq j}^{N-1} \{2\cdot 1\{S_i > S_j\} - 1\} K\left(\frac{X_i\beta - X_j\beta}{h_1}\right) k\left(\frac{Z_i'\hat{\delta} - Z_j'\hat{\delta}}{h_2}\right) \tag{2.3}$$

where the second stage regressors have been collected into X, and the h_1 and h_2 are appropriate bandwidths which decline to zero as $N \to \infty$. The estimator relies on the idea that if $Z_i'\hat{\delta} = Z_j'\hat{\delta}$, then $X_i\beta > X_j\beta \Leftrightarrow Pr(S_i > S_j) > Pr(S_j > S_i)$, which comes from the assumed monotonicity of $F(u, \varepsilon)$ and (u, ε) being independent of Z_1 above. The first stage logit assumption amounts to assuming a marginal distribution of F, but allows the full bivariate distrusting F to be unspecified.

The results of the semi-parametric Pairwise Smooth Maximum Score estimation are presented in Table 2.6. The kernel functions used are the normal CDF and PDF, and h_1, h_2 are given by Silverman's Rule with the initial standard deviation coming from OLS indices of the pairwise differences. Excluded from the separation estimation, the Z_1 are the age at menarche and its interaction with race, which is noticeably different for Black and Hispanic women, along with an indicator for whether menstrual problems occurred during adolescence. The results in Table 2.6 although considerably less efficient, still accord with those OLS specifications already outlined.[22] One difference however given the pairwise structure of the estimator is lack of use of survey weights if 2.6. As a check on these results, I drop individuals who were part of the unrepresentative ethnic over-samples, and re-estimate the selection correction model. The estimates presented in Table 2.7 are quite similar to those in Table 2.6 with the exception that an affect now appears from medical abortion costs as well. Overall it appears selection into pregnancy, of particular concern here given the birth control choices that underly the observed outcomes, is not driving the results in Table 2.5.

2.4.4 Bias and Instrumenting

In the estimation of (2.1), bias in the coefficient of interest β_1 may arise from the interaction of variables $LowCost_L$ and $Birth_i$ being related to unobserved factors. I divide these factors into two major groups, match quality μ_i and stigma $Stigma_L$, so we have the following:

$$Separate_i = \beta_0 + \beta_1 LowCost_L \times Birth_i + ... + \beta_S Stigma_L + \beta_M \mu_i + \tilde{\varepsilon}^i \qquad (2.4)$$

Firstly, abortion costs themselves may create selection in the levels of μ_i. If abortion is relatively cheaper, then observed couples who give birth should be of higher average match quality, and therefore unobservably more likely to stay together. This is because lower costs should allow some poorly matched couples at the margin to switch from birth to abortion. Alternatively the theory of AYK might be more relevant than the selection: when the costs of fertility control are lower, men will be less willing to take on the costs of child rearing, and women who chose to give birth in such environments face a higher probability of becoming single mothers. The selection on match quality creates another bias toward zero in β_1. Secondly, if $Stigma_L$

[22] The same variables from Columns (1) and (2) of Table 2.5 are used in the semiparametric estimations.

includes unobserved factors such as support services to single mothers, or decreased stigma associated with being a single mother, which are correlated with greater abortion availability and a higher likelihood of birth, we could see the biasing away from zero.[23] This bias may be more or less important than selection from abortion costs; in the estimation section a set of county observable characteristics are included, which are likely correlated with unobserved stigma. Thirdly we expect the $LowCost_L \cdot Birth_i$ choice by the woman to be positively related to the unobservable individual level factors that affect whether or not the couple stays together following the pregnancy, μ_i, creating a bias toward zero. This because of two positive correlations, the selection effect of abortion costs on match quality outlined above and the naturally higher likelihood of staying together and giving birth when match quality is higher.[24] Discussed in more detail in estimation, figuring which of the last two effects dominate will require the IV approach.

Another important caveat in interpreting results is that in Add Health data we do not observe who ended the relationship. If we knew for certain that the variable $Separate_i$ was not just the event of separation, but additionally that it was the man's unilateral choice we could straightforwardly interpret this specification as able to answer the question at hand. However, since we cannot distinguish who initiates separation, the model presented here aggregates over two sub-groups of separation: (i) female initiated (ii) female uninitiated.[25] This creates bias in my estimates of β_1. To examine the likely sign let β_1^M and β_1^F denote the impact of birth in a low cost abortion environment for male initiated (M) and female initiated (F) separations. The parameter β_1^F captures the impact of birth in a low cost abortion environment

[23] If $Cov(LowCost_L \cdot Birth_i, Stigma_L) < 0$, and $\beta_S < 0$, so stigma reduces separation, the bias is positive and away from zero.

[24] That is if $Cov(\mu_i, LowCost_L \cdot Birth_i) > 0$ and $\beta_M < 0$, the bias is negative and toward zero.

[25] Mutual separation can be classified as female or male initiated.

on the probability that a woman chooses to leave her partner. If it is the case that women in areas with lower cost abortions are also those more inclined to choose to leave a partner, it would create a bias away from zero, i.e. $\beta_3^F < 0$, arguing that estimates could be simply bias. Two plausible explanations for this sign are abuse and a preference for "going-it-alone."

Add Health data contain reported abuse measures, I find abuse by the partner in the raw data is negatively correlated with abortion availability. Abuse may well drive the bias in the opposite direction, leading to systematic bias of β_1 toward zero. If women value future potential partners, the case in which $\beta_3^F < 0$ arises from a preference for single parenthood less as well. This is because single women with children in low cost abortion environments are at a strategic disadvantage in marriage market terms, competing against more and childless single women. Furthermore, some sociological evidence on relationship attachment shows that when few potential mates are available, individuals invest more in their current relationship.[26]

By not modeling the process through which women arrive at the decision of birth or abortion, clearly information is lost. It is clear that both sex participation and birth control intensity choices should create a selection bias in the major parameter of interest, the bargaining externality of abortion costs, β_1 in (2.4). If women with very low bargaining power(those with a high pregnancy cost who are unwilling to adopt abortion) see that they face a greater risk of separation, they will be more selective in choosing a partner, use birth control more intensely, or delay sex until marriage where the costs of leaving are relatively higher. In any of these events this creates a downward bias in the magnitude of the bargaining estimate β_1, since those most likely to be left with a child should they choose to give birth will avoid pregnancies that expose them to that risk.

[26] Jemmott, Ashby, and Lindenfeld (1989) conduct interviews with college age men and women currently in relationships.

All the biases outlined, save one, translate in (2.1) as biasing towards zero of the magnitude of β_1. Given the bias from of female strategic considerations, the selection effects of abortion costs and birth control, and the effects of unobserved match quality, a finding that β_1 is negative, even without instrumenting, appears to be evidence in favor of the theory of AYK. To further strengthen the case, and eliminate much of the bias discussed here, the next section will exploit miscarriage as an instrument to deal with the endogeneity of birth and pregnancy.

2.4.5 Miscarriage, IV and Bounding

Regarding the impact of birth on separation, miscarriage, conditional on a set of behaviors such as smoking during pregnancy, may provide quasi-random variation in whether or not a birth occurs. The maintained assumption necessary for the IV strategy to point identify the parameters of interest will be that conditional on a set of behaviors, miscarriage is a random event, allowing us to compare separation of miscarrying couples to that of couples who gave birth. This strategy is adopted from Hotz, McElroy, and Sanders (2005) who use it to estimate labor, marriage and education market impacts of teen pregnancy. In prior work, Hotz, Mullin, and Sanders (1997) established the validity of this "contaminated" natural experiment for estimating bounds which shrink to the IV estimate when sequentially adding the maintained assumptions. In the case that miscarriage is not random, then using data on the prevalence of non-random miscarriage due to smoking and drinking during pregnancy, one can calculate worst case bounds of the effect.[27]

The bounding strategy is adapted here to deal with both non-random miscarriage and additionally the fact to some miscarriages occurred after the separation choice.

[27] Add health data show very similar levels of drinking and smoking during pregnancy, and I calculate 0.82 as the proportion of miscarriages which are random, along with assuming the probability of being a latent birth type is equal to the proportion of births among non-miscarriages, 0.76 in the sample used here.

Following the work of Hotz, McElroy, and Sanders (2005), let S_1 be the separation outcome that occurs if a woman gives birth, and S_0 be the separation outcome that would occur with the woman does not give birth. The treatment effect of interest is given by $\beta_1(X) = E(S_1|B, X) - E(S_0|\tilde{B}, X)$, the difference in separation means due to the presence of a child not attributable to difference in latent type. The second term is unobservable but can be rewritten as follows :

$$E(S_0|\tilde{B}, X) = E(S_0|\tilde{B}, X, M) = \frac{1}{\lambda^*}E(S_0|X, M) + (1 - \lambda^*)E(S_0|\tilde{A}, X, M) \quad (2.5)$$

where the first equality follows from the assumption of conditionally random miscarriage, the second equality comes from HMS (1997). The term λ^* is proportion of miscarriages occurring randomly to latent birth type women. From (2.5) one can see that the unobserved expectation is a weighted sum of the expectation of miscarriages and a correction term for miscarriages who were not latent birth types. Worst case bounds are calculated by plugging in zero and one for this unobserved expectation. The observed expectation $E(S_0|X, M)$ can be further rewritten as:

$$\begin{aligned} E(S_0|X, M) = E(S_0|Leave < t_M, M)P(leave < t_M|X, M) + \\ + E(S_0|t_{S_0} > t_M, X, M)P(t_{S_0} > t_M|X, M). \end{aligned} \quad (2.6)$$

Here the event $\{Leave < t_M\}$ is the event of a separation prior to a miscarriage, and the event $t_{S_0} > t_M$ refers to the time of separation, if any occurred, being after the date of the miscarriage. The expectation $E(S_0|Leave < t_M, M) = 1$ trivially, so the extra term $P(leave < t_M|X, M)$ will serve to widen the worse case bounds. The second term as well suggests the instrument available for IV point identification under the assumption of random miscarriage: miscarriage interacted with the couple staying together at least until the time of miscarriage will give pseudo-random variation in the birth outcome. The worst case bounds in the event miscarriage is non-random can be expressed as:

$$\beta_1(X) \in \left[E(S_1|B,X) - \frac{1}{\lambda^*}I - (1-\lambda^*), E(S_1|B,X) - \frac{1}{\lambda^*}I \right] \tag{2.7}$$

where $I = P(leave < t_M|X,M) + E(S_0|t_{S_0} > t_M, X, M)P(t_{S_0} > t_M|X,M)$, a weighted difference in outcomes between those who give birth and miscarry under different assumptions about the outcomes of those who would not have given birth if they had not miscarried.

Noted above, the data used here have a relatively high reporting rate for abortion surveys, indicating that miscarriages are not made up in any large measure by misreported abortions. These two ideas, the plausible randomness of biological complications and low levels of misreporting indicate that miscarriage should provide an informative instrument for birth in attempts to estimate β_1. Traditional instrumental variables estimates will be presented along with the worst case bounds derived from the OLS estimates. All regressions will include births, abortions, and early term miscarriages and any variable interacted with birth will be instrumented for by its interaction with miscarriage and the relationship lasting at least until the time of miscarriage.

Table 2.8 presents estimates of the IV and worst case bounds outlined, including the full set of controls, individual characteristics, county controls, and state fixed effects. The upper panel gives IV estimates as well as worst case bounds on the birth abortion access interaction terms. The IV estimates uncover interesting differences compared to OLS estimates in Table 2.5. The positive impact on the clinical interaction is not insignificant, instead a large positive and significant coefficient on physician provided services is estimated. This difference in results is consistent with two ideas already discussed namely stigma and match quality. Unobserved stigma capturing the difficulty of having children as a single mother may be correlated with provision on abortion services within the county and with birth, leading to a bias in the OLS coefficients away from zero. The clinical interaction coefficient is consistent with stigma having a dominating effect in areas with clinics since the OLS estimates are larger than the 2SLS estimates. In contrast bias may arise from unobserved match quality. Where abortion is more available couples who give birth might be better able to match well, so giving birth in lower cost environments creates a bias in the OLS results toward zero. This explanation appears to be the dominant effect in areas with physician provided abortion services: the OLS estimates are considerably smaller than the 2SLS estimates.

Given the structure of abortion market, these results imply that increases in access from no provider to a small (physician) provider creates the positive impact. The additional effect of clinics in areas with physician providers appears negligible. Very few locations observed have clinics without physician provided services(71 observations from 2046), meaning for most observations, the clinical indicator is capturing the impact of a clinic in addition to the physician provided services.

The worst case bounds on the physician provided coefficient are greater than zero at all time horizons estimated. Given the variety combinations of types of abortion providers, the lower panel of Table 2.8 provides estimates of the bounds for the most relevant combinations of providers.

2.4.6 Checks on the Results

The sample used here is less than ideal in a number of ways. The data were gathered as a retrospective history, meaning observations from the beginning of the 1995-2001 window may suffer from recall bias, while those reporting relationships nearer to the 2001 cutoff will less time of exposure to a separation. While focusing on short time horizons deals with this to some extent, I include the distance in time from 2001 in the estimation as a way of dealing with both issues related to the timing of data collection.

2.5 Conclusion

The study of selection into out-of-wedlock parenthood has generally suffered from a lack of detailed micro data describing the environment in which decisions are made. In particular abortion decisions, a main channel of selection into single parenthood, usually suffer from drastic underreporting in individual level data sets. The findings presented here, using an important new source of data on both partners and pregnant women, provide strong evidence that partner choices and the abortion cost environment which pregnant women face affect their demand for children. In particular the results provide evidence that policies which decrease abortion costs could have negative welfare impacts on some women and children by increasing the prevalence of female headed households. Fortunately this source of possible immizeration can be characterized in terms of fathers decision making. Since the marriage market behavior of fathers underpins this conclusion, the level and enforcement of child support may provide an even more important policy response in attempts to redress single mothers' welfare losses. Behavioral models of fertility and relationship decisions as they relate to the child support environment, or more generally the cost of child-rearing, seem like another important step in this line of research.

2.6 Tables and Figures

Table 2.1: Implications of a Decrease in Abortion Costs

Model-Group	(1) Pregnancies	(2) Birth	(3) Abortion	(4) Abortion Rate	(5) IWC	(6) OWC	(7) $Frac_{OWC}$ [a]
(1) KS-Small	↑	↑	↑	?	↑	-	↓
(2) KS-Large	-	↓	↑	↑	-	↓	↓
(3) AYK-Sex. Active	-	↓	↑	↑	↓	↑	↑
(4) AYK-Starters	↑	-	↑	↑	-	-	-
(5) AYK-Stoppers	↓	↓	-	↑	↓	-	↑

[a] Fraction out-of-wedlock is *OWC /(OWC+IWC)*

Table 2.2: Add Health Pregnancies

	Number of Preg.
Total Female Reported	4959
Whites	2253
Blacks	1572
Others	1134
Live Birth	2924
Whites	1395
Blacks	902
Others	627
Abortion	860
Whites	317
Blacks	289
Others	254
Miscarriage	627
Still Birth(at least one)	113
Multiple Birth	122
Unresolved	313

*Valid responses include the date of resolution.

Table 2.3: Add Health: Estimation Sample*

N(first pregnancies)	2046	
Pregnancy Outcome [28]		
Birth	64.76	
Abortion	22.39	
Miscarriage	12.85	
Separated Post Pregnancy, by:		
1 Mo.	11.63	
1 Yr.	26.05	

	Female	Partner
Age (Years)		
Mean	18.78	21.77
5%-tile	15	16
95%-tile	22	30
Race		
White	46.09	41.00
Black	32.01	33.53
Hispanic	15.15	16.47
Other	6.74	8.99
Education		
<HS Diploma.	43.74	32.70
HS Diploma.	44.77	41.25
Some College	8.50	18.52
Bachelors Deg.	0.98	3.67
Unknown	-	3.86

Table 2.4: Distribution of Abortion Providers

	Availability		
Availability	No Clinic	Clinic	Total
No Physician	890	70	960
Physician	249	826	1,075
Total	1,139	896	2035

Table 2.5: Probability of Separation Beyond Preg., Selected LPM Coefficients

Controls: (i, p) Characteristics[a]	1-Month	3-Months	6-Months	9-Months	1-Year
Birth × Clinic	0.145	0.132	0.131	0.168	0.146
	(0.056)*	(0.061)*	(0.075)	(0.076)*	(0.086)
Clinic	-0.120	-0.118	-0.113	-0.150	-0.123
	(0.048)*	(0.048)*	(0.054)*	(0.056)*	(0.065)
Birth × Hospital	-0.007	0.024	-0.006	-0.013	0.012
	(0.047)	(0.051)	(0.058)	(0.067)	(0.074)
Hospital	-0.003	-0.014	-0.009	0.014	-0.011
	(0.039)	(0.038)	(0.039)	(0.050)	(0.055)
Birth × Physician	-0.095	-0.078	-0.052	-0.083	-0.089
	(0.060)	(0.068)	(0.078)	(0.081)	(0.080)
Physician	0.093	0.072	0.090	0.106	0.099
	(0.050)	(0.048)	(0.052)	(0.061)	(0.064)
Birth	0.026	-0.010	-0.009	-0.039	-0.060
	(0.032)	(0.034)	(0.034)	(0.037)	(0.040)
R^2	0.072	0.061	0.056	0.058	0.060
Controls: All					
Birth × Clinic	0.140	0.130	0.144	0.180	0.158
	(0.058)*	(0.064)*	(0.080)	(0.084)*	(0.094)
Clinic	-0.107	-0.095	-0.108	-0.178*	-0.131
	(0.059)	(0.063)	(0.070)	(0.076)	(0.078)
Birth × Hosp	-0.030	-0.001	-0.042	-0.049	-0.028
	(0.053)	(0.056)	(0.064)	(0.072)	(0.083)
Hospital	-0.052	-0.062	-0.052	-0.031	-0.045
	(0.047)	(0.049)	(0.054)	(0.066)	(0.069)
Birth × Physician	-0.075	-0.059	-0.034	-0.076	-0.069
	(0.064)	(0.073)	(0.085)	(0.090)	(0.087)
Physician	0.111	0.113	0.133	0.169	0.142
	(0.063)	(0.062)	(0.071)	(0.080)*	(0.080)
Birth	0.019	-0.022	-0.011	-0.036	-0.060
	(0.036)	(0.038)	(0.037)	(0.040)	(0.043)
R^2	0.100	0.096	0.092	0.093	0.095

[a] Standard errors in parenthesis, results are from separate regressions, all of which have N=2046

Table 2.6: Pairwise Smooth Maximum Score Estimates

	Logit on Pregnancy			PSMS on Separation[a]	
Z_1	Coeff.	S.e.	Z_2	Coeff.	S.e.
Age at Menarche	-0.0711	(0.034)*	Birth × Medical	0.1466	(0.133)
Black × AgeMenar.	0.0902	(0.048)	Birth × Clinical	0.2415	(0.113)*
Hips. × AgeMenar.	0.2301	(0.057)*	Birth	-0.3684	(0.095)*
Other × AgeMenar.	0.1460	(0.140)	Medical	-0.0772	(0.127)
Black	-0.4258	(0.597)	Clinical	-0.1623	(0.109)
Hips.	-2.4472	(0.750)*	Partner Age	0.0158	(0.029)
Other	-1.7078	(1.785)	Partner Age^2	-0.0149	(0.050)
Menstrual Problems	-0.1904	(0.154)	Part. Relig.	-0.0251	(0.022)
Age at 1st Sex	0.5042	(0.160)*	Current Student	0.0263	(0.110)
Age at 1st Sex^2	-0.0211	(0.005)*	Partner HS Dip.	0.0022	(0.065)
Youth Weight	0.0028	(0.001)*	Partner Some Col.	-0.1251	(0.091)
Youth Exercise 1	-0.2512	(0.116)*	Part Col. Deg.	0.0123	(0.132)
Youth Exercise 2	-0.2121	(0.131)	Partner Black	0.1563	(0.102)
Youth Exercise 3	-0.3042	(0.145)*	Partner Hips.	0.0219	(0.084)
Constant	-3.9634	(1.452)*	Partner Other	0.1138	(0.098)
			Age	0.0957	(0.131)
			Age^2	-0.324	(0.333)
			Relig.	-0.0029	(0.015)
			HS Dip.	-0.1049	(0.066)
			Some Col.	-0.0557	(0.100)
			Col. Deg.	0.1509	(0.243)
			Black	-0.0163	(0.109)
			Hips.	-0.1826	(0.093)
			Other	-0.2436	(0.116)
			Drink Preg.	0.114	(0.112)
			Smoke Preg	-0.0188	(0.069)
			Age at 1st Sex	0.125	(0.093)
			Age at 1st Sex^2	-0.0032	(0.003)
			Youth Weight	-0.0424	(0.092)
			Youth Exercise 1	-0.0156	(0.067)
			Youth Exercise 2	0.0357	(0.066)
			Youth Exercise 2	0.0259	(0.072)
N	16273		N	1485	

[a] PSMS based on 100 clustered bootstrap samples.

Table 2.7: Pairwise Smooth Maximum Score Estimates, Core Sample

	Logit on Pregnancy			PSMS on Separation[a]	
Z_1	Coeff.	S.e.	Z_2	Coeff.	S.e.
Age at Menarche	-0.0772	(0.032)*	Birth × Medical	0.2652	(0.120)*
Black × AgeMenar.	0.0634	(0.049)	Birth × Clinical	0.2742	(0.123)*
Hips. × AgeMenar.	0.2667	(0.062)*	Birth	-0.3887	(0.089)*
Other × AgeMenar.	0.1752	(0.098)	Medical	-0.0786	(0.108)
Black	-0.1328	(0.588)	Clinical	-0.2029	(0.106)
Hips.	-2.9485	(0.810)*	Partner Age	0.0231	(0.033)
Other	-2.0825	(1.285)	Partner Age^2	-0.0396	(0.059)
Menstrual Problems	-0.2099	(0.149)	Part. Relig.	-0.0055	(0.017)
Age at 1st Sex	0.5491	(0.172)*	Current Student	-0.0853	(0.103)
Age at 1st Sex^2	-0.0228	(0.005)*	Partner HS Dip.	0.0309	(0.059)
Youth Weight	0.4133	(0.137)*	Partner Some Col.	0.0014	(0.093)
Youth Exercise 1	-0.2363	(0.109)*	Part Col. Deg.	0.0627	(0.143)
Youth Exercise 2	-0.2557	(0.115)*	Partner Black	-0.0015	(0.109)
Youth Exercise 3	-0.3204	(0.119)*	Partner Hips.	-0.0406	(0.101)
Constant	-3.7199	(1.541)*	Partner Other	-0.0035	(0.144)
			Age	0.053	(0.130)
			Age^2	-0.2129	(0.314)
			Relig.	-0.0146	(0.015)
			HS Dip.	-0.0851	(0.068)
			Some Col.	0.0652	(0.112)
			Col. Deg.	-0.1973	(0.183)
			Black	0.1093	(0.112)
			Hips.	-0.0371	(0.101)
			Other	-0.2728	(0.151)
			Drink Preg.	0.0875	(0.088)
			Smoke Preg	0.0438	(0.062)
			Age at 1st Sex	0.1458	(0.135)
			Age at 1st Sex^2	-0.0038	(0.004)
			Youth Weight	0.041	(0.097)
			Youth Exercise 1	-0.0077	(0.081)
			Youth Exercise 2	0.0612	(0.079)
			Youth Exercise 3	0.014	(0.081)
N	10776		N	927	

[a] PSMS based on 100 clustered bootstrap samples. Core sample excludes ethnic and other non-representative demographic over-samples.

Table 2.8: Probability of Separation by Post-Pregnancy, Selected IV Estimates

Controls: All[a]	1-Month	3-Months	6-Months	9-Months	1-Year
Birth × Clinic	-0.047	-0.084	-0.138	-0.169	-0.110
	(0.092)	(0.113)	(0.125)	(0.150)	(0.157)
	[-0.260,0.116]	[-0.302*,0.075]	[-0.365**,0.012]	[-0.403*,-0.026]	[-0.332,0.045]
Birth × Hosp.	-0.151	-0.065	-0.063	-0.023	-0.051
	(0.091)	(0.107)	(0.124)	(0.140)	(0.149)
	[-0.336,0.041]	[-0.243*,0.134]	[-0.241,0.136]	[-0.202,0.174]	[-0.231,0.146]
Birth × Phys.	0.217	0.237	0.280	0.236	0.234
	(0.093)*	(0.109)*	(0.120)*	(0.134)	(0.149)
	[0.095,0.472]	[0.121,0.498***]	[0.173,0.550***]	[0.135,0.512***]	[0.121,0.497**]
Birth	0.201	0.130	0.145	0.129	0.118
	(0.047)***	(0.056)*	(0.061)*	(0.066)	(0.073)
Clinic	0.010	0.040	0.072	0.044	0.040
	(0.069)	(0.087)	(0.095)	(0.113)	(0.117)
Hospital	0.018	-0.027	-0.042	-0.049	-0.038
	(0.055)	(0.067)	(0.074)	(0.087)	(0.090)
Physician	-0.089	-0.092	-0.087	-0.054	-0.069
	(0.072)	(0.080)	(0.088)	(0.100)	(0.105)
R^2	0.039	0.044	0.040	0.041	0.046
Joint F-Test:[b]					
All	0.390	0.118	0.194	0.336	.255
Clinic and Phys.	0.039*	0.083	0.147	0.330	.225
Phys. and Hosp.	0.252	0.079	0.051*	0.0934	.134
Joint Bounds					
All	[-0.184,0.193]	[-0.106,0.271**]	[-0.116,0.261**]	[-0.152,0.225*]	[-0.125,0.252*]
Clinic and Phys.	[-0.01,0.370***]	[-0.022,0.355***]	[-0.034,0.343**]	[-0.110,0.268]	[-0.052,0.324*]
Phys. and Hosp.	[-0.082,0.294*]	[0.037,0.414**]	[0.091,0.467**]	[0.092,0.469**]	[0.048,0.425*]

[a] Standard errors in parenthesis, worst case bounds are in brackets; results are from separate regressions, all of which have N=2046. Stars indicate significance at 5,1,.01% levels.

[b] P-Value for One Sided test

Table 2.9: County Descriptive Statistics

	Availability[ab]		
	(N)	(M)	(C)
Total Non-marital Fertility Rate	1029.18	1016.25	1039.42
Aged 15-19	40.06	39.37	47.48
Aged 20-24	75.29	66.02	64.49
Child/Woman Ratio, Never Married Women	0.153	0.131	0.162
Per Capita Annual Income	$11,238	$13,757	$15,642
Monthly AFDC Per Recipient	$90.41	$132.85	$132.71
% Census Urban	0.131	0.459	0.836
N(counties)	51	20	38

[a] All series measured in 1990. Fertility data were compiled by Add Health from National Center for Health Statistics and Alan Guttmacher Institute data. Other data was drawn from the 1990 Census.

[b] N-Counties with no abortion providers, M-Only Medically Provided Services, C-Both Clinical and Medical Services

Table 2.10: Probability of Separation, W/ Non-marital Fertility

	Estimation	
	(OLS)	(IV)
Non-marital Fertility Rate		
Aged 15-19	-.0072	-.0078
	(.0035)*	(.0045)
Aged 20-24	.0052	.0039
	(.0020)**	(.0027)
Non-marital Fertility Rate		
Aged 15-19 $\times$ Birth	.0063	.0076
	(.0028)*	(.0048)
Aged 20-24 $\times$ Birth	-.0051	-.0035
	(.0018)**	(.0029)
(i, p) Characteristics	Yes	Yes
Background Controls	Yes	Yes
County Controls	Yes	Yes
State F.E.	Yes	Yes
N	1485	1485

3

Competing For The Opposite Sex: An Equilibrium Model of High School Sex and Dating

3.1 Introduction

The sexual revolution brought about enormous changes in the manner in which the sexes relate to one another over the prior half century. Central to these changes have been dramatically different views about, and increases in, sexual activity outside of traditionally defined relationships. The General Social Survey in the United States indicates the percentage of people viewing premarital sex[1] as always wrong fell from 35% in 1972 to 11% in 2006. Views on extra-marital sexual relationships saw similar changes: in 1973, 69% of people viewed it as always wrong, compared to just 35% in 2006. The dissociation of sex with longer term relationships is viewed by many as a liberation from social mores which often needlessly impose costs of stigma and shame on individuals. The advent of fertility control technologies and the generally changing attitudes toward sex have been seen as allowing both men and women greater control over, and enjoyment of sex while reducing many of the long term negative

[1] Throughout this paper 'sex' refers to vaginal intercourse.

consequences.

But do men and women both benefit? If women value sex within longer-term, more committed relationships, they may suffer if they find it more difficult to obtain one in the changed setting. Competitive pressures may force women to concede sex in exchange for having any relationship at all. Also women may, as a result of changes in the norms surrounding sex, find themselves more likely to be single mothers;[2] even biologically women may be more affected by sexually transmitted diseases(STD) than men.[3] The dissociation of sex with relationships in this line of thinking is a result of decreased bargaining power for women, meaning they are engaging in sex on worse terms, and some suffer welfare losses from doing so.

In this paper we estimate a model of relationship choice that allows us to uncover preferences for relationships that may differ between men and women. We do this by relying on the competitive behavior of men and women when searching for a partner. The main idea is that when men outnumber women, we should observe relationships that are characterized by what women want more often, and the opposite would be true if women outnumbered men. If men and women value matches differently, but one group of searchers is more scarce, then the more populous group must compete with each other in order to match. One form of such competition would be to enter less preferred relationships, meaning that the types of matches preferred by the more scarce group are more likely to occur. Empirically this translates into exploiting variation in the ratio of men to women in particular searching environments. For this reason we use a unique data set in this paper, the National Longitudinal Survey of Adolescent Health(hereafter Add Health), which captures a cross section of sex ratios

[2] National Center for Health Statistics data show the out-of-wedlock childbearing rate was 26.4 in 1970, by 2005 the number had increased to 47.5 live births per 1,000 unmarried women aged 15-44.

[3] The most prevalent STD in the United States, the human papillomavirus (HPV) in 2008 is projected to be responsible for approximately 20,000 female cancer cases, relative to just 3,200 male cancer cases, according to the Centers for Disease Control Division of STD Prevention (2008)

within U.S. high schools. The high school is viewed as one of the principal matching "markets" for young people, and Add Health also data provide the other essential element: detailed match specific data in a relationship history from a sample a students at each school. The strategy of using sex-ratio variation to explain differences in sex patterns is used in Cornwall and Cunningham (2008). They find incarceration induced declines in the male population lead to significant increases in the number of sexual partners among black males.

Using the combination of sex ratios and match specific data, we estimate a simple model of searching for a partner which takes into account the likelihood of matching. Firstly we subdivide the school into observable groups by grade and race. In our model individuals make an exclusive choice over the type of partner and relationship to search for, but maximize expected utility, where there is uncertainty over matching. Thus in choosing to search for a partner, individuals take into account their preferences for partner and relationship characteristics as well as the perceived probability they will match. The model is closed by combining the search choices of the entire school, via a matching function, to determine the equilibrium probability of matching with a partner. Because of the structure, all the sex ratios of various types to one another feed back into the problem because individuals consider all types of partners when choosing.

Estimation results show that, indeed, men value sexual relationships relatively more than women. Estimates of the structural model indicate that, absent matching concerns, 45% of women and 59% of men would prefer to be in a sexual relationship. Add Health asks a separate question about whether one would want to have sex in their ideal relationship. A remarkable finding is that 45% of women and 63% of men responded that sex would be a part of their ideal relationship. Hence, a structural model estimated on observed matches is able to back out preferences for sex that match the self reports, providing some validity for both self-reported data and the estimates of the model. Between the self reports and the estimates of the structural model, clear evidence exists that men prefer sex relative to women. Observed changes in sexual behavior may then lead to welfare increases for one gender over another.

This paper is the spirit of Choo and Siow (2006) who estimate a static non-parametric transferable utility model of the marriage market. The difficulty with using transferable utility models is that there is not a clean way to uncover differences in preferences between men and women. Suppose we observe a match that has sex. We do not know if side payments have been made by the man such that the woman will have sex or if side payments have been made by the woman so that the man will have sex. The model therefore does not have predictions about the relationship between sexual behavior and, for example, the gender ratio. By working with a non-transferable framework which makes clear how men and women compete for each other we are able to disentangle male and female preferences.

The rest of the paper proceeds as follows. The next section covers recent work on sex ratios and matching, followed in Section three by the structural model. Section four describes the data as well as showing how the data map into the structural model. Section five presents the results and shows how the structural model can be used to back out preferences in the absence of competitive effects. Section six concludes.

3.2 Review

To our knowledge the equilibrium behavioral effects of the sizes of various opposite sex populations has yet to be studied within economics. Outside economics this topic was addressed directly, Jemmott, Ashby, and Lindenfeld (1989) found that individual's who perceived the availability of the opposite sex as lower were more committed to their romantic relationship and invested more in their relationships. Students at two colleges were interviewed, and these results come from subjective responses to questionnaires. The results, however, do intuitively accord with the economic theory put forth by on the Family (1981) regarding marriage rates: individuals faced with fewer possible options for matching alter behavior in order to maintain a relationship with a current partner.

Angrist (2002) gives a detailed review of the influence of sex ratios on a variety of social outcomes including marriage, labor supply, and child welfare. He includes numerous historical examples and anecdotal evidence as well as a thorough review of the empirical study surrounding gender ratios. Angrist also finds, using data on immigration flows, that increased gender ratios in immigrant communities in the United States are correlated with higher marriage rates for both men and women, higher incomes for families and couples, and lower female labor force participation. He also confirms the notion that these changes arise primarily through changes in female bargaining power.

In recent work Chiappori, Fortin, and Lacroix (2002) estimate a collective model of household labor supply in which distribution factors change the relative bargaining power between husbands and wives. The authors use data on statewide indices of both the sex ratio and divorces laws as these factors. With regard to the sex ratio, the authors settle on using the proportion of males of the same age and race as the husband of the household. Using this as a proxy for the behavior-relevant ratio from the household's perspective, they report variations in the age restrictions do not change the results, and that the sex ratio does affect within household resource distributions. Given their data they are only able consider same-race marriages.

Extending the work of Dagsvik (2000), Becker (1973) and Becker (1974), Choo and Siow (2006) construct and estimate a transferable utility model of the marriage market. Individuals in their model belong to a set of mutually exclusive discrete types and each makes a discrete choice over what type of spouse to marry or whether to remain single. In their estimation Choo and Siow differentiate types primarily by age using a panel of U.S. Census data. This strategy allows identification of the average gains from marriage, which aggregates over gender, but also allows Choo and Siow to measure changes in this average gain due to policy changes like national legalized abortion in the United States.

In a non-transferable framework, Hitsch, Hortacsu, and Ariely (2006) provide a thorough analysis of mate preferences using data from an online matching service. Separate preferences over mate characteristics are identified for men and women using their unique data set. Online matching, by recording the pages browsed, captures the choice set as well as the subsequent choice to email for each individual. With a large data set Hitsch et al. are able to catalogue in detail what qualities are most sought after by men and women. Of great relevance to our work here is their general review of the importance of what is termed "strategic behavior": because there are costs associated with approaching a possible mate, individuals choices may not reflect just preferences over mate qualities, but also result from the expected probability of an offer being accepted. In the presence of this form of strategic behavior, estimates of mate preferences contain serious bias. Hitsch et al. argue that the online matching environment provides a very low cost way to approach potential mates, thus reducing the resulting bias from strategic behavior. While this seems quite plausible in online matching, traditional matching still suffers from a possibly large dis-utility from remaining unmatched and/or being rejected, leading individuals to substitute towards mates with a higher chance of matching.

This prior work on the impact of sex ratios on match formations and the distribution of gains within relationships motivate our framework. In contrast to the transferable utility framework that rationalizes the aggregate data, our identification in the non-transferable framework will come from individual level data combined with information on the searching environment, similar the identification strategy in Hitsch, Hortacsu, and Ariely (2006). Additionally our data and model of matching will allow for non-matching to be the result of search frictions rather than individual choice. Further, our model will account for the strategic behavior mentioned by explicitly modeling the equilibrium search decisions in each school.

3.3 Model and Estimation

We consider only opposite sex one-to-one matching.[4] We categorize each male (female) as a type j (k), belonging to a finite set with J (K) elements. An individual's type denotes some collection of characteristics such as age, grade, race, or attractiveness. For males (females) there are then K (J) types of mates. Let j_i indicate the ith member of type j. There are n markets which have differing numbers of each type of man and woman and we suppress the market subscripts throughout this section.

We index the type of things that can happen in the relationship by $r \in \{1, ..., R\}$. We model search as being completely directed: men and women are able to target their search on both the characteristics of the partner as well as the terms of the relationship. Each man (woman) then makes a discrete choice to search in one of $J \times R$ ($K \times R$) markets, with $J \times K \times R$ types of matches.

The timing of the model is such that individuals first decide in which market to search. Then, with some probability that depends upon how many same-sex and opposite-sex individuals chose to search in the same market, they are matched. Search is then modeled as a one-shot game: there are no dynamics in the model.

[4] Only 2% of the sample reported multiple sexual matches and 1% reported multiple relationships, though clearly some reporting problems may exist here. We proceed in modeling one-to-one matching given the complexity of modeling multiple matches.

3.3.1 Individuals

An individual's expected utility for searching in a particular market depends upon three factors:[5]

1. the probability of matching in the market where the probability of a j-type man matching with a k-type woman in an r type relationship is P_j^{kr},

2. a deterministic portion of utility conditional on matching given by μ_j^{kr} for a j-type man,

3. and an individual-specific preference term $\epsilon_{j_i}^{kr}$.

Note that the only individual-specific part of expected utility are the $\epsilon_{j_i}^{kr}$'s. Further, the $\epsilon_{j_i}^{kr}$'s are known to the individual before making their decision: there is no match-specific component beyond what occurs on types. Hence, the only uncertainty from the individual's perspective is their probability of finding a match. Finally, note that the probability of matching is only affected by male and female type and relationship type: all males of type j searching in the k, r market have the same probability of finding a match.

We normalize the utility of not matching to zero. Expected utility from searching in a particular market is then the probability of matching in the market times the utility conditional on matching. We specify the functional form of the utility such that expected utility for a j-type man searching for a k-type woman of relationship type r as:

$$E\left(U_{j_i}^{kr}\right) = P_j^{kr} \cdot e^{\mu_j^{kr} + \epsilon_{j_i}^{kr}} \tag{3.1}$$

[5] The corresponding terms for women are P_k^{jr}, μ_k^{jr}, and $\epsilon_{k_i}^{jr}$.

We assume that the ϵ_{ji}^{kr}'s are i.i.d. Type I extreme value errors and are unknown to the econometrician. Taking logs and yields:

$$\ln\left(E\left(U_{ji}^{kr}\right)\right) = \mu_j^{kr} + \ln\left(P_j^{kr}\right) + \epsilon_{ji}^{kr} \tag{3.2}$$

We treat the ϵ_{ji}^{kr}'s as unobserved. If we observed the search decisions (as opposed to the actual matches) of individuals coupled with the different types of men and women and we observed the probabilities of matching in each market, the probability of a j-type man searching for a k-type woman in an r-type relationship, ϕ_j^{km} would follow a multinomial logit:

$$\Pr(k, r|j) = \phi_j^{kr} = \frac{\exp\left(\mu_j^{kr} + \ln\left(P_j^{kr}\right)\right)}{\sum_{k'}\sum_{r'}\exp\left(\mu_j^{k'r'} + \ln\left(P_j^{k'r'}\right)\right)} \tag{3.3}$$

where the μ's for one of the markets for both men and women would be normalized to zero. However, we do not actually observe the search decisions except through those who successfully match. The search decisions for those who do not match are unobserved. Hence, we also do not directly observe the probabilities of matching conditional on searching in a particular market.

3.3.2 Matching

In order to estimate the probability of matching in a particular market, we specify the number of relationships that result from the searching behavior of individuals in each school as following from a matching technology. This mechanism is essentially a production function, taking as inputs the number searching men and the number of searching women in each market and giving the number of matches in each market as output. In this section we discuss specifying the matching function as having a constant elasticity of substitution (CES) as well as discussing special cases of a CES matching function, Cobb-Douglas and Leontief.

CES Matching

We parameterize the number of matches, X, in market j, k, m as depending upon the number of j-type men and k-type women searching in the j, k, r market. Let M_j and W_k indicate the number of j-type men and number of k-type men. Recall that ϕ_j^{kr} and ϕ_k^{jr} give the probability of j-type men and k-type women who search in the j, k, r market which are also the market shares of searching men and women in the j, k, r market. The number of matches in the j, k, r market is then given by:

$$X_{jkr} = A\left[\left(\phi_j^{kr} M_j\right)^{\frac{1}{\rho}} + \left(\phi_k^{jr} W_k\right)^{\frac{1}{\rho}}\right]^{\rho} \tag{3.4}$$

where ρ determines the elasticity of substitution and A is a scaling parameter. When $\rho \rightarrow 0$ CES becomes Cobb-Douglas and $\rho \rightarrow -\infty$ CES becomes Leontief. (cf. Mass-Colles, Winston and Green CP. 3). Note that $X_{jkr} = X_{kjr}$ for all j, k, and r.

Under the assumption that all j-type men (k-type women) searching in the same market have the same probabilities of matching, P_j^{kr} is given by:

$$\begin{aligned} P_j^{kr} &= \frac{X_{jkr}}{\phi_j^{kr} M_j} \\ &= \frac{A\left[\left(\phi_j^{kr} M_j\right)^{\frac{1}{\rho}} + \left(\phi_k^{jr} W_k\right)^{\frac{1}{\rho}}\right]^{\rho}}{\phi_j^{kr} M_j} \\ &= A\left[1 + \left(\frac{\phi_k^{jr} W_k}{\phi_j^{kr} M_j}\right)^{\frac{1}{\rho}}\right]^{\rho} \end{aligned} \tag{3.5}$$

The log of this term then enters into the multinomial logit probabilities of searching in particular markets and captures the influence of the sex ratio on market search decisions.

Cobb Douglas Matching

A limiting case of the CES function comes form when ρ approaches zero and the matching function becomes Cobb-Douglas:

$$X_{jkr} = A\left(\phi_j^{kr}M_j\right)^{1/2}\left(\phi_k^{jr}W_k\right)^{1/2}$$

The probability of matching can then be written as:

$$\begin{aligned} P_j^{kr} &= \frac{A\left(\phi_j^{kr}M_j\right)^{1/2}\left(\phi_k^{jr}W_k\right)^{1/2}}{\phi_j^{kr}M_j} \\ &= A\left(\frac{\phi_k^{jr}W_k}{\phi_j^{kr}M_j}\right)^{1/2}. \end{aligned}$$

But now consider how these terms enter into the utility function. Utility in discrete choice models is only relative to one of the choices. This implies that these probabilities of matching will only enter in relative to one of the options. Let the normalized option for a j-type man be the k^*, r^* market. The difference in log probabilities between market k, m and k^*, m^* is:

$$\begin{aligned} \ln\left(\frac{P_j^{kr}}{P_j^{k^*r^*}}\right) &= \left(\frac{\phi_k^{jr}W_k}{\phi_j^{kr}M_j}\right)^{1/2}\left(\frac{\phi_j^{k^*r^*}M_j}{\phi_{k^*}^{jr^*}W_k}\right)^{1/2} \\ &= \left(\frac{\phi_j^{k^*r^*}\phi_k^{jr}W_k}{\phi_j^{kr}\phi_{k^*}^{jr^*}W_{k^*}}\right)^{1/2} \end{aligned}$$

and the number of searching men drops out. If there is only one type of woman, then $W_k = W_{k^*}$ and the number of women drop out as well. In this case it would not be possible to disentangle male and female preferences using variation in the sex ratio as the Cobb-Douglas matching function leads to the sex ratio playing no role in the search decisions. However, to the extent that the sex ratio does affect individual search decisions then this is indicative of the matching function not following the limiting Cobb-Douglas case.

Leontief Matching

At the other extreme, the Leontief function results as $\rho \rightarrow -\infty$. In this case the matching function is given by:

$$X_{jkr} = A \min \left\{ \phi_j^{kr} M_j, \phi_k^{jr} W_k) \right\}$$

With Leontief matching, the number of matches is given by whichever side of the market has fewer searchers. Hence, the sex ratio has an extreme effect on the group that is in the minority in a particular market with no effect on the group in the majority. How variation in the sex ratio affects the probabilities of matching both when a group is in the majority and in the minority then allows us to distinguish between the two limiting cases through the parameter ρ.

3.3.3 Equilibrium

The probabilities of searching in a particular market, the ϕ's, give the share of a particular set individuals who will search in a particular market. These ϕ's also affect the probabilities of matching, the P's. We rewrite equation (3.6) to make the dependence of P_j^{kr} on ϕ_j^{kr} and ϕ_k^{jr} explicit:

$$\phi_j^{kr} = \frac{\exp\left(\mu_j^{kr} + \ln\left[P_j^{kr}\left(\phi_j^{kr}, \phi_k^{jr}\right)\right]\right)}{\sum_{k'}\sum_{r'}\exp\left(\mu_j^{k'r'} + \ln\left[P_j^{k'r'}\left(\phi_j^{k'r'}, \phi_{k'}^{jr'}\right)\right]\right)} \tag{3.6}$$

Equilibrium in our model is then characterized by stacking the $J \times K \times M$ shares and solving for the fixed point.

3.3.4 Estimation

We now describe how these parts of the model translate into a maximum likelihood problem where the μ's and the parameters of the matching function, ρ and A, are the parameters to be estimated. The outcomes we will observe in the data are 1) whether a particular individual matched and 2) if the individual matched, the characteristics of his or her partner and the terms of the relationship. Hence, we will observe the search decisions of those who match but will not observe the search decisions for those who did not match. The likelihood for those who do not match then needs to integrate out over the search decision. Denote Y as the outcome we observe in the data, where $Y_j = \{k, r\}$ for a j-type man who successfully matched with a k-type women in an r type relationship and $Y_j = 0$ if the individual did not match. The log likelihood is then:

$$
\begin{aligned}
L &= \sum_r^R \sum_k^K \sum_j^J \sum_i^{M_j} 1(Y_{ij} = k, r) \left(\ln\left(\phi_j^{kr}\right) + \ln\left(P_j^{kr}\right)\right) + \sum_j^J \sum_i^{M_j} 1(Y_{ij} = 0) \ln\left(\sum_r^R \sum_k^K \phi_j^{kr} P_j^{kr}\right) \\
&+ \sum_r^R \sum_j^J \sum_k^K \sum_i^{W_k} 1(Y_{ik} = j, r) \left(\ln\left(\phi_k^{jr}\right) + \ln\left(P_k^{jr}\right)\right) + \sum_k^K \sum_i^{W_k} 1(Y_{ik} = 0) \ln\left(\sum_r^R \sum_j^J \phi_k^{jr} P_k^{jr}\right)
\end{aligned}
$$

Taking a likelihood contribution from all individuals including those who failed to match, we can maximize L while solving the equilibrium fixed point at each iteration.

3.4 Data and Descriptive Characteristics

The data we use come from the National Longitudinal Survey of Adolescent Health. This survey of adolescents in the United States was organized through the Carolina Population Center and data were collected in three waves, in 1994-95, 1995-96 and 2001-02. They include a large variety of information in multiple levels of detail. The largest sample consists of data denoted as "In-School" and comes from surveys of almost 90,000 seventh to twelfth grade students at a randomly sampled set of 80 communities across the United States.[6] Attempts were made to have as many students as possible from each school fill out the survey during a school day, and questions consist mainly of individual data like age, race, and grade, as well as information on academics and extra-curricular activities. From this data we construct the school level

[6] A school pair, consisting of a high school and a randomly selected feeder school (middle school or junior high school from the same district) were taken from each community.

aggregates by observable characteristics, grade and race, which serve as estimates of the various sex ratios.

The next level of data are denoted as "In-Home" and consist of a detailed survey with 40 separate categories of questions, one of which includes a relationship history as well as a separate section on sexual behaviors. Respondents who filled out the in-school survey, or who were listed on the school roster, were eligible to enter the in-home sample, which contains a sample of around 15,000 students. The relationship histories include both relationships and casual partners, which give us match specific data, and information on a number of activities including sex behaviors.[7] A naturally arising problem in the survey design is the issue what constitutes a relationship to respondents. The main problem is whether men and women define their match differently. Here we follow the Add Health definition that a "relationship" referred to from here on, consists of all the following (i) as holding hands, (ii) kissing, and (ii) saying "I love you." This definition results in the most symmetric distribution of responses within schools and allows for the most data in the survey to be accessed.[8]

The school level information was gathered only once, so we focus on the first wave of data and we restrict attention to schools which enroll both men and women. Generally the primary matching market for the vast majority of students at single sex schools is not the high school. Indeed it is not clear that a primary matching market even exists in this setting: a number of sets of people, in extracurricular activities, neighborhoods, or church communities most likely combine to create the population from which matches are drawn.[9] Since the focus here will be on a cross section of the matching distribution, we count only currently ongoing matches within the same school.

Our sample is nationally representative at the school selection level and so is drawn

[7] Respondents were asked to give information about a number of partner characteristics including race and grade.

[8] Applying this definition 48.6% of ongoing in-school relationships came from men and 51.4% from women, the closest to parity of any definition we imposed.

[9] A sample 13,380 recent relationships from all types of schools showed 46.5% of partners met in the same school. While only 23% met via friends and were not in the same school, and only 6% and 5% met partners in their place of worship of neighborhood respectively.

from all types of schools, though two thirds come from traditional high schools(with 9th-12th grades). The data used throughout the analysis focus only on the 9th through 12th grade students at these schools.[10] Schools from whom we observe fewer than 10 in-home interviews are dropped from the estimation sample. We drop 1 all boys school, 1 vocational education school for high school dropouts, and we drop 6 schools without meaningful numbers of 9th-graders.[11] After these adjustments, our primary sample contains schools drawn from 74 communities.

We focus our attention on current, in-school, relationships. In theory, men and women should report roughly the same number of relationships but in practice this is not the case. Given that we observe double reporting in these data, i.e. men are asked to report their matches within a school and so are women, we can see these differences. Men reported 621 relationships where sex occurred and 498 relationships where sex did not occur, while women reported 515 relationships where sex occurred and 466 relationships where sex did not occur. To deal with the issue of misreporting we use information about matches reported by women when dealing with match specific descriptive statistics and in the estimation sample. The final sample of observations used for estimation is 11,218 students from the 74 schools.

3.4.1 Preferences for Sex Behavior

To gain insight into male and female differences in preferences we examine the responses to a number of questions asked of both men and women in the in-home interview. When asked if an individual had ever had sex, not relating this behavior to any information about the partner, the Add Health responses accord with other sources: beginning at a twelfth grade sex participation rate in the low 60% range,

[10] While occasionally 9th grades are part of junior high schools, that is they are the maximum grade in a school distinct from the high school, the results throughout do not change significantly with their exclusion, accordingly we effectively count them as part of each high school we we a large enough feeder school.

[11] These schools on average had around 300 students in each of the grades 10-12, but on average 9 students in the 9th grade. Because of the sampling design of Add Health, which only probabilistically included the most relevant junior high or middle school for a particular high school, it appears the relevant 9th grade observations for these schools we not observed.

and falling roughly 10% per grade, is consistent with data from the NLSY97 (cf. Arcidiacono, Khwaja, and Ouyang (2007)).

In Table 1 we show statistics on whether an individual is in a current relationship and/or currently having sex. Here we see some of the reporting problems, with women reporting more relationships and more sex.

The Add Health data also include questions regarding an individuals' ideal romantic relationship over the next year and the answers to these questions can be compared to what actually happens in the data. A set of events were given by the interviewer and the individual either included or excluded the events from their ideal relationship, and then imposed their preferred order on the events. Some results of these stated preferences are given in the bottom set of rows of Table 1.

The self-reported data indicate that many more individuals would prefer to be in a relationship than are actually in a relationship. This suggests significant search frictions. While preferences for relationships are the same for both men and women, preferences for sex or not. The final row of Table 1 presents evidence for differing preferences regarding sex behaviors. Men reported wanting to be in a sexual relationship at a 63% rate compared to 45% of women.

3.4.2 Grade Profile of Matching

In order to examine patterns of matching present in the data we focus on grade and race as major classifications of partners. Of particular interest in our setting is how the grade distribution at a high school impacts individual decisions about whom to search for as a possible partner. Table 2 includes only matches at the same school ongoing at the time of survey, and shows a number of patterns. Firstly note the age profiles for women and men on the far right and last row respectively. Men have an increasing chance of matching as they age, while women's likelihood of matching is nearly monotonically decreasing, though at a slower rate. This a familiar result, men value a woman's youth, women value a man's age. In the context of our discussion though, it raises the issue that both older men and younger women may be in a position to gain from sex ratio shifts, while the opposite is true of younger men and older women. This implies that whether sex ratio shifts lead to more or less sex will depend on how men and women value sexual relationships with partners of varying ages. The maxima in each row and column are the diagonal elements, though note it never exceeds 50% of matches; there is considerable cross grade variation in matching. This result as well suggests that changing one gender ratio, e.g. the 12th to 9th grade ratio, will have effects on entire observed distribution of matches. This fact points toward the need to explicitly estimate the matching process if one wants to investigate how choices change in response to sex ratios.

3.4.3 Cross-Race Matching Patterns

A large literature within sociology and demography gives evidence on inter-racial dating. Other studies have used multiple sources to quantify which races and genders do and do not engage in inter-racial dating: Lee and Edmonston (2005) offer many descriptives using U.S. Census data to track inter-racial marriage (and therefore assumed dating in the U.S.) over the last 40 years. The census shows a clear pattern, black men and Asian women date and marry outside their race far more than black women and Asian men. Qian (1997) catalogues the determinants of inter-racial marriage using census data as well, and reports that whites marry most frequently Asians, Hispanics and lastly blacks. In order to confirm these patterns the aggregate distribution of parter races is recorded in Table 3. As can be seen from the diagonal elements of the table, our data show the expected matchings with own race partners. In the set of minorities, Hispanic students date outside their race most often, followed by Asians, and then blacks. The asymmetries in Asian and black dating across genders also shows up in this table. The most frequent interracial couple are Hispanic men and white women. Importantly blacks make up larger fraction of matches than they do as a percentage of the populations in our sample. Hence, even though black men are relatively more likely to match outside of their race, black women match more than their share of the population would suggest.

3.4.4 Gender Ratio Variation

The variation in black and white gender ratios in our sample is catalogued in Table 3.4. Each cell in Table 3.4 is the percentage of female students for each grade-race pairing.[12] As can be seen from the table, the total gender ratio is centered around one-half as we would expect. The percentage of female students at schools is more dispersed in non-white populations within high schools, and as an example the case for Black students is given in the lower panel of Table 3.4. This dispersion is even more pronounced for Hispanic and Asian students. Breaking out the gender ratio along different dimensions spreads the initially condensed distribution outside the 48-52% range, as can be seen in Column 3 where the interquartile range is reported. While gender ratios do not vary much in larger populations, the variable of interest here is the sex behavior relevant gender ratio. Essentially this will vary with the race and age distributions of the communities sampled, and this variation is what will identify the impact of the gender ratio on sex behaviors. That is, for example, identification comes from a minority student in a more integrated school having a preference for same race partners similar to that of a minority student in a more segregated school, but integration or segregation making the match less or more likely to be observed.

One concern is the high school dropout rate driving this variation. The 75th percentile column in Table 3.4 shows increases in both white and non-white percent female as grade increases, consistent with a drop out rates being higher for men. However the 25th percentile column also shows a decreases in the percent female for both groups, the opposite of the expected dropout effect. Although some variation in the grade specific sex ratio undoubtedly comes from dropouts, it also appears that some is due to cohort variation. Given that the focus here will be on explaining within school matching patterns, the assumption required for individuals who match outside the school, including those matching with dropouts, is that they searched for the same type of partner within the school but did not match. Students dropping out may have stronger preferences for sex, which would create downward bias in our

[12] A minimum of 5 observations from the race or grade-race pair is required for a school to enter Table 3.4 was required.

preference estimates. However, it may also be the case that sex participation imposes a trade off between school effort and relationship effort on all students. In such a setting dropouts engage in sex more often, but not due to stronger preferences for sex but due to lower opportunity costs, leading to a positive bias in the coefficients estimated.[13]

3.4.5 From the data to the model

Having discussed the trends in the data, we now turn to integrating the data into the model. First, types of men and women are defined at the grade/race level as suggested by the clear differences in matching patterns across race and grade. Second, we classify relationships as one of two types: those that are having sex and those that are not. An individual is defined as being in a relationship without sex if the person meets the standards described previously (holding hands, etc.). An individual is classified as having a relationship with sex if the individual is currently having sex, regardless of his relationship status. With two types of relationships, four grades, and four races, there are then thirty-two markets.

Rather than having separate μ's for every type of relationship, we put some structure on the μ's. Namely, sex in the relationship works solely as an intercept shifter: the same bonus or penalty applies regardless of the characteristics of the partner. Second, cross-race effects do not vary with grade. Grade effects of the partner are then allowed to vary by whether the individual is a male or female, but not by race.

Finally, we do not observe all matches but only those in the in-home data set. We take the relationships as defined by the women in the Add Health. However, we still need to incorporate the search decisions of the men. We take these from the women as well: the number of males that do not match are given by the number of males in the in-home sample minus the number of men who were reported to match by the women in the in-home sample. This assume that the ratios of men and women are

[13] Although the data, gathered in schools, cannot identify dropouts, the school level dropout rate did have a positive but insignificant correlation with the school level sex participation rate. See Sabin and Reeds (2008) for a thorough discourse on sex participation and high school graduation.

roughly the same in the in-home sample as in the in-school sample.

3.5 Results

The estimates of the structural model are presented in Table 5. Consistent with the descriptive statistics, women value age more than men, though both male and females prefer older partners. There is also evidence for men and women preferring partners of the same age.

Somewhat surprisingly, we see that both black men and black women are preferred. This could be seen somewhat from the descriptive statistics as black women matched at a higher rate than their sample shares in spite of same-race preferences. Hispanics and whites seem to be similarly valued with those in the omitted category having lower values for both men and women.

The parameters of the matching function, ρ and A, are identified through variation in matches across schools with different sex ratios and the overall match rate respectively. It is these parameters that allow for differences across males and females in their preferences for sex. Here we see that men prefer sex relative to women.

Between the general equilibrium and the non-linear nature of the specification, the coefficients themselves are difficult to interpret. However, we can use the coefficient estimates to back out the fraction of men and women who prefer sex to no sex if they did not have to worry about matching. Namely, we can turn off the effects of the probability of matching and see what choices would have been made in the absence of competition. Backing out male and female preferences for sex in this way yields women preferring sex 45% of the time and men preferring sex 59% of the time.

What is the remarkable is that these sex preferences–45% for women and 59% for men–are quite close to the self-reported preferences for sex of 45% and 63% respectively for men and women (see Table 1). The structural model was able to successfully disentangle male and female preferences while only observing data on matches.

3.6 Conclusion

The contribution on this paper is two-fold. First, we shown how a directed search model can disentangle male and female preferences for different types of relationships using variation in the sex ratio. When the researcher's goal is to understand differences in male and female preferences, directed search provides an alternative to transferable utility models: transferable utility models are difficult to use here since we generally do not observe all the transfers.

Second, we have the applied the directed search model to the teen sex and dating market. In this way we were able to uncover male and female differences in preferences for sex. The uncovered preferences from the structural model match the self-reported references, providing some validity for the approach. That men and women value sex differently suggests that changes in sexual behavior may have different welfare effects for men then for women.

3.7 Tables and Figures

Table 3.1: Preferences and Participation

	Women	Men
Actual		
In a relationship	46.4%	41.1%
Having sex	32.3%	27.5%
N	5795	5391
Want		
Relationship	84.35%	85.22%
Sex	45.2%	63.2%
N	5728	5320

Table 3.2: Cross-Grade Matching Distribution

	Male Grade					
Female Grade	9th	10th	11th	12th	Total	Pact. of Sample
9th[a]	**0.086**	0.062	0.055	0.037	0.240	0.260
10th	0.029	**0.091**	0.081	0.082	0.281	0.250
11th	0.021	0.040	**0.094**	0.088	0.243	0.249
12th	0.005	0.015	0.070	**0.146**	0.236	0.242
Total	0.141	0.208	0.300	0.352	1.000	1.000
Pact. of Sample	0.263	0.262	0.260	0.216	1.000	

[a] Numbers are percent of 981 total matches observed.

Table 3.3: Cross-Race Matching Distribution

	Male Race					
Female Race:	White	Black	Hispanic	Other	Total	Pact. of Sample
White[a]	0.563	0.013	0.039	0.008	0.623	0.583
Black	0.006	0.197	0.010	0.000	0.213	0.206
Hispanic	0.029	0.005	0.084	0.001	0.118	0.152
Other	0.011	0.007	0.008	0.019	0.046	0.058
Total	0.609	0.222	0.141	0.029	1.000	1.000
Pact. Sample	0.595	0.181	0.160	0.065	1.000	

[a] Numbers are percent of 981 total matches observed.

Table 3.4: Gender Ratio Variation

Pact. Female by Race-Grade:	.25	.75	IQ
White	0.480	0.533	0.053
9th	0.466	0.542	0.077
10th	0.467	0.551	0.084
11th	0.447	0.533	0.087
12th	0.481	0.567	0.087
Black	0.438	0.539	0.102
9th	0.400	0.567	0.167
10th	0.447	0.585	0.138
11th	0.400	0.571	0.171
12th	0.353	0.563	0.210
Total[a]	0.486	0.527	0.040

[a] Based on a sample of 74 schools.

Table 3.5: Model Estimates

	Estimate	S.E
Sex-Match Utility		
Male	0.3547	0.1365
Female	-0.1964	0.1493
All-Match Utility		
Same Grade	0.5200	0.0578
Partner Grade × Male	0.3291	0.0563
Partner Grade × Female	1.1409	0.0595
Same Race	1.0139	0.0884
Partner Black × Male	2.918	0.2607
Partner Hisp. × Male	-0.3777	0.3392
Partner Other × Male	-2.7153	0.3854
Partner Black × Female	4.0297	0.2487
Partner Hisp. × Female	-0.1269	0.3158
Partner Other × Female	-2.9805	0.3782
Matching Parameters		
ρ	-3.978	0.8701
A	0.2798	0.0079
-log(L)	9.3068	
N	11186	

Appendix

Chapter 1 Appendix

Prices

As outlined, the price observed is the mean of 10-week procedures with local anesthesia at the county level. This mean includes price from small and large non-hospital providers. I assume this mean arises from a mixture two prices, a high and low, or non-clinic and clinic respectively, in each market. So within each market the observed mean can be decomposed into:

$$\mu_{obs} = \frac{1}{N_r} \sum_{N_r} (N_{nc}) p_{nc} + N_c p_c \tag{3.7}$$

where N_r is the number of respondents in the market, N_c and N_{nc} is the number of firms in the market who are clinics and non-clinics, p_c is the clinic price and $p_n c$ is the non-clinic price. What allows solving for the two prices (p_{nc}, p_c) is that fact that I also observe the standard deviation of prices within the county. This can be rewritten as:

$$\sigma^2_{obs} = \frac{1}{N_r} \sum_{N_r} N_{nc}(p_{nc} - \mu_{obs})^2 + N_c(p_c - \mu_{obs})^2 \tag{3.8}$$

by simply rearranging the sum and substituting in the two prices. Taking from the counts of firms the number of large and small clinics within each market, along with the reported number of firms who responded to the pricing survey, I observe everything except the two prices. These two equations form a non-linear system with two unknowns which can be solved with a non-linear solving routine in most software applications.

Instruments

In estimating price elasticities, the excluded instruments for large providers are second trimester and locating near hospital requirements interacted with hospitals per capita, license laws interacted with physicians per capita and its' square and physicians per hospital, and physicians per capita interacted with hospital location requirements. The excluded instruments for small providers are license laws interacted with physicians per hospital, per capita, and per capita squared. Second trimester hospitalization laws interacted with hospitals per capita and physicians per hospital, and locating near hospital requirements interacted with per capita physicians and its square. The included instruments for small providers are the state level marriage rate, per capita income, total population, population density, percent of all women, black women, and Hispanic women aged 15-44 and their squares, the number of Catholics, Southern Baptists and total religious adherents, and physicians and hospitals per capita, physicians per hospital, and the square of physicians per capita. Large providers include all variables for small providers and population, income and density squares and an indicator for population greater than 3.5 million.

Chapter 2 Appendix

Control Definitions

Individual and Partner Characteristics: Female and partner age at pregnancy resolution; Education level at pregnancy: < HS Diploma, HS Diploma, Some College, Bachelors Degree or more and Indicator of partner currently enrolled at time of pregnancy; Religious Attendance in year of pregnancy(six values: 1=never-6=more than once per week), Race: Indicators of Black non-Hispanic, Hispanic, Other.

Background Controls: Welfare Recipient in year of pregnancy; Work status (majority of time in pregnancy year) part time or full time

County Level Controls: Income, 1990 Census county per capita and median income; Population: 1990 Census population level, density, census designated percent urban;

Religiosity, county percent adherents, percent adherents and percent population in conservative and liberal denominations, and proportion Catholic, from Churches and Church Membership 1990 data; Voting data, county percent voting Republican and Democrat in 1992 presidential election.

State Level Controls: Enough valid observations remained for fixed effects estimation using 30 States in the U.S.

Bibliography

Abrevaya, J., K. Hausman, and S. Khan (2007): "Testing for Causal Effects in a Generalized Regression Model with Endogenous Regressors," Working paper.

Aguirregabiria, V., and P. Mira (2007): "Sequential Estimation of Dynamic Discrete Games," *Econometrica*, 75(1), 1–53.

Akerlof, G., J. Yellen, and M. Katz (1996): "An Analysis of Out-of-Wedlock Childbearing in the United States," *Quarterly Journal of Economics*, 11(2), 277–317.

Angrist, J. (2002): "How Do Sex Ratios Affect Marriage And Labor Markets? Evidence From America'S Second Generation," *The Quarterly Journal of Economics*, 117(3), 997–1038.

Arcidiacono, P., and J. B. Jones (2003): "Finite Mixture Distributions, Sequential Likelihood and the EM Algorithm," *Econometrica*, 71(3), 933–946.

Arcidiacono, P., A. Khwaja, and L. Ouyang (2007): "Habit Persistence and Teen Sex: Could Increased Access to Contraception have Unintended Consequences for Teen Pregnancies?," .

Arcidiacono, P., and R. A. Miller (2008): "CCP Estimation of Dynamic Discrete Choice Models with Unobserved Heterogeneity," .

Bajari, P., C. L. Benkard, and J. Levin (2007): "Estimating Dynamic Models of Imperfect Competition," *Econometrica*, 75(5), 1331–1370.

Becker, G. S. (1973): "A Theory of Marriage: Part I," *Journal of Political Economy*, 81(4), 813–46.

——— (1974): "A Theory of Marriage: Part II," *Journal of Political Economy*, 82(2), S11–S26.

Bishop, K. (2007): "A Dynamic Model of Location Choice and Hedonic Valuation," Working paper.

Bitler, M., and M. Zavodny (2001): "The effect of abortion restrictions on the timing of abortions," *Journal of Health Economics*, 20(6), 1011–1032.

Blank, R. M., C. C. George, and R. A. London (1996): "State abortion rates the impact of policies, providers, politics, demographics, and economic environment," *Journal of Health Economics*, 15(5), 513–553.

Chiappori, P.-A., B. Fortin, and G. Lacroix (2002): "Marriage Market, Divorce Legislation, and Household Labor Supply," *Journal of Political Economy*, 110(1), 37–72.

Choo, E., and A. Siow (2006): "Who Marries Whom and Why," *Journal of Political Economy*, 114(1), 175–201.

Cornwall, C., and S. Cunningham (2008): "Sex Ratios and Risky Sexual Behavior," Working paper.

Dagsvik, J. K. (2000): "Aggregation in Matching Markets," *International Economic Review*, 41(1), 27–57.

Donohue, J. J., and S. D. Levitt (2003): "Further Evidence that Legalized Abortion Lowered Crime: A Reply to Joyce," NBER Working Papers 9532, National Bureau of Economic Research, Inc.

Doraszelski, U., and M. Satterthwaite (2007): "Computable Markov-Perfect Industry Dynamics: Existence, Purification, and Multiplicity," Discussion paper, UCLA Department of Economics.

Ericson, R., and A. Pakes (1995): "Markov-Perfect Industry Dynamics: A Framework for Empirical Work," *Review of Economic Studies*, 62(1), 53–82.

for Disease Control Division of STD Prevention, C. C. (2008): "Genital HPV Infection - CDC Fact Sheet," Report.

Ginther, D., and R. Pollack (2004): "Family Structure and Children's Educational Outcomes: Blended Families, Stylized Facts, and Descriptive Regressions," *Demography*, 41(4), 671–696.

Gruber, J., P. Levine, and D. Staiger (1999): "Abortion Legalization And Child Living Circumstances: Who Is The "Marginal Child"?," *The Quarterly Journal of Economics*, 114(1), 263–291.

Haas-Wilsom, D. (1996): "The impact of state abortion restrictions on minors' demand for abortions," *Journal of Human Resources*, 31(1), 140–158.

Heckman, J. (1979): "Sample Selection Bias as a Specification Error," *Econometrica*, 47(1), 153–61.

Heckman, J., and B. Singer (1984): "The Identifiability of the Proportional Hazard Model," *Review of Economic Studies*, 51(2), 231–41.

Henshaw, S., and L. Finer (2003): "The Accessibility of Abortion Services In the United Staes, 2001," *Perspectives on Sexual and Reproductive Health*, 35(1), 16.

Henshaw, S., J. Forrest, and E. Baine (1984): "Abortion Services In the United States, 1981 and 1982," *Family Planning Perspectives*, 16(3), 119.

Henshaw, S., and J. Van Vort (1994): "Abortion Services in the United States, 1991 and 1992," *Family Planning Perspectives*, 26(3), 100–112.

Hitsch, G. J., A. Hortacsu, and D. Ariely (2006): "What Makes You Click? Mate Preferences and Matching Outcomes in Online Dating," Working paper.

Hotz, V., S. McElroy, and S. Sanders (2005): "Teenage Childbearing and Its Life Cycle Consequences: Exploiting a Natural Experiment," *Journal of Human Resources*, 40(3), 683–715.

Hotz, V., C. Mullin, and S. Sanders (1997): "Bounding Causal Effects Using Data From a Contaminated Natural Experiment: Analysis the Effects of Teenage Chilbearing," *The Review of Economic Studies*, 64(4), 575–603.

Hotz, V. J., and R. A. Miller (1993): "Conditional Choice Probabilities and the Estimation of Dynamic Models," *Review of Economic Studies*, 60(3), 497–529.

Jemmott, J., K. Ashby, and K. Lindenfeld (1989): "Romantic Commitment and the Perceived Availability of Opposite-Sex Persons: On Loving the One You're With," *Journal of Applied Social Psychology*, 19, 1198.

Jones, R., M. Zolna, S. Henshaw, , and L. Finer (2008): "Abortion in the United States: Incidence and Access to Services, 2005," *Perspectives on Sexual and Reproductive Health*, 40(1), 6–16.

Joyce, T. (2004): "Further Tests of Abortion and Crime," NBER Working Papers 10564, National Bureau of Economic Research, Inc.

Kane, T. J., and D. Staiger (1996): "Teen Motherhood and Abortion Access," *The Quarterly Journal of Economics*, 111(2), 467–506.

Kleibergen, F., and R. Paap (2006): "Generalized Reduced Rank Tests Using The Singular Value Decomposition," *Journal of Econometrics*, 133(1), 97.

Lakdawalla, D., and T. Philipson (1998): "Nonprofit Production and Competition," NBER Working Papers 6377, National Bureau of Economic Research, Inc.

Lee, S., and B. Edmonston (2005): "New Marriages, New Families: U.S. Racial and Hispanic Intermarriage," *Population Bulletin*, 60(2), 3–36.

Levine, P. B. (2003): "Parental involvement laws and fertility behavior," *Journal of Health Economics*, 22(5), 861–878.

Levine, P. B., A. B. Trainor, and D. J. Zimmerman (1996): "The effect of Medicaid abortion funding restrictions on abortions, pregnancies and births," *Journal of Health Economics*, 15(5), 555–578.

Lundberg, S., and R. D. Plotnick (1990): "Effects of State Welfare, Abortion and Family Planning Policies on Premarital Childbearing Among White Adolescents," *Family Planning Perspectives*, 22(6), 246–251.

——— (1995): "Adolescent Premarital Childbearing: Do Economic Incentives Matter?," *Journal of Labor Economics*, 13(2), 177–200.

Medoff, M. (2007): "Price, Restrictions and Abortion Demand," *Journal of Family and Economic Issues*, 28(4), 583–599.

Medoff, M. H. (1988): "An Economic Analysis of the Demand for Abortions," *Economic Inquiry*, 26(2), 353–59.

Newey, W. K. (1999): "Consistency of Two-Step Sample Selection Estimators Despite Misspecification of Distribution," *Economics Letters*, 63(2), 129–132.

on the Family, A. T. (1981): *Gary Becker*.

Pagan, A., and F. Vella (1989): "Diagnostic Tests for Models Based on Individual Data: A Survey," *Journal of Applied Econometrics*, 4(S), S29–59.

Pakes, A., M. Ostrovsky, and S. Berry (2004): "Simple Estimators for the Parameters of Discrete Dynamic Games (with Entry/Exit Examples)," Harvard Institute of Economic Research Working Papers 2036, Harvard - Institute of Economic Research.

Qian, Z. (1997): "Breaking the racial barriers: Variations in interracial marriage between 1980-1990," *Demography*, 34(2), 263.

Riley, A. P. (1994): "Determinants of Adolescent Fertility and its Consequences for Maternal Health, With Special Reference to Rural Bangladesh," *Annals of the New York Academy of Sciences*, 709(1), 86–100.

Rust, J. (1987): "Optimal Replacement of GMC Bus Engines: An Empirical Model of Harold Zurcher," *Econometrica*, 55(5), 999–1033.

Ryan, S. (2005): "The Costs of Environmental Regulation in a Concentrated Industry," Working Papers 0510, Massachusetts Institute of Technology, Center for Energy and Environmental Policy Research.

Staiger, D., and J. H. Stock (1997): "Instrumental Variables Regression with Weak Instruments," *Econometrica*, 65(3), 557–586.

Stock, J. H., J. H. Wright, and M. Yogo (2002): "A Survey of Weak Instruments and Weak Identification in Generalized Method of Moments," *Journal of Business & Economic Statistics*, 20(4), 518–29.

Welch, T. R. (2005): "Dawning of The Age of Menarche," *The Journal of Pediatrics*, 147(6), A2.

Willis, R. J. (1999): "A Theory of Out-of-Wedlock Childbearing," *Journal of Political Economy*, 107(S6), S33–29.

Biography

My name is Andrew Wyatt Beauchamp, and I was born at 5:59pm EST on April 27, 1982 at Providence Hospital in Southfield, Michigan. Following graduation from Southfield High School I attended Michigan State University, in East Lansing, Michigan, from which I graduated with with a Bachelors degree with majors in Economics and Mathematics in 2004. In 2004 I was also admitted to the Economics Ph.D. program at Duke University with a full scholarship. I recieved my Master of Arts in Economics from Duke in the Spring of 2005. While at Duke I won a course proposal competition and was a Bass Instructor from Fall 2008 through Spring 2009. Following graduation from Duke I will begin a position as an Assistant Professor in the Department of Economics at Boston College in Chestnut Hill, Massachusettes. I also count among my accomplishments my once having stared at the sun, for over an hour.