7-29-2011

Three Essays in Economics

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Three Essays in Economics

by

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A Dissertation

Submitted in Partial Fulfillment of the

Requirements for the Degree of

Doctor of Philosophy

Major: Business Administration, Economics

The University of Memphis

August 2011

ACKNOWLEDGEMENTS

I am immensely indebted to both William T. Smith and Alex Nikolsko-Rzhevskyy for their research guidance, encouragement, for believing in my ideas, and always being willing to discuss them.

I am also very grateful to Dr. Andrew J. Hussey and Dr. Pinaki Bose who played a vital role in my dissertation.

Further, I thank seminar participants at the University of Memphis in general for comments towards all three chapters of my dissertation. Finally, I want to thank two anonymous referees and the managing editor of the *Journal of Human Resources* for helpful comments on the paper "The Gender Pay Gap Beyond Human Capital."

ABSTRACT

Jetter, Michael, Ph.D. The University of Memphis. June 2011. Three Essays in Economics. Major Professor: William T. Smith, Ph.D.

My dissertation consists of three essays analyzing the results of decisions made by workers, both on the microeconomic as well as the macroeconomic level. My first essay, which is a co-production with Wayne Grove and Andrew Hussey, investigates the determinants of the gender wage gap. Specifically, the paper points out that noncognitive skills, preferences for life and career, but also preferences for work ethics and work environment, are able to account for as much as one third of the explained portion of the gender wage gap.

My second essay, which is co-authored with Dr. Pinaki Bose, provides a possible explanation why some tax amnesties are successful in terms of revenue collection and participation rates (for example Ireland, Colombia, India twice, and France), whereas others are not. In particular, I am modeling the taxpayer's decision whether to accept an amesty offer from the tax authority and derive conditions under which she will be inclined to do so. The results show that if economic conditions change substantially, for example by a trade liberalization of the domestic country, a perfectly rational agent will find it optimal to accept a tax amnesty.

In my third essay, I am developing a theoretical model identifying the relationship between the volatility of private sector wages and growth. The model suggests two distinct channels in which wage volatility affects growtg: a positive direct way (working through precautionary savings) and a negative indirect way (working through the mediating role of government size). Applying a 3SLS approach to a panel of 19 countries, my empirical

analysis provides strong evidence for the existence of both effects. Thus, this paper establishes *wage* volatility as a growth determinant and explains why previous growth analyses on other sorts of volatility could not reach a consensus, as the indirect effect was not recognized.

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CHAPTER 1

INTRODUCTION

The following three essays are, at first glance, to be placed into three different categories within Economics: the first article focuses on discimination in the labor market, the second provides a theoretical examination of tax amnesties, and the third essay analyzes the effects of uncertainty in wages on the growth rate of an economy. Also, the methods used in these three articles vary. However, the one main theme that ties them all together is the economic phenomenon of workers making decisions under certain circumstances. My dissertation analyzes the path and the outcome of people's decisions in a variety of ways: (1) in an empirical way to analyze the reasons for the gender wage gap, (2) in a theroetical framework to assess the impact of a tax amnesty, and (3) in both a theoretical and an empirical way to analyze how uncertainty in one's wage ultimately affects a country's growth rate of Gross Domestic Product.

The first essay uses a unique dataset to shed light on why women continue to earn less than men. In addition to previously found contributing factors, I am able to identify a variety of new variables, which allow us to ulitmately explain up to 82 percent of the gender wage gap. By using empirical methods that are specifically designed for discrimination analyses (such as the Oaxaca-Blinder or the Gelbach decomposition), the paper shows that noncognitive skills, but especially preferences for life, career, and whether a job contributes to society, are able to explain a major remaining part of the gender wage gap.

In the second essay I analyze the fact why tax amnesties have been very successful in terms of revenue and participation rates in some countries, but not in others. Examining a tax evader's decision whether to accept an amnesty or not, the model shows that an amnesty will be attractive to a worker if new possibilities arise within the legal sector. In reality, one could think of new trade arrangements with other countries, newly available technologies, or other forms of development that make businesses more profitable. In fact, countries that experienced success in their tax amnesties confirm our theory, as they all have been going through strong economic periods during the time of amnesty declaration.

In the third and final essay I examine worker's decisions from a more macroeconomical point of view, focusing on the growth rate of a country's Gross Domestic Product. Previous analyses have neglected a possible impact of uncertainty in wages on the growth rate. My model shows that there are two distinct channels in which wage volatility (wage uncertainty) affects growth: in a positive direct way through precautionary savings and in a negative indirect way through the composition of the labor market. Finally, I analyze the theoretical implications on a panel data set with over 600 observations of mostly developed economies, using a 3-Stage-Least-Squares approach. All results confirm the theoretical predictions, showing that wage volatility is indeed a significant predictor of growth. This being a result in itself, this essay also provides a possible explanation as to why previous papers did not find a consensus on how various sorts of volatilities affect growth: the significant indirect effect has been neglected before.

In summary, my main interests in Economics circle around people's decisions. Why, how, and what kind of decisions they make, is what ties my dissertation and my future research interests together.

CHAPTER 2

THE GENDER PAY GAP BEYOND HUMAN CAPITAL: HETEROGENEITY IN NONCOGNITIVE SKILLS AND IN LABOR MARKET TASTES[*]

2.I. Introduction

While the gender earnings gap has narrowed sharply since World War II, women continue to earn 20 percent less than men.[1] Aware of gender pay disparity, Americans, according to a 2004 survey, attribute it (i) largely and equally to women's priority for family over careers and to employers' discrimination against women in hiring and promotion practices, then to (ii) differences in noncognitive skills, namely assertive negotiating, and finally, and least importantly, to (iii) the possession of education and skills needed for high paying jobs (Hill and Silva, 2005, p. 3). After decades of publications investigating male-female earnings differences, economists have formed a consensus that human capital variables—like education, work experience and skills—explain more and discrimination explains less of the gender income gap than the public thinks.[2] Despite the

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[*] For helpful comments, we thank Catherine Eckel, Madonna Harrington Meyer, Paul Oyer, Sol Polachek, Anne Winkler, participants of our session at the 2009 Southern Economic Association meeting, and participants of the University of Memphis seminar. All errors are our own.

1. For gender wage gap literature surveys, see Altonji and Blank (1999) and Polachek (2006).

2. Although the unexplained component of the gender wage gap is often attributed to discrimination, it may also result from a misspecification of the relationships or from unobserved gender heterogeneity (Polachek and Kim 1994; Altonji and Blank 1999). Regarding discriminatory behavior, see, for example, Neumark et al. (1996) and Goldin and Rouse (2000). Although we do not test for discrimination, Montgomery and Powell (2003), using the first three

public's common sense understanding that career success is influenced by noncognitive skills, such as confidence, motivation, and assertiveness, and by work/life preferences, economists cannot offer a consensus judgment regarding the wage gap effect of either. The human capital model of Becker (1964) predicted earnings differences to arise from differences in the broad array of individual abilities and in educational investments. Due to the ease of using cognitive test scores and the difficulty of empirically operationalizing personality traits and noncognitive characteristics, to date empirical analyses have used cognitive test scores to proxy for "individual ability".[3] Social scientists, able to typically account for only half of the gender pay gap with human capital models based on nationally representative datasets, have long hypothesized that gender heterogeneity may characterize noncognitive skills[4] and a variety of work/life preferences, both of which cause wage differences.[5] Now a burgeoning literature, especially by those conducting lab and field experiments, reports gender heterogeneity of preferences and noncognitive skills (Croson and Gneezy 2009; Booth 2009). Economists and others, though, are just beginning to test the labor market outcomes of such gendered work-life choices and personality traits.[6]

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waves of our dataset, found that obtaining an MBA sharply diminishes the gender wage gap, comparing wages of MBAs and non-MBAs.

3. Regarding the challenges of systematically analyzing the labor market outcomes of noncognitive skills, see Borghans et al. (2008) and ter Weel (2008).

4. Psychologists prefer the term character or personality traits (see Thiel and Thomsen 2009).

5. For example, Blau and Kahn (1997), using the Panel Study of Income Dynamics (PSID) for full-time workers with incomes and labor market experience, found an unadjusted male-female wage ratio of 72.4 percent in 1988. Controlling for human capital variables, occupation, industry and unionism explains half of the gap. Polachek and Kim (1994), also using the PSID, estimate that half of the male-female earnings differences results from unobserved gender heterogeneity.

6. See, for example, Bowles et al.'s (2001) review of the early explanations of wage differences due to personality and the 2008 *Journal of Human Resources* symposium issue entitled

Using an especially rich national dataset, the twin goals of this paper are (1) to identify noncognitive and preference sources of otherwise unobserved gender heterogeneity and then (2) to estimate whether such heterogeneity accounts for more of the male-female earnings gaps than can be explained by an extensive set of human capital variables. We view our analysis, then, as part of a broad agenda to enrich the human capital model as envisioned by Becker (1964) by more fully understanding the variation of individual abilities, especially of noncognitive skills and of work/life preferences, and how such heterogeneity influences labor market outcomes.

Economists have taken three approaches to better understand the gender pay gap. First, the growing lab and field experiment findings about gender differences in, for example, confidence, career-orientation, and assertiveness, are consistent with gender earnings gaps, with the under-representation of women in the upper tier of leadership in professions and corporations, and with the anecdotal evidence of professional women "opting out" of careers[7]; to date, though, little empirical analysis has investigated those potential relationships (Thiel and Thomsen 2009). The notable exceptions focus on the personality traits of the Big Five (see Braakmann 2009; Mueller and Plug 2006) and measures of locus of control and self-esteem (Fortin 2008; Urzua 2008). We test the role of various confidence measures and 15 noncognitive skills (deemed especially important

"The Noncognitive Determinants of Labor Market Outcomes and Behavioral Outcomes." In response to criticisms of narrowly measuring ability, as of July 2009 the GRE includes a formal measure that attempts to capture noncognitive skills (the "Personal Potential Index").

7. A recent survey by Catalyst, for example, found that "26 percent of women at the cusp of the most senior level of management don't want the promotion" (Belkin 2003). For anecdotal evidence of high powered professional women "opting out" of careers, see Belkin's (2003) widely read article in *The New York Times Magazine*. In contrast, Stone (2007) argues that mostly professional women want to but cannot manage to raise children and function in demanding careers (see also Leonhardt 2010). However, Antecol (2010) find that professional women largely return to work within two years of childbirth.

for business professionals) in explaining the MBA male-female pay gap.

Secondly, scholars have focused upon gender differences in labor market tastes such as the priority of family, career, wealth, and job characteristics. According to Long (1995) and Fortin (2008), the priority of work and money contributes to the pay gap. Chevalier (2007) finds that women with a preference for childbearing earn less even before they have children due to their choice of college major and because they engage less intensively in job searching (also see Goldin and Polachek 1987). Our data contain a variety of individuals' priorities regarding family and career, as well as reported importance of non-pecuniary job attributes, recorded about eight years prior to the earnings data we assess.

Finally, because nation-wide datasets, like the Panel Study of Income Dynamics (PSID), lack information regarding, for example, college quality, college major and detailed work histories, researchers have sought smaller specialized and homogeneous data sets with greater educational and labor market detail; examples from individual institutions of higher education include studies based on surveys of undergraduates from Harvard College (Goldin and Katz 2008), lawyers from the University of Michigan (Wood, Corcoran, and Courant 1993), and MBAs from the University of Chicago (Bertrand et al. 2009) and the London School of Business (Graddy and Pistaferri 2000). Children, according to Bertrand et al. (2009), mainly contribute to female MBAs' reduced earnings via fewer hours worked and increased career interruptions.[8] Furthermore, from the Harvard and Beyond dataset, female MBAs have greater difficulty balancing careers and

8. A recent New York Times article entitled "A Labor Market Punishing to Mothers" (Leonhardt 2010), which cites Bertrand et al. (2009), makes a similar argument about professional women generally, noting that the three recent female Supreme Court nominees do not have children.

children than do medical doctors, lawyers, or Ph.D.s (Goldin and Katz 2008; Herr and Wolfram 2009). In addition to children, though, Bertrand et al. (2009) also attribute the gender wage gap to differences in MBA training and hours worked. Because these data sets come from individual elite institutions, it is not clear how their results generalize either to typical MBAs or to other average highly educated professionals.

The existence of a unique and especially rich dataset, the GMAT Registrant Survey, allows us to estimate the role of preferences and noncognitive skills in explaining the gender earnings gap. A stratified random sample of all registrants for the Graduate Management Admission Test (GMAT), the GMAT Registrant Survey, contains longitudinal data in four waves from 1990 to 1998. After registering to take the GMAT but prior to enrolling in an MBA program (Wave I), respondents provided information regarding career and family priorities, 15 noncognitive skills, expected future managerial responsibility, individuals' job preferences regarding the importance of non-monetary job characteristics, and information used to create five confidence measures. The data set also provides detailed information about both undergraduate and MBA educational experiences, work histories, earnings, family background, marriage, children, and more. Drawn from a national sample of aspiring MBAs, this data set includes the wide range of MBA program qualities and types available in the United States (Arcidiacono et al. 2007), rather than merely graduates of the most elite programs (for example Bertrand et al. 2009; Graddy and Pistaferri 2000).[9]

Among our sample of MBAs, females employed full-time earn 15.5 percent less per year than do males, a smaller gap than is found in economy-wide datasets (for instance

9. Since a majority of the overall increase in wage inequality from 1973 to 2003 resulted from wage differences across levels of educational attainment (Lemieux 2006), our sample allows us to focus on differences between men and women with the same graduate degree (MBAs).

Blau and Kahn 1997). When we add basic human capital variables (for example family background, work experience, ability measures, undergraduate and MBA educational experiences), the unexplained gap falls to 9.5 percent, and then further to 6.5 percent with the addition of hours worked and current employment characteristics. Finally, the addition of work/life preferences and noncognitive variables to the human capital model yields a marginally significant earnings gap of 4.3 percent.

The results from Oaxaca-Blinder and Gelbach decompositions (Gelbach, 2009) clarify how differently men's and women's experiences, expectations, preferences, and noncognitive skills influence career outcomes and how much these novel variables help account for the gap. The final decomposition analysis, based on all of our variables, accounts for up to 82 percent of the raw gender pay gap (versus 49-69 percent with just the human capital variables). Of the explained gap, about a quarter is accounted for by gender heterogeneity in labor market tastes and noncognitive skills – remarkably, about the same proportion explained by both hours worked and current job characteristics; human capital variables explain the remaining half. To put our results in context, Fortin (2008), the study most similar to ours, explains up to 25 percent of the raw gender pay gap, of which her set of noncognitive skills accounts for 5-6 percent.[10]

"Good citizen" characteristics and behaviors of female MBAs, namely their high ethical standards and choice of jobs that contribute to society, account for some of the earnings gap. Thus, the MBA women in our sample apparently desire to work differently than do male MBAs, and consequently earn less.

10. Fortin (2008), investigating the role of self-esteem, locus of control, priority on money and work, and the importance of family, finds the priority on money and work to most influence the gender pay gap.

2.II Data

The data used in our analysis comes from the GMAT Registrant Survey, a longitudinal survey of individuals who registered for the Graduate Management Admission Test (GMAT), an admission requirement for the vast majority of MBA programs in the United States. The survey, sponsored by the Graduate Management Admission Council (GMAC), was mailed to the same individuals in four waves, between 1990 and 1998, whether or not they actually took the GMAT.[11] The Wave I survey occurred from April 1990 to May 1991, shortly after test registration, but prior to MBA enrollment. Of the 7,006 registrants initially surveyed, 5,885 responded to the first survey, 4,327 to the third survey, and 3,771 to the fourth in 1998.[12]

The GMAT Registrant Survey includes information about the following seven categories: (1) demographics and family status, (2) previous higher education (college major, area of study,[13] GPA, school quality, and whether they possessed a post-baccalaureate degree other than an MBA), (3) an employment history including prior earnings, industry, and work experience, (4) a set of self-assessed noncognitive skills deemed important for success in business, (5) preferences regarding work/life priorities and non-pecuniary job characteristics, and career expectations, (6) MBA concentration,

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11. These data were collected by the Battelle Memorial Institute (Seattle, Washington State) for the Graduate Management Admission Council (GMAC). The same dataset has been used by Montgomery (2002), Montgomery and Powell (2003), Arcidiacono, et al. (2007) and Grove and Hussey (forthcoming).

12. Though attrition more heavily affected those who never entered into an MBA program than those who did, those who left the sample look similar to those who remain in a number of different observable characteristics, including gender, race, test scores, and labor market outcomes. An appendix characterizing the attrition in more detail is available on request.

13. Rather than individual majors, we only know which of the following five broad areas students studied: business, engineering, the humanities, science, and social science.

program quality, pace (full- or part-time), and type (whether an executive program), and (7) current employment, earnings, and information about non-monetary assessments of their job.

Of the 3,771 respondents to the fourth and final survey, we limit our analysis to those who: (1) obtained an MBA in the sample period (approximately 43 percent of respondents); (2) worked full-time (35 hours per week or more) at the time of the fourth survey and reported the associated earnings information (82 percent of the remaining individuals); (3) took the GMAT and had non-missing values for the multitude of control variables included in the analysis (70 percent of remaining individuals). Our final sample includes 933 individuals, of whom 586 are males and 347 females.

For descriptive statistics of our sample, see Table 1 in which we report separate means and standard deviations by gender and p-values for tests of the equality of means between males and females. The dependent variable is the logarithm of total annual earnings on the job, for currently employed individuals at the time of the fourth survey (note we also conduct our analyses for hourly wage and hours worked; see the Robustness section). The average male in our sample earned \$67,116, which is \$9,483 more per year (in 1997 dollars) than the average female, for a raw wage gap of about 15.5 percent. To account for some variation in the timing of survey responses, we used the Consumer Price Index to adjust all earnings to January 1997 dollars.

Human Capital Control Variables

In order to explain the gender gap in earnings, we begin by considering demographic variables, namely age, race, and both the mother's and father's years of schooling attainment. Our sample of MBAs contains slightly younger females and more black women than black men.   Family circumstances differ substantially, with men much more likely to be married and twice as likely to be married with children.

Total work experience and current job tenure were constructed from responses to questions in the initial survey regarding the total number of years the respondent worked full-time for pay since the age of 21 and then with subsequent surveys' questions about starting and stopping dates (to the nearest month) of jobs.   Women have fewer years of total work experience and job tenure at the time of the Wave I survey.   Brown and Corcoran (1997) attribute as much as a third of the gender wage gap in their sample to work experience (also see Joy 2003 and Daymont and Andrisani 1984).

To account for differences in undergraduate educational background, we include cumulative grade point average (out of 4.00), college major, and measures of the selectivity of the college attended (from Barron's *Profiles of American Colleges*). Females earned higher undergraduate grades than males, a typical finding in the higher

Table 1
Descriptive Statistics of Sample, by Gender

Variable	*(1) Male* mean	*(1) Male* standard deviation	*(2) Female* mean	*(2) Female* standard deviation	*difference: (1) - (2)*	*p-value for male=female*
Annual Salary ($)	67116	27813	57633	23467	9483	0.00
Demographic/Background						
Age	34.84	6.00	34.07	5.82	0.77	0.06
Asian	0.13	0.34	0.12	0.32	0.01	0.61
Black	0.07	0.25	0.18	0.38	-0.11	0.00
Hispanic	0.15	0.36	0.17	0.38	-0.02	0.36
Mother's education (years)	14.49	3.55	14.03	3.80	0.45	0.07
Father's education	13.63	3.15	13.62	3.25	0.02	0.94
Employment Experience						
Work experience (years)	10.75	6.70	9.98	6.03	0.78	0.08
Tenure (years at current job)	4.35	4.61	3.61	3.41	0.74	0.01
Family Variables						
Married	0.72	0.45	0.59	0.49	0.13	0.00
Kids (1 = yes)	0.48	0.50	0.26	0.44	0.22	0.00
Married*Kids	0.47	0.50	0.22	0.41	0.25	0.00
Undergraduate Variables						
Highly selective	0.22	0.41	0.21	0.41	0.01	0.70
Moderately selective	0.31	0.46	0.25	0.44	0.06	0.06
Business major	0.46	0.50	0.56	0.50	-0.10	0.00
Social science major	0.18	0.38	0.16	0.36	0.02	0.39
Humanities major	0.06	0.25	0.11	0.31	-0.04	0.02
Engineering major	0.19	0.40	0.07	0.26	0.12	0.00
Science major	0.10	0.30	0.10	0.30	0.00	0.96
Cumulative GPA	3.02	0.41	3.15	0.40	-0.13	0.00
Ability Measures						
Quantitative GMAT	32.39	8.00	28.31	7.51	4.08	0.00
Verbal GMAT	30.70	7.12	29.88	7.35	0.82	0.09
MBA Variables						
Cumulative GPA	3.33	0.88	3.28	0.91	0.05	0.40
Top 10	0.06	0.24	0.05	0.22	0.01	0.37
Top 11 – 25	0.08	0.28	0.08	0.27	0.00	0.88
Part-time program	0.50	0.50	0.52	0.50	-0.02	0.60
Executive program	0.07	0.26	0.04	0.20	0.03	0.07
Finance concentration	0.23	0.42	0.13	0.34	0.10	0.00
Marketing	0.10	0.30	0.14	0.35	-0.05	0.04
Accounting Concentration	0.05	0.22	0.06	0.24	-0.01	0.37
MIS concentration	0.06	0.23	0.05	0.22	0.01	0.56

Table 1 *continued*, **Descriptive Statistics of Sample, by Gender**

Variable	*(1) Male*		*(2) Female*		*difference: (1) - (2)*	*p-value for male=female*
	mean	*standard deviation*	*mean*	*standard deviation*		
International Concentration	0.06	0.24	0.04	0.19	0.02	0.11
Other concentration	0.19	0.39	0.28	0.45	-0.10	0.00
Noncognitive Skills						
Initiative	3.54	0.54	3.61	0.53	-0.07	0.05
High ethical standards	3.66	0.54	3.76	0.45	-0.10	0.00
Communication skills	3.36	0.59	3.45	0.58	-0.10	0.02
Work with diversity	3.57	0.59	3.66	0.55	-0.09	0.03
Shrewdness	2.77	0.74	2.59	0.74	0.18	0.00
Ability to organize	3.49	0.59	3.59	0.56	-0.10	0.01
Physical attractiveness	3.03	0.59	3.11	0.60	-0.08	0.05
Assertiveness	3.16	0.64	3.20	0.60	-0.05	0.27
Ability to capitalize on change	3.18	0.64	3.13	0.62	0.05	0.23
Ability to delegate tasks	3.25	0.67	3.22	0.69	0.03	0.51
Adapt theory to practical situations	3.19	0.68	3.08	0.68	0.11	0.02
Understanding business in other cultures	2.54	0.83	2.58	0.87	-0.04	0.46
Good intuition	3.27	0.64	3.33	0.66	-0.06	0.19
Ability to motivate others	3.25	0.67	3.33	0.60	-0.08	0.07
Being a team player	3.60	0.56	3.64	0.55	-0.04	0.28
Confidence: Ability						
Quantitative expectations	3.85	0.81	3.43	0.78	0.42	0.00
Verbal expectations	3.48	0.73	3.55	0.67	-0.07	0.17
Work/Life Preferences						
Family important	0.89	0.31	0.90	0.31	0.00	0.86
Career important	0.51	0.50	0.47	0.50	0.04	0.22
Wealth important	0.20	0.40	0.14	0.35	0.06	0.03
Relatives/friends important	0.49	0.50	0.66	0.48	-0.17	0.00
Confidence: Admissions	25.22	6.57	25.57	6.79	-0.35	0.44
Confidence: Connections						
Knowing the right people: admissions	3.79	2.41	3.74	2.48	0.05	0.76
Knowing the right people: managerial success	2.55	0.77	2.53	0.71	0.02	0.69
Managerial Goals						
High managerial responsibility	0.70	0.46	0.69	0.46	0.00	0.88

Table 1 *continued*, **Descriptive Statistics of Sample, by Gender**

Variable	*(1) Male*		*(2) Female*			
	mean	*standard deviation*	*mean*	*standard deviation*	*difference: (1) - (2)*	*p-value for male=female*
Medium managerial responsibility	0.23	0.42	0.27	0.44	-0.04	0.20
Job Preferences						
Non-monetary job attributes	33.75	3.45	34.62	3.37	-0.87	0.00
Contributes to society	0.11	0.31	0.19	0.39	-0.08	0.00
Current Job: Hours and Characteristics						
Hours per week	50.26	8.54	48.94	8.82	1.32	0.02
Self-employed	0.05	0.21	0.02	0.13	0.03	0.02
Large firm	0.36	0.48	0.39	0.49	-0.03	0.34
Medium sized firm	0.50	0.50	0.48	0.50	0.03	0.41
Small firm	0.13	0.34	0.13	0.34	0.00	0.88
Non-profit	0.04	0.20	0.10	0.29	-0.05	0.00
Government	0.12	0.32	0.14	0.35	-0.03	0.24
Agricultural, forestries & fisheries	0.01	0.08	0.00	0.00	0.01	0.12
Manufacturing	0.28	0.45	0.21	0.41	0.07	0.02
Service industries	0.29	0.45	0.35	0.48	-0.07	0.04
Finance, insurance & real estate	0.17	0.38	0.15	0.36	0.02	0.48
Public administration	0.09	0.29	0.11	0.32	-0.02	0.28
Percent female in occupation	0.41	0.13	0.44	0.15	-0.04	0.00
Observations	586		347			

Notes: Sample includes respondents to both the first and fourth waves of the GMAT Registrant Survey who obtained an MBA, were employed in a full-time job (>=35 hours/week) at the time of the fourth survey, and had non-missing values for all variables (except for MBA GPA, for which a missing value dummy variable was included in all regressions). Most variables were obtained from Wave I of the survey, except for current employment variables, job tenure, work/life preferences variables, the ‘contributes to society’ variable (which were obtained from Wave IV), and work experience (which was determined from all four survey waves).

education literature.[14] Using Barron's selectivity categories,[15] men attended somewhat more “moderately selective” undergraduate institutions but no statistically significant differences existed in graduating from “highly selective” schools. Although our data includes information regarding students’ general areas of study, rather than specific majors, according to Weinberger (1998) narrowly or more broadly measuring college major causes no notable differences in estimated gender wage gaps. We include dummy variables for whether or not the individual received a degree in the social sciences, humanities, sciences, or engineering, with business as the omitted category. Twice as many males majored in engineering as undergraduates, whereas females were more likely to have majored in business and the humanities.

An advantage of our data is that the survey information was merged with GMAT registration and testing records; thus, we have actual quantitative and verbal GMAT scores, not self-reported standardized test scores, as is typical of higher education studies.[16] Males received much higher scores on the quantitative GMAT than did females (14 percent higher) and slightly higher verbal scores (3 percent higher).

Regarding the MBA experience, we include cumulative grade point average (out of 4.00) and indicators of program quality and program schedule, namely whether part-time,

14. This reflects fewer science and math courses taken by women (Montmarquette et al. 2002).

15. We collapsed the various undergraduate admission selectivity categories as designated in Barron’s into the following three categories: Highly Selective (19 percent of our sample), Moderately Selective (26 percent), and the omitted category representing the least selective schools and those not included in the Barron’s guide (55 percent).

16. While we refer to GMAT scores as ability measures, according to the Graduate Management Admission Council the GMAT "is a standardized test designed to measure verbal, mathematical, and analytical writing skills that have been developed over a long period of time through education and work."

full-time, or an Executive program. Unlike with undergraduate grades, MBA's grade point averages did not statistically differ by sex (Table 1). For program quality, we include variables indicating whether the program attended was ranked in either the Top 10 or Top 11-25, according to *U.S. News and World Report* 1992 rankings. No gender divide existed for MBA attainment from top programs. Note that only about five percent of our sample attended Top 10 and about eight percent Top 11-25 programs; thus, our sample is of the average MBA graduates in the U.S., whereas other prominent MBA gender gap studies have been of graduates of elite programs, such as the University of Chicago (Bertrand et al. 2009) and the London School of Business (Graddy and Pistaferri 2000).

Consistent with greater work experience, men were more likely to attend Executive MBA programs than women (Table 1). Grove and Hussey (forthcoming) found, as in the context of undergraduate studies, that particular areas of emphasis in graduate business studies affect post-MBA earnings as much as can overall program quality. Thus, we include variables indicating whether or not the individual focused their studies in particular areas of concentration (finance, marketing, accounting, management information systems (MIS), international business, or others[17]). Females were more likely to concentrate in marketing, while males were about twice as likely to concentrate in finance (which Grove and Hussey [forthcoming] find results in higher earnings).

In several specifications we control for differences in current employment characteristics. Since our dependent variable is annual earnings, we include hours worked per week (although recall that our sample is already limited to those working 35 hours or

17. The "other" category includes the following reported concentration areas: human resources, health care administration, entrepreneurial management, industrial management, production/operations management, public administration, real estate, statistics or operations research, transportation, and economics. Due to small numbers of individuals reporting concentrations in these areas, we collapsed them into one variable.

more per week). Females in our sample report working about one hour less per week than men, a statistically significant difference (see Table 1). Since an earnings premium for employees of larger firms has consistently been found in the literature (see Oi and Idson 1999 for a review), we include variables indicating employment at a large firm (defined as having 25,000 or more employees worldwide), a medium firm (between 100 and 25,000 employees), or a small firm (less than 100 employees). No gender differences exist in employment by firm size (Table 1).

Using 2-digit industry codes, we include indicator variables for five broad industry areas, as well as indicator variables for self-employment and whether employed by the government or a non-profit organization. Men were significantly more likely to be self-employed and to work in manufacturing, whereas women were more likely to work at a non-profit organization or in the service industry (see Table 1). Three-digit occupational codes and a Bureau of Labor Statistics variable representing the estimated percentage of females within the occupation reveal that women, in this sample, worked in occupations with a high percentage of females (Table 1). Although Boraas and Rodgers (2003) find that occupational segregation constitutes the largest component of the gender wage gap, MacPherson and Hirsch (1995) attribute it to less than 7 percent of the male-female wage gap.

Gender Heterogeneity of Non-Traditional Variables

Beyond the human capital and employment variables, the GMAT Registrant Survey allows us to construct and include several variables related to individuals' noncognitive skills, confidence, expectations, and preferences. Although economists have only recently begun to pinpoint these factors as potentially relevant in helping to explain the gender earnings gap, individual differences due to personality have long been a core research agenda among personality psychologists (see, for example, Roberts, Kuncel, Shiner, Caspi and Goldberg 2007).

The first survey wave asked individuals to rate the extent to which they have fifteen different noncognitive skills (what psychologist prefer to label as character or personality traits; see Thiel and Thomsen 2009), deemed relevant for success as a manager or business professional. We include variables for responses ranging from one ("not at all" having the characteristic or skill) to four ("very much" having the characteristic or skill) for each of the following: initiative; high ethical standards; communication abilities; ability to work with people from diverse backgrounds; shrewdness; ability to organize; physical attractiveness; assertiveness; ability to capitalize on change; ability to delegate tasks; ability to adapt theory to practical situations; understanding business in other cultures; good intuition; ability to motivate others; and being a team player. Montgomery and Powell (2003) combined all of these responses into a single variable, which they refer to as a "confidence index." In order to relate our results to the scholarship focused on gender heterogeneity in noncognitive skills, we enter each trait separately to isolate its individual effect. Of the 15 self-reported traits, eight exhibit statistically significant (at the 5 percent level) gender differences. Specifically, females rated themselves as possessing greater initiative, higher ethical standards, better communication abilities, better organizational abilities, and a stronger ability to work with people from diverse backgrounds. Males, on the other hand, reported greater shrewdness and ability to adapt theory to practical situations. At the 10 percent level of significance, women self-reported greater physical attractiveness and ability to motivate others.

We create five confidence measures which may help to explain earnings and the gender earnings gap, since individuals may either sort into jobs or be rewarded on the job due to their perceived, rather than actual, abilities. First, we include variables intended to represent one's confidence in their quantitative and verbal abilities. Immediately after registering to take the GMAT but before taking the exam, respondents were asked, in the first survey wave, how well they expected to do on the quantitative and verbal sections of the GMAT. Responses ranged from one ("excellent") to five ("poor") which we reversed so that a higher number means greater confidence. Since actual GMAT scores are controlled for in all of the specifications where we include these expectations, we interpret these expectations of verbal and quantitative performance as indicating confidence in one's own abilities. Men reported significantly more confidence in their quantitative abilities but not more in their verbal abilities than did women. Actual GMAT scores reveal that, on average, men received much higher quantitative and marginally higher verbal GMAT scores (Table 1).

In addition, we include an admission confidence measure. The initial survey, on a scale from one ("very") to four ("not at all"), asked how difficult particular steps in the admission process would be, such as obtaining letters of recommendation, preparing for the GMAT, or making the right impression on the application form.[18] We reverse the order of these responses and, using equal weight for each response, combine them into a single index, which we call "admission confidence." No differences exist in men's and

18. The following is a complete listing of the included admission steps: Prior work experience; Undergraduate grades; Letters of recommendation; Preparing for the GMAT; Doing well on the GMAT; Knowing the right people; Visiting graduate schools; Making the right impression on the application form; Paying application fees.

women's confidence of succeeding in admission-related tasks (Table 1).

Finally, because personal connections may importantly affect job success, we include two related measures of confidence in one's connections. First, we extract one component of the admission confidence index – "knowing the right people" – and include it on its own. Second, we include a variable from the noncognitive skill self-assessment section of the initial survey of "knowing the right people," ranging from one ("not at all") to four ("very much"). Here, women and men report similar levels of confidence in both types of connections (Table 1).

Different family and career priorities may sort women and men into higher or lower paying jobs. The fourth survey asked individuals to evaluate, on a scale from one to four, the importance of various aspects of their lives. In particular, we include separate variables indicating whether or not the surveyees reported as "very important" (the highest category) each of the following: family and children, career and work, friends and acquaintances, and wealth. The importance of family and career do not statistically differ but more males considered wealth and females considered friends and acquaintances as very important aspects of life (Table 1).

We also include variables reflecting future job expectations, intended to pick up potential differences between males and females in their managerial aspirations. In the initial survey wave (approximately seven to eight years prior to the earnings observations included in our analysis), individuals were asked about their expected employment situation five years in the future. We include variables indicating whether the individual reported expecting to be a non-manager (the omitted category), an entry-level manager, or a mid- to upper-level manager. Two-thirds of both men and women report expecting “high managerial responsibility” and a quarter of both expected “medium managerial responsibility.”

The initial survey also asks individuals to indicate the importance of several work environment characteristics for the position they expect to have five years later. We combine these responses (each on a scale from one to four) into an index intended to capture individual preferences over non-monetary job characteristics.[19] Females reported significantly higher importance of the non-monetary job attributes of their expected future job. Finally, we allow for possible gender differences in preferences over the social stewardship of their work. In deciding to take their current job, 19 percent of females reported (in Wave IV surveys) their job contributing to society was “very important”, while only 11 percent of males reported the same thing – a statistically significant difference.[20]

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19. The following characteristics are included in this index, giving equal weight to responses for each: the work is interesting; the people I work with are friendly; the chances for promotion are good; the job security is good; my responsibilities are clearly defined; I am free from the conflicting demands that others make of me; the hours are good; promotions are handled fairly; my employer is concerned with everyone getting ahead; I have enough time to get the job done.

20. This variable ranges from one ("Not at all important/Not applicable") to four ("Very important"). For variables where answers range from one to four (or five respectively), we tried using dummies in various combinations (for example grouping responses of one – not at all having the attribute – and two vs. three and four) but our results did not meaningfully change.

2.III Empirical Methodology

We begin by specifying the following model of earnings determination:

$$Ln(S_i) = \gamma_f Female_i + X_i^b \beta_b + X_i^e \beta_e + \varepsilon_i \qquad (1)$$

where S_i is reported annual log earnings and ε_i is an individual error term. Our primary parameter of interest is γ_f, the coefficient on the Female indicator variable. $X^b{}_i$ contains a vector of the basic human capital control variables, as described in the previous section. This analysis assumes that the social processes under examination operate the same way for men and women. We initially run regressions containing only these covariates, and do so by adding each variable or subset of variables sequentially. We then include $X^e{}_i$, which contains our expanded set of controls, also described in the previous section. Once again, particular variables or classes of variables are added in sequential regressions in order to investigate the effect of their inclusion on the estimate of γ_f.

While some information regarding the contribution of each set of variables can be gleaned from sequential addition of these variables to the model, the observed effect of each set of variables is influenced by the order in which they are added, a point which is emphasized by Gelbach (2009). To address this concern, we also carry out two types of decompositions to more concretely explore the role of particular variables in explaining the gender earnings gap. In the first method, in the style of Oaxaca (1973) and Blinder (1973), earnings for each gender (g) are estimated by:

$$Ln(S_{ig}) = X_{ig}\beta_g + \varepsilon_{ig} \tag{2}$$

where X_{ig} contains, alternatively, either our basic set of human capital variables, our expanded set of variables, or both. The male and female models can be subtracted from each other to decompose the mean gender salary gap into the mean difference in observed characteristics and the difference in returns to these characteristics:

$$\overline{Ln(S_M)} - \overline{Ln(S_F)} = \overline{(X_M - X_F)}\beta_F + \overline{X_M}(\beta_M - \beta_F) \tag{3}$$

where the first term on the right-hand side represents the explained part of the gender salary gap – the group differences in observed characteristics, and the second term allows for gender differences in returns to characteristics. Equation (3) is written from the perspective of females, describing their predicted outcome if they had males' characteristics and returns to those characteristics. Of course, it could also be written from the perspective of males. Depending on the choice of reference group – and therefore the point of view – results will vary. As an alternative, it may be useful to employ a weighting scheme in assigning a reference group, rather than placing full weight on one gender versus the other. The discrimination literature offers several such alternatives.[21] For the Oaxaca-Blinder decomposition analyses, we use three such weighting schemes. We report decompositions where all of the weight is placed alternatively on either male or female coefficients.[22] In our preferred specification, following the approach advocated by Neumark (1988) and Chevalier (2007), we use the coefficients from a pooled regression over both males and females. In this case, the salary gap can be decomposed as follows:

$$\overline{Ln(S_M)} - \overline{Ln(S_F)} = \overline{(X_M - X_F)}\beta^* + \overline{X_M}(\beta_M - \beta_F) + (\beta^* - \beta_F)\overline{X_F} \qquad (4)$$

21. Reimers (1983), for example, suggested the use of the average coefficients over both groups: $\beta^* = 0.5\beta_m + 0.5\beta_f$. Similarly, Cotton (1988) proposed the use of coefficients weighted by sample group sizes: $\beta^* = n_m/(n_m + n_f)\beta_m + n_f/(n_m + n_f)\beta_f$.

22. In addition to robustness, an advantage of reporting both of these decompositions is that, unlike the initial pooled regressions including both genders, they provide some insight into the different magnitudes of returns to certain characteristics across genders.

where β^* is the vector of pooled coefficient estimates. In each case, we focus on the "explained" portion of the gap, the first term in equations (3) and (4).

Apart from the Oaxaca-Blinder decompositions, we also employ an approach advocated by Gelbach (2009). Unlike the Oaxaca-Blinder approach, this decomposition is grounded in the formula for sample omitted variables bias. Gelbach's approach provides a method to decompose cross-specification differences in pooled OLS estimates of the female coefficient (along the lines of our multitude of specifications from Tables 2 and 5), but does so in a path-independent manner. [23] We view this approach as an additional robustness check against the results obtained from the traditional Oaxaca-Blinder decomposition using pooled coefficients. Like in the explained portion of the Oaxaca-Blinder decompositions, whether gender heterogeneity in a variable (or set of variables) increases or decreases the gap depends on whether, conditional on other covariates, the variable positively or negatively affects wages, and whether the mean of the variable is higher for males or females.

2.IV Empirical Results

2.IV.A Standard Human Capital Model Variables

2.IV.A.1. Pooled OLS Estimates

The estimates from a series of pooled OLS regression models are shown in Table 2. Moving from left to right in the table coincides with the inclusion of additional control

23. In particular, Gelbach notes that if X_i contains K variables, the contribution of the k-th variable to the gap $\overline{Ln(S_M)} - \overline{Ln(S_F)}$ is given by $\hat{\beta}_k^*$ multiplied by $\hat{\alpha}_k$, where $\hat{\alpha}_k$ are the estimates of the coefficients on the *female* variable from K auxiliary regressions of each of the k covariates on *female*. See Gelbach (2009) for more details. In addition, the Stata code for the Gelbach decomposition can be found on the author's website: http://gelbach.eller.arizona.edu/papers/b1x2/. We thank an anonymous referee for suggesting this procedure.

variables, which are generally added in groups by variable classification. The primary coefficient of interest is that on the Female variable, which, due to the log specification of the dependent variable, represents the unexplained percentage gap in salary between male and female MBA graduates in the dataset.

Table 2
Pooled OLS Estimates of Gender Salary Gap: Human Capital Variables

Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Female	**-0.155****	**-0.137****	**-0.138****	**-0.129****	**-0.109****	**-0.134****	**-0.114****
	(0.026)	(0.026)	(0.026)	(0.027)	(0.026)	(0.026)	(0.027)
Demographic							
Age		0.104**	0.045	0.042	0.055*	0.057*	0.058*
		(0.019)	(0.032)	(0.032)	(0.032)	(0.031)	(0.031)
Asian		0.060	0.076**	0.079**	0.032	0.025	0.031
		(0.038)	(0.038)	(0.038)	(0.038)	(0.038)	(0.038)
Black		0.003	0.011	0.016	0.003	0.038	0.084**
		(0.042)	(0.041	(0.042)	(0.041)	(0.041)	(0.042)
Hispanic		0.039	0.046	0.051	0.040	0.046	0.066*
		(0.036)	(0.035)	(0.035)	(0.035)	(0.034)	(0.034)
Mother's education		0.008*	0.009**	0.009**	0.006	0.005	0.004
		(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Father's education		0.011**	0.011**	0.011**	0.009*	0.009*	0.007
		(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Employment Experience							
Experience			0.038**	0.037**	0.032**	0.033**	0.030**
			(0.011)	(0.011)	(0.011)	(0.011)	(0.011)
Tenure			-0.004	-0.004	-0.005	-0.007	-0.005
			(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
Family Variables							
Married				0.007	0.008	-0.000	0.005
				(0.032)	(0.031)	(0.030)	(0.030)
Kids				-0.087	-0.074	-0.081	-0.068
				(0.087)	(0.086)	(0.084)	(0.084)
Married*Kids				0.114	0.113	0.120	0.111
				(0.092)	(0.090)	(0.089	(0.088)
Undergraduate Variables							
Highly selective					0.194**	0.201**	0.160**
					(0.033)	(0.033)	(0.034)
Selective					0.073**	0.076**	0.060**
					(0.029)	(0.028)	(0.028)
Engineering major					0.080**	0.098**	0.068*
					(0.037)	(0.037)	(0.038)
Grade Point Average						0.172**	0.135**
						(0.030)	(0.031)
Ability Measures							
Quantitative GMAT							0.005**
							(0.002)
Verbal GMAT							0.004
							(0.002)
R-Square	0.04	0.09	0.12	0.12	0.17	0.20	0.21

continued

Table 2 continued, **Pooled OLS Estimates of Gender Salary Gap: Human Capital Variables**

Variable	(8)	(9)	(10)	(11)
Female	**-0.092****	**-0.095****	**-0.069****	**-0.065****
	(0.026)	(0.026)	(0.025)	(0.024)
MBA Variables				
Executive program	0.127**	0.126**	0.124**	0.107**
	(0.053)	(0.052)	(0.049)	(0.049)
Top 10	0.396**	0.385**	0.280**	0.295**
	(0.053)	(0.053)	(0.050)	(0.049)
Top 11 - 25	0.170**	0.189**	0.118**	0.140**
	(0.044)	(0.044)	(0.041)	(0.041)
Finance concentration	0.121**	0.119**	0.104**	0.071**
	(0.035)	(0.034)	(0.032)	(0.032)
Cumulative GPA		0.100**	0.041	0.039
		(0.046)	(0.043)	(0.042)
Current Job: Hours and Characteristics				
Hours per week			0.015**	0.014**
			(0.001)	(0.001)
Large firm				0.087**
				(0.036)
Medium firm				0.070**
				(0.034)
Non-profit				-0.142**
				(0.047)
Government				-0.190**
				(0.048)
Finance, insurance & real estate				0.094**
				(0.037)
Percent female in occupation				-0.252**
				(0.083)
R-Square	0.29	0.30	0.39	0.43

Notes: Dependent variable is log of annual salary of current, full-time (>= 35 hours/week) jobs of MBA graduates reported in Wave IV (933 observations in each regression). Models (2)-(11) include age^2; (3)-(11) include experience^2 and tenure^2; (5)-(11) control for social science, humanities, and science majors; (8)-(11) include the variables of (7), dummies for part-time program, and various concentrations: Marketing, Accounting, MIS, International, and Other; (11) includes whether the individual is self-employed and dummies for the following industries: agriculture, forestries & fisheries, manufacturing, service, and public administration. Statistical significance of the coefficient at the 5 and 10 percent levels are indicated by ** and *.

As shown in column 1, in terms of raw differentials, females earn approximately 15.5 percent less than males in the sample. Not surprisingly, this gender gap is smaller than nationwide estimates since ours is of a more homogeneous group: MBAs. The inclusion of demographic variables slightly decreases the gap to below 14 percent (the specification in column 2). Despite significantly lower average female job tenure (at the 1 percent level) and marginally lower work experience (at the 10 percent level), the inclusion of the employment experience variables, both years of work experience and tenure in the current job, does not alter the wage gap, even though total work experience is highly related to earnings in all specifications (column 3). Because of the nonlinearity in returns to both experience and tenure, the combined returns to these variables flatten out somewhat by their sample means (about 10.5 and 4 years, respectively), resulting in relatively little effect on the earnings gap due to the modest differences in experience between men and women. Furthermore, these variables are highly correlated with age, and the coefficient on age decreased substantially in this specification. Excluding age from the regressions results in the work experience variables decreasing the gender earnings gap by 1.3 percentage points. As exemplified here, the fact that the order in which variables are added influences their perceived effect provides motivation for the decompositions performed in the next section. Under the decompositions, the work experience variables generally explain positive and significant portions of the gap. Still, the relatively small effect of work experience observed here contrasts with the findings of, for example, Brown and Corcoran (1997), who report that differences in work experience account for as much as about one third of the 24 percent wage gap for women with some college education.[24]

24. This difference is due to the fact that men in our sample only had about 7 percent more work experience than did women, whereas in their sample of college graduates the difference

While more males are married and have children than females in the sample, including these control variables, as well as an interaction term of married with children, decreases the gender salary gap by 6.5 percent, from 13.8 to 12.9 percent; surprisingly though, none of those variables significantly influences salaries. This outcome is in stark contrast to the labor market literature and to Bertrand et al. (2009) and Wood et al. (1993), who find a strong mother penalty for University of Chicago MBAs and University of Michigan lawyers, respectively. Although the inclusion of human capital variables in subsequent specifications does not change these relationships, married-with-children becomes strongly significant with the introduction of hours worked (column 10) and then with the addition of employer characteristics (column 11). The only child penalty we find is for unmarried women (but not unmarried men; from results not displayed here). Note that the average age in our sample was 34 for women and 35 for men, by which point female University of Chicago MBAs had already experienced a child penalty, according to Bertrand et al. (2009).

The model specifications presented in columns 5 through 9 correspond to the addition of several human capital and ability variables. Columns 5 and 6 show an interesting effect of undergraduate variables—the gap decreases by 2 percentage points when controlling for college major choice and selectivity of undergraduate institution attended. The results concur with previous findings in the literature that choice of major is one reason for raw gender gaps; here, the effect is smaller than in previous studies (McDonald and Thornton 2007; Joy 2003; Daymont and Andrisani 1984), perhaps because the average individual in the sample is 12 years beyond college graduation. Although having attended a highly selective or moderately selective college strongly influences

exceeded 35 percent (Brown and Corcoran 1997, Table 1, p. 436).

earnings, again despite being years after graduation, only those from the highly selective undergraduate institutions continue to have that effect in all specifications (not shown in Table 2).[25]

Despite the passage of time, undergraduate grades prove to strongly predict earnings, to the extent that increasing one's GPA by one letter grade increases their earnings by 17.2 percent (column 6). Taking the respondent’s undergraduate GPA into account sharply increases the unexplained salary gap back up to over 13 percent, since females in our sample report higher grades than their male counterparts.

Adding GMAT scores to the regression (column 7) decreases the gender salary gap to 11.4 percent. These quantitative score results are similar to the relationship reported by Paglin and Rufolo (1990) between quantitative GRE scores and wages. Interestingly, the addition of MBA experience variables (column 8) causes quantitative GMAT scores to lose significance and verbal GMAT scores to gain significance (not reported in Table 2), suggesting that perhaps part of the reason for GMAT scores’ high returns is through their ability to get students into a better quality MBA program or for students to select particular areas of concentration. Though not shown, it is worth noting that while quantitative GMAT scores’ significance continued to decrease with the addition of employment characteristics (in columns 10 and 11), verbal GMAT scores’ significance increased, suggesting that quantitative abilities may serve to sort individuals into particular types of jobs, while verbal abilities appear to independently affect earnings.

The addition of MBA variables (column 8) dramatically reduces the wage gap by 2 percentage points. The effect of the graduate program variables parallels that of the

25. In the specification reported in column 11 of Table 2, the coefficient for highly selective undergraduate institutions was 0.06** and 0.032 for schools of moderate selectivity.

undergraduate variables: aspects of the program such as overall quality (we included Top 10 and Top 11-25) and the choice of particular study concentrations decrease the gap to about 9 percent. Both MBA program selectivity measures are strongly significant in all specifications. Only those who concentrated in finance earned more than others (similar to the result found by Grove and Hussey, forthcoming).

As with undergraduate grades, adding MBA GPA (column 9) slightly increases the size of the unexplained gap (even though those grades did not significantly differ by sex); unlike with undergraduate grades, though, MBA GPA loses significance when work characteristics are included. Respondents' work hours strongly influence wages (column 10), reducing the unexplained gap by more than 25 percent or 2.6 percentage points; adding hours worked causes MBA grades to lose significance, but the married with children coefficient to gain significance (neither shown in Table 2). Finally, the inclusion of various characteristics of the individual's firm in Wave IV, namely company size, types and industries (column 11), narrows the gender wage gap slightly to 6.5 percent. Those employed in big and medium sized firms and in the finance industry earn more compared to nonprofit or government employees who make significantly less. Although our results confirm the literature regarding the role of firm size on wages (Oi and Idson 1999), unlike Graham et al. (2000), firm size explains little of the gender salary gap because in our sample women and men with MBAs do not work in different sized firms (see Table 1). Lastly, women disproportionately work in occupations with a high percentage of women which strongly and negatively affects earnings (akin to MacPherson and Hirsch's [1995] finding of a small but important role in accounting for gender wage gaps, rather than the largest component of it as reported by Boraas and Rodgers 2003, 2009).

In sum, these detailed demographic, family, and human capital measures explain 58 percent of the raw gender wage gap [(15.5 – 6.5)/15.5]. However, because the order in which we add control variables affects these results, we now turn to the decomposition analysis to examine the simultaneous contribution of each set of our basic variables in explaining the male-female earnings gap.

2.IV.A.2 Decomposition Analyses for Standard Human Capital Model Variables

As described in Section III, to determine the contribution of each category of variables in explaining the raw wage differentials, we conduct several decompositions. Initially, we perform Oaxaca-Blinder decompositions using coefficients from pooled (male and female) regressions; then, we compare these results to similar decompositions using coefficients from either male-only or female-only regressions, as well as Gelbach decompositions (2009). Table 3 illustrates the contribution of each individual category in explaining the wage gap, based on the coefficients from a pooled model. Columns 1-11 display, for each category individually, (1) the amount of explained contribution, (2) the standard errors in parenthesis, and (3) the percent of the contribution to the overall raw salary gap. Column 12 contains all categories together except the hours worked and job characteristics variables, which explain 59 percent of the gap. Finally, in column 13, all categories together explain 69 percent of the male-female earnings gap.

Table 3

Oaxaca-Blinder Decompositions of Gender Log Salary Gap: Explained Contributions of Human Capital Variables

Included Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
Demographic/ Background	0.02** 15.2%											0.00 5.4%	0.00 0.7%
Employment Experience		0.01 5.7%										0.02** 12.9%	0.02** 10.3%
Family Variables			0.03** 20.1%									0.02** 12.4%	0.02** 15.3%
Undergrad Variables				0.03** 16.2%								0.02** 9.9%	0.01** 8.0%
Undergrad GPA					-0.01** -9.1%							-0.01* -5.4%	-0.01* -4.8%
Quantitative GMAT						0.05** 30.7%						0.01* 9.2%	0.01 4.2%
Verbal GMAT							0.01 6.0%					0.00 1.5%	0.00 2.2%
MBA Variables								0.02* 13.4%				0.02** 11.7%	0.01* 8.0%
MBA GPA									0.005 3.0%			0.00 1.3%	0.00 0.5%
Current Job: Hours										0.03** 16.3%			0.02** 12.2%
Current Job: Characteristics											0.03** 22.2%		0.02** 12.2%

Notes: Reported are explained contribution and percent contribution (percentage of the raw gap explained). Each class of variables corresponds to variables from Table 1. Each specification includes 933 observations. ** and * indicates coefficient is statistically significantly different from zero at the 5 and 10 percent level.

So, for example, quantitative GMAT scores by themselves can explain 30.7 percent of the salary gap (column 6) but only a marginally significant 9 percent with all variables except work hours (column 12), and then lose significance with the addition of current job characteristics (column 13). Several classes of variables individually explain modest but significant portions of the gap; quantitative GMAT scores explain almost a third of it, even more than the job variables can on their own. Altogether in column 13, the most important classes of variables determining male-female wage differences are family variables (15.3 percent), hours worked and current job characteristics (each 12.2 percent), employment experience (10.3 percent), and undergraduate and MBA variables (each 8.0 percent).

We now investigate the robustness of these results by carrying out alternative decompositions, including a Gelbach decomposition and Oaxaca-Blinder decompositions using either male or female coefficients. Table 4 displays the results, as well as those from the previous decomposition for comparison. Conducting separate analyses by gender also allows us to determine whether men's and women's outcomes are influenced differently by their demographic and family backgrounds, educational and work experience, and current work environment.[26] Whereas five categories of variables are strongly significant in the pooled coefficient decompositions, only three are when using male coefficients and two with female coefficients; only one variable, hours worked per week, mattered for both men and women and employment experience was only significant in the pooled results.

26. Full regression results separated by gender are available on request.

Table 4
Multiple Decompositions of Gender Log Salary Gap: Explained Contributions of Human Capital Variables

Variable (group)	*Oaxaca-Blinder* *Using pooled coefficients*		*Oaxaca-Blinder* *Using male coefficients*		*Oaxaca-Blinder* *Using female coefficients*		*Gelbach* *Decomposition*	
	contribution	*% of gap*	*contribution*	*% of gap*	*contribution*	*% of gap*	*contribution*	*% of gap*
Demographics/Background	0.001	0.7%	-0.004	-2.6%	0.007	4.6%	-0.001	0.8%
Employment Experience	0.016**	10.3%	0.012	7.8%	0.010	6.6%	0.015*	9.9%
Family Variables	0.024**	15.3%	0.025**	15.8%	0.005	3.0%	0.020**	12.7%
Undergraduate Variables	0.012**	8.0%	0.014**	8.8%	0.003	1.7%	0.012**	7.5%
Undergraduate GPA	-0.007*	-4.8%	-0.009	-5.9%	-0.011	-7.2%	-0.009**	-6.0%
Quantitative GMAT	0.006	4.2%	-0.008	-4.9%	0.019	12.3%	0.002	1.3%
Verbal GMAT	0.003	2.2%	0.006	3.8%	0.000	0.2%	0.004	2.4%
MBA Variables	0.012*	8.0%	0.012	7.5%	0.007	4.7%	0.010	6.7%
MBA GPA	0.001	0.5%	0.001	0.6%	-0.001	-0.4%	0.001	0.5%
Current Job Hours	0.019**	12.2%	0.022**	14.0%	0.015**	9.7%	0.019**	12.0%
Current Job Characteristics	0.019**	12.2%	0.006	3.9%	0.032**	20.7%	0.018**	11.5%
Total	0.107**	68.9%	0.076**	48.8%	0.086**	55.5%	0.090**	57.8%

Notes: For each variable or set of variables, reported are the net explained contribution of the raw salary gap and the percentage of the gap explained due to gender differences in values of each category of variables. Gelbach decomposition follows Gelbach (2009). Each specification includes all of the variables from Table 1, and includes 933 observations. ** and * indicate explained contribution is statistically significantly different from zero at the 5 and 10 percent level.

While hours matter for both men and women in explaining earnings, other significant effects on the wage gap are gendered: when the male coefficients are used, family circumstances and undergraduate experiences account for 16 and 9 percent of the gap, respectively; and when the female coefficients are used job characteristics account for 21 percent of the gap.

Furthermore, our results suggest that the effect of college quality on earnings is larger for males than for females, as the estimated explained contribution of these variables is significantly larger when male's coefficients are used than when female's coefficients are used. Alternatively, the positive return to quantitative GMAT scores appears to be driven solely by females and not males.[27] Finally, the results from the Gelbach decomposition are found to be very similar to the Oaxaca-Blinder decomposition using coefficients from the pooled model. The same sets of variables tend to be statistically significant predictors of the earnings gap, though the percentage of the gap explained by the Gelbach decomposition is generally slightly lower for each set of variables, and the overall gap explained is also lower (57.8 percent for the Gelbach decomposition as opposed to 68.9 percent for the pooled Oaxaca-Blinder decomposition).

In summary, then, while the effects of several variables are fairly robust to the specification of decomposition used, other variables affect the earnings gap in strikingly different ways for men and women drawn from a relatively homogeneous pool: MBA recipients. Overall, the decompositions using slope coefficients estimated from both males and females resulted in a higher percentage of the raw gap explained (in particular

27. Recall that males have higher GMAT scores than females (Table 1). A larger percentage of the earnings gap is explained by quantitative GMAT scores when female coefficients are used in the decomposition as opposed to male coefficients (due to females' estimated high return to quantitative GMAT, compared to no return for males).

the pooled Oaxaca-Blinder approach, explaining 69 percent of the gap), and the specification using male coefficients performed the worst (explaining only 49 percent of the gap).

2.IV.B Results for Human Capital Model, Noncognitive Skills, and Labor Market Tastes

2.IV.B.1 Pooled OLS Estimates

Beyond the standard set of demographic and human capital variables discussed above, we now wish to investigate the role of noncognitive factors and preferences on incomes, as long speculated by social scientists. We specifically evaluate gender heterogeneity among proxies for some noncognitive skills, various measures of confidence, and work and life preferences. In Table 5, the initial OLS gender wage gap estimate of 9.5 percent (column 1) corresponds to the specification of column 9 in Table 3, including all human capital variables but not hours and job characteristics. In columns 2-8 of Table 5, we sequentially add the following: self-assessed noncognitive skills (column 2), confidence in quantitative and verbal abilities (column 3), work and life preferences (column 4), confidence of admission to MBA program (column 5), confidence to “have the right connections” (column 6), managerial expectations (column 7), and non-monetary job preferences (column 8). All told, adding these variables to our full human capital model, in specification 9, reduces the unexplained gap to just 4.3 percent.

Table 5
Pooled OLS Estimates of Gender Salary Gap: Addition of Noncognitive Skills and Labor Market Tastes

Variable	(1)	(2)	(3)	(4)	(5)
Female	**-0.095****	**-0.093****	**-0.089****	**-0.079****	**-0.078****
	(0.026)	(0.027)	(0.027)	(0.027)	(0.027)
Noncognitive Skills					
Initiative		0.056**	0.055**	0.048**	0.048**
		(0.023)	(0.023)	(0.023)	(0.023)
High ethical standards		-0.076**	-0.076**	-0.069**	-0.071**
		(0.023)	(0.023)	(0.023)	(0.023)
Communication skills		0.023	0.023	0.026	0.027
		(0.022)	(0.022)	(0.022)	(0.022)
Work with diversity		0.010	0.011	0.013	0.016
		(0.022)	(0.022)	(0.022)	(0.022)
Shrewdness		-0.006	-0.006	-0.012	-0.015
		(0.017)	(0.017)	(0.017)	(0.017)
Physical attractiveness		0.032	0.031	0.030	0.028
		(0.020)	(0.020)	(0.020)	(0.020)
Assertiveness		0.050**	0.050**	0.050**	0.050**
		(0.021)	(0.021)	(0.021)	(0.021)
Adapt theory to practice		0.029	0.028	0.030	0.034*
		(0.019)	(0.019)	(0.019)	(0.019)
Being a team player		0.027	0.025	0.027	0.028
		(0.022)	(0.022)	(0.022)	(0.022)
Confidence: Ability					
Quantitative expectations			0.021	0.017	0.021
			(0.018)	(0.018)	(0.018)
Verbal expectations			-0.006	-0.001	0.002
			(0.018)	(0.018)	(0.018)
Work/Life Preferences					
Family important				0.019	0.019
				(0.039)	(0.039)
Career important				0.071**	0.072**
				(0.023)	(0.023)
Wealth important				0.070**	0.066**
				(0.030)	(0.030)
Relatives/ friends important				-0.011	-0.010
				(0.023)	(0.023)
Confidence: Admissions					0.004**
					(0.002)
R-Square	0.30	0.34	0.34	0.35	0.36

continued

Table 5 *continued*, **Pooled OLS Estimates of Gender Salary Gap: Addition of Noncognitive Skills and Labor Market Tastes**

Variable	(6)	(7)	(8)	(9)
Female	**-0.072****	**-0.070****	**-0.059****	**-0.043***
	(0.027)	(0.027)	(0.026)	(0.025)
Confidence: Connections				
Knowing the right people:	0.016	0.016	0.014	0.021
managerial success	(0.014)	(0.014)	(0.014)	(0.013)
Managerial Goals				
High managerial responsibility		0.077	0.070	0.052
		(0.047)	(0.047)	(0.044)
Job Preferences				
Non-monetary job attributes			-0.011**	-0.009**
			(0.003)	(0.003)
Contributes to society			-0.118**	-0.087**
			(0.032)	(0.032)
Current Job: Hours and Characteristics				
Hours per week				0.012**
				(0.001)
Large firm				0.080**
				(0.035)
Non-profit				-0.129**
				(0.047)
Government				-0.172**
				(0.049)
Finance, insurance & real estate				0.096**
				(0.037)
Percent female in occupation				-0.202**
				(0.082)
R-Squared	0.36	0.37	0.39	0.47

Notes: Dependent variable is log of annual salary of current, full-time (>=35 hours/week) jobs of MBA graduates reported in Wave IV (933 observations in each regression). Models (2)-(9) include ability to organize, to motivate others, to capitalize on change, to delegate tasks, understanding business in other cultures, and good intuition; (5)-(9) include all variables from Model (4); (6)-(9) control for knowing the right people for admissions; (7)-(9) include medium managerial responsibility; (9) controls for self-employed, medium firm size, agriculture, forestries & fisheries, manufacturing, service industry, and public administration. Statistical significance of the coefficient at the 5 and 10 percent levels are indicated by ** and *.

The inclusion of all 15 noncognitive skills only slightly decreases the wage gap. Three of those traits are statistically significant: initiative and assertiveness positively influence earnings, whereas high ethical standards do so negatively. While for each of the three coefficients the magnitude and significance diminishes as more control variables are added, Assertiveness loses significance in the final specification whereas ability to Adapt theory to practice gains significance. Individually, while initiative, assertiveness, and high ethical standards significantly affect wages, their effects cancel each other out (the two former positively and the latter negatively); thus, we find no evidence of an important net role for these particular proxies for noncognitive skills in explaining wage inequality by sex (neither in the OLS results from Table 5, nor in either set of the decomposition results reported in Tables 6 and 7).[28]

Next, we consider the influence of five confidence measures on the gender earnings gap. The first indicates respondents' expectations about their quantitative and verbal scores on the GMAT exam, namely whether they expected to perform in a range from well above average to well below average. Including those expectations marginally narrows the gap but the confidence measures themselves are not significant (Table 5, column 3). Also, respondents indicated how confident they were that they would be admitted to an MBA program. Although that variable positively and significantly influences wages when introduced in column 5, it loses significance thereafter (not shown here). Finally, we probe two confidence indicators associated with having the right connections. "Knowing the right people" as a criterion for getting into an MBA program is positive but not significant. On the other hand, the extent to which individuals think they "know the

28. Initiative serves to slightly increase the unexplained salary gap, since women report slightly more of that characteristic, whereas women's self-reported higher ethical standards decreased the unexplained gap.

right people" as a criterion for being a successful manager strongly influences wages in all specifications. The addition of these two connection measures decreases the gap by about 8 percent, from 7.8 percent to 7.2 percent (columns 5 and 6).

The final set of non-traditional labor market variables that might help explain the observed male-female salary gap relate to labor market tastes regarding family, careers, and jobs. Including work and life preferences decreases the wage gap by a full percentage point, from 8.9 to 7.9 percent (column 4). Career importance remains significant in all specifications, but the priority of wealth loses significance in the final specification (not shown in Table 5). Job aspirations, in terms of expected managerial status (whether respondents reported expecting to be an entry-level manager or a mid-to-upper-level manager relative to a non-manager) are not significant, yet slightly lower the gap when included (column 7).

We include two job preference categories: (1) an index of non-monetary job attributes (for instance friendly people, job security, chances for promotions, hours are good, clear responsibilities) collected from the Wave I surveys and (2) the importance of making a positive contribution to society when choosing their current job. Both are strongly significant and negative in all specifications (column 8), suggesting that these characteristics serve as compensating differentials. They also appear to importantly account for the gender earnings gap, decreasing the unexplained portion by 1.1 percentage points, which corresponds to almost 16 percent of the remaining gap.

Collectively, additional variables representing preferences, confidence, and self-assessed noncognitive skills, when added to the initial set of background and human capital variables, serve to substantially decrease the gender gap, from 9.5 percent down to

5.9 percent. In comparison, the addition of these less traditional variables is shown to be more effective than was the inclusion of several actual job characteristics, which resulted in an unexplained difference of 6.5 percent (Table 2). In our final model specification (column 9) in Table 5, in which we add hours worked and other current job characteristics (as in Table 2), the unexplained gender wage gap narrows to a marginally significant 4.3 percent; that represents merely 28 percent of the raw differential found in our sample, so this model explains over 70 percent of the gap.

Of the novel gender heterogeneity variables, seven individually influence wages in the final specification: three noncognitive skills (initiative, assertiveness, and high ethical standards), the importance of career, knowing the right people as a key to managerial success, and preferences for (i) jobs with non-monetary attributes and (ii) work that contributes to society. The earnings-gap-reducing role of "knowing the right people" for MBAs is especially interesting since it has been shown to disadvantage female business leaders (Bartlett and Miller 1985).

2.IV.B.2 Decomposition Analyses

Next we use decomposition analysis to isolate the overall effects of particular classes of less traditional variables, namely various proxies for or measures of confidence, expectations, and preferences, as we did with the more basic human capital model in Tables 3 and 4. Table 6 depicts the sequential addition of these variables using pooled regression coefficients. We begin including each class of variables separately in the first column, labeled (1)-(7) to signal that each of these results corresponds to carrying out separate regressions with only that set of variables. The second column, labeled (8), includes decomposition results for a model containing all of the novel variables without our full set of human capital variables. Then, the next seven columns (9-15) include our full set of human capital variables (excluding current employment characteristics), adding in separately each class of non-traditional variables.

Although at least some variables in four of the non-traditional categories were significant in earnings regressions (Table 5), only two groups as a whole significantly explain differences in men's and women's salaries when human capital variables are included (Table 6, column 16): work/life preferences and job preferences. Note that, for example, ability confidence (not significant in OLS results reported in Table 5) loses significance with the inclusion of the human capital variables (in column 16), suggesting that self-evaluation of one's managerial noncognitive skills is embodied in other human capital variables. Job Preferences (prioritizing non-monetary job attributes and employment that contributes to society) are strongly significant in all decomposition specifications shown in Table 6, explaining 10 percent of the gender wage gap when all variables are included (column 17). Work/Life Preferences, though, matter only until job characteristics are included (column 17). Thus, work/life preferences, in particular the importance respondents attributed to career and wealth, seem to predict actual selection into jobs.

Table 6
Oaxaca-Blinder Decompositions of Gender Log Salary Gap: Explained Contributions of Full Model

Included Variables	(1)-(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)
Noncognitive	0.002	-0.006	0.000							-0.002	0.000
Skills	1.1%	-3.7%	0.2%							-1.2%	0.0%
Confidence:	0.036**	0.031**		0.019**						0.006	0.006
Abilities	23.5%	20.2%		11.9%						4.1%	3.8%
Work/Life	0.013**	0.010*			0.010*					0.009*	0.003
Preferences	8.3%	6.4%			6.6%					6.1%	1.9%
Confidence:	0.000	0.000				0.000				0.001	0.000
Admissions	0.3%	0.3%				0.3%				0.6%	0.2%
Confidence:	0.001	0.001					0.003			0.003	0.004
Connections	0.4%	0.9%					1.8%			1.8%	2.3%
Managerial	0.003	0.003						0.001		0.001	0.001
Goals	1.7%	2.1%						0.5%		0.8%	0.5%
Job	0.022**	0.023**							0.015**	0.019**	0.016**
Preferences	13.9%	14.9%							9.9%	12.4%	10.0%
Basic Human			0.089**	0.072**	0.083**	0.083**	0.086**	0.087**	0.074**	0.077**	0.066**
Capital Variables			57.4%	46.5%	53.5%	53.6%	55.6%	55.8%	47.7%	49.6%	42.5%
Current Job:											0.032**
Characteristics & Hours											20.5%
Total Percentage Explained		41.1%	57.7%	58.4%	60.1%	53.8%	57.4%	56.3%	57.6%	74.2%	81.6%

Notes: Reported are the explained contribution (using coefficients from a pooled model) and percent contribution (percentage of the raw gap explained). Each specification includes Basic Human Capital Variables from Table 2 other than Current Job variables. Coefficients in columns labeled (1)-(7) are from separate regressions including only each class of variables separately. Each specification includes 933 observations. ** and * indicate coefficient is statistically significantly different from zero at the 5 and 10 percent level.

Finally, in Table 7, like in Table 4, we display the Oaxaca-Blinder and Gelbach decompositions with all variables included. As just discussed, of the new classes of noncognitive variables only job preferences significantly explain the wage gap (in all four specifications), although such preferences matter much more when using the female coefficients (accounting for 13 percent of the gap) than with the male coefficients (8 percent). Beyond that, even more notable than from the human capital model analysis in Table 5, is the starkness of the sources of gender differences: only hours worked and job preferences are commonly important in the decompositions using either male or female coefficients; job characteristics only significantly explain the gap with female coefficients and account for 17 percent of it.[29] Four other categories explain the gap using male coefficients—family circumstances (13 percent), undergraduate variables and grades (9 and -7 percent, respectively), and prior employment experience (9 percent). Note that employment experience and undergraduate GPA only gained significance in Table 7 with the presence of the non-traditional classes of variables (see, by contrast, Table 4).

29. That is, hours worked are positively related to earnings and nonmonetary job preferences are negatively related to earnings in both female-only and male-only regressions. Since males report more hours worked and females report greater preferences towards nonmonetary job attributes, both explain a portion of the gap when either male or female coefficients are used in the Oaxaca-Blinder decompositions. Interestingly, actual job characteristics are more important to female earnings than they are to male earnings, so male-female differences in these variables result in a larger portion of the earnings gap explained when female coefficients are used in the decomposition than when male coefficients are used.

Table 7
Multiple Decompositions of Gender Log Salary Gap: Explained Contributions of Full Model

Variable (group)	*Oaxaca-Blinder Using pooled coefficients*		*Oaxaca-Blinder Using male coefficients*		*Oaxaca-Blinder Using female coefficients*		*Gelbach Decomposition*	
	contribution	*% of gap*	*contribution*	*% of gap*	*contribution*	*% of gap*	*contribution*	*% of gap*
Demographic/Background	0.001	0.8%	-0.008	-5.0%	0.012	7.8%	0.000	-0.1%
Employment Experience	0.017**	11.1%	0.014*	8.8%	0.011	6.9%	0.017*	10.8%
Family Variables	0.019**	12.3%	0.020**	12.8%	-0.001	-0.7%	0.016**	10.6%
Undergraduate Variables	0.014**	9.3%	0.014**	9.1%	0.008	5.0%	0.014**	9.0%
Undergraduate GPA	-0.009**	-5.6%	-0.010**	-6.6%	-0.008	-5.3%	-0.010**	-6.3%
Quantitative GMAT	0.008	5.1%	-0.004	-2.4%	0.026	16.8%	0.006	3.8%
Verbal GMAT	0.004	2.4%	0.005	3.1%	0.002	1.4%	0.004	2.5%
MBA Variables	0.010	6.7%	0.010	6.5%	0.008	5.1%	0.009	6.0%
MBA GPA	0.001	0.5%	0.001	0.4%	0.000	0.1%	0.001	0.5%
Current Job Hours	0.016**	10.4%	0.019**	12.1%	0.014**	9.1%	0.016**	10.3%
Current Job Characteristics	0.015**	10.0%	0.006	3.7%	0.026**	17.0%	0.015**	9.7%
Noncognitive Skills	0.000	0.0%	0.000	-0.2%	-0.007	-4.7%	-0.002	-1.4%
Confidence: Ability	0.006	3.8%	0.005	3.1%	-0.002	-1.0%	0.005	3.0%
Work/Life Preferences	0.003	1.9%	0.006	3.7%	-0.006	-3.9%	0.002	1.3%
Confidence: Admissions	0.000	0.2%	0.001	0.3%	0.001	0.6%	0.000	0.1%
Confidence: Connections	0.004	2.3%	0.003	2.2%	0.002	1.6%	0.003	2.2%
Managerial Goals	0.001	0.5%	0.000	0.1%	0.001	0.5%	0.001	0.5%
Job Preferences	0.016**	10.0%	0.013**	8.2%	0.020**	12.7%	0.015**	9.7%
Total	0.126	81.6%	0.093	60.0%	0.107	69.0%	0.111	72.2%

Notes: For each variable or set of variables, reported are the net explained contribution of the raw salary gap and the percentage of the gap explained due to gender differences in values of each category of variables. Gelbach decomposition follows Gelbach (2009). Each specification includes all of the variables from Table 1 and includes 933 observations. ** and * indicate explained contribution is statistically significantly different from zero at the 5 and 10 percent level.

Finally, we should note that adding these non-traditional variables increased the total explained percentage of the gender wage gap by 11-13 percentage points.[30]

In sum, then, the addition of noncognitive skills and labor market tastes accounts for about a quarter of our explained gender earnings gap[31]; quite remarkably, this approximately equals that accounted for by hours worked and current job characteristics. The results in Table 7 also serve to indicate the way that experiences, noncognitive skills, and priorities distinctly shape men's and women's outcomes—even among a group of relatively homogeneous individuals, MBAs. Women's socially desirable choices of jobs that contribute to society and personality traits, namely high ethical standards, significantly reduce their earnings.

2.V Robustness Checks

In this section we discuss some additional specifications carried out to check the robustness of our results. First, throughout our previous analysis we have used annual salary as the dependent variable. While this specification of earnings has been used in other studies of highly educated professionals (see Altonji and Blank 1999), the number of hours an individual works may be endogenously determined. To the degree that females often work fewer hours than males, this may be of particular concern in the context of explaining the gender earnings gap. However, the gap in hours worked is relatively small among our sample of MBAs. Nonetheless, to investigate the effect of our choice of dependent

30. The difference between the total explained percentage of the gender wage gap from Tables 4 and 7 is 11.2 percentage points with the male coefficients (60.0-48.8), 13.5 with the female coefficients (69.0-55.5), 12.7 (81.6-68.9) using pooled coefficients, and 14.4 (72.2-57.8) with the Gelbach decompositions.

31. Adding the percentage of the gap explained by the last seven categories in Table 7 equals 18.7 percent which is 23 percent of the total explained gap of 81.6 percent.

variable, we repeated our analysis from Tables 2, 5, and 7 using hourly wage instead of annual earnings. These results are given in Appendix Tables 1 through 3. It can be seen that, throughout our sequential OLS specifications, the coefficients on the female variable are a little smaller than the coefficients obtained from the corresponding annual salary regressions in Tables 2 and 5. This is not surprising, since including hours explicitly in Table 2 caused the gap to decrease, and using hourly wage effectively controls for hours in all specifications. Thus, the influence of variables in our OLS regressions changes very little whether our dependent variable is annual salary or hours worked. Decomposition results also indicate that the choice of hourly wage or annual salary is generally not a pivotal one, since the contribution to the explained gap of each set of variables is generally very similar with either dependent variable.[32]

32. One interesting difference is that the amount of the gender gap explained by the Oaxaca-Blinder decomposition using female coefficients increases substantially when hourly wage is used as the dependent variable, while the percentage explained when male coefficients are used decreases under the hourly wage specification. Most notably, quantitative GMAT scores account for a full 24 percent of the explained wage gap under the female coefficient specification.

Appendix Table 1
Pooled OLS Estimates of Gender Wage Gap: Human Capital Variables

Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Female	**-0.128****	**-0.111****	**-0.110****	**-0.093****	**-0.073****	**-0.091****	**-0.077****
	(0.023)	(0.024)	(0.023)	(0.024)	(0.024)	(0.024)	(0.024)
Demographic/Background							
Age		0.086**	0.038	0.031	0.044	0.046	0.045
		(0.018)	(0.029)	(0.029)	(0.029)	(0.028)	(0.028)
Asian		0.029	0.044	0.048	0.004	-0.001	0.011
		(0.035)	(0.034)	(0.034)	(0.034)	(0.034)	(0.034)
Black		-0.007	0.002	0.008	-0.004	0.021	0.062
		(0.038)	(0.037)	(0.037)	(0.037)	(0.037)	(0.038)
Hispanic		0.023	0.030	0.037	0.025	0.030	0.048
		(0.032)	(0.032)	(0.032)	(0.031)	(0.031)	(0.031)
Mother's education		0.006*	0.007*	0.007*	0.005	0.004	0.004
		(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Father's education		0.005	0.005	0.006	0.004	0.004	0.002
		(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Employment Experience							
Experience			0.032**	0.030**	0.025**	0.026**	0.023**
			(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
Tenure			-0.003	-0.004	-0.005	-0.006	-0.004
			(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
Family Variables							
Married				-0.001	-0.002	-0.007	-0.003
				(0.028)	(0.028)	(0.028)	(0.027)
Children				-0.121	-0.109	-0.114	-0.100
				(0.078)	(0.077)	(0.076)	(0.076)
Married*children				0.183**	0.180**	0.185**	0.173**
				(0.083)	(0.081)	(0.080)	(0.080)
Undergraduate Variables							
Highly selective					0.162**	0.167**	0.131**
					(0.030)	(0.030)	(0.031)
Selective					0.057**	0.059**	0.044*
					(0.026)	(0.026)	(0.026)
Engineering major					0.089**	0.102**	0.081**
					(0.034)	(0.033)	(0.034)
Grade point average						0.122**	0.087**
						(0.027)	(0.028)
Ability Measures							
Quantitative GMAT							0.003
							(0.002)
Verbal GMAT							0.005**
							(0.002)
R-Square	0.03	0.08	0.11	0.12	0.16	0.18	0.20

continued

Appendix Table 1 *continued,* **Pooled OLS Estimates of Gender Wage Gap: Human Capital Variables**

Variable	(8)	(9)	(10)
Female	**-0.060****	**-0.061****	**-0.056****
	(0.024)	(0.024)	(0.024)
MBA Variables			
Executive program	0.126**	0.126**	0.111**
	(0.049)	(0.049)	(0.049)
Top 10	0.258**	0.250**	0.261**
	(0.049)	(0.049)	(0.049)
Top 11 - 25	0.092**	0.098**	0.116**
	(0.040)	(0.041)	(0.040)
Finance concentration	0.101**	0.100**	0.066**
	(0.032)	(0.032)	(0.032)
MIS concentration	0.101**	0.101**	0.083*
	(0.049)	(0.049)	(0.048)
Cumulative GPA		0.023	0.018
		(0.042)	(0.042)
Current Job: Hours and Characteristics			
Large firm			0.077**
			(0.036)
Medium firm			0.060*
			(0.034)
Non-profit			-0.117**
			(0.046)
Government			-0.167**
			(0.048)
Finance, insurance & real estate			0.107**
			(0.037)
Percent female in occupation			-0.227**
			(0.083)
R-Square	0.25	0.25	0.29

Notes: Dependent variable is log of hourly wage of current, full-time (>=35 hours/week) jobs reported in Wave IV. Each regression includes 933 observations. Models (2)-(10) include age^2; (3)-(10) include experience^2 and tenure^2; (5)-(10) control for social science, humanities, and science major; (8)-(10) include the variables from (7), whether the program was part-time and the following concentrations: marketing, accounting, international, and other; (10) includes whether the individual is self-employed and dummies for the following industries: agriculture, forestries & fisheries, manufacturing, service, and public administration. Statistical significance of the coefficient at the 5 and 10 percent level is indicated by ** and *.

Appendix Table 2

Pooled OLS Estimates of Gender Wage Gap: Addition of Noncognitive Skills and Labor Market Tastes

Variable	(1)	(2)	(3)	(4)
Female	**-0.061****	**-0.057****	**-0.053****	**-0.051****
	(0.024)	(0.025)	(0.025)	(0.025)
Noncognitive Skills				
Initiative		0.045**	0.044**	0.044**
		(0.021)	(0.022)	(0.022)
High ethical standards		-0.067**	-0.067**	-0.066**
		(0.021)	(0.021)	(0.022)
Communication skills		0.014	0.014	0.015
		(0.021)	(0.021)	(0.021)
Work with diversity		0.006	0.007	0.008
		(0.020)	(0.020)	(0.020)
Shrewdness		-0.004	-0.004	-0.006
		(0.016)	(0.016)	(0.016)
Physical attractiveness		0.023	0.022	0.022
		(0.019)	(0.019)	(0.019)
Assertiveness		0.027	0.028	0.027
		(0.020)	(0.020)	(0.020)
Adapt theory to practice		0.029	0.027	0.028
		(0.018)	(0.018)	(0.018)
Ability to motivate		0.014	0.014	0.013
		(0.019)	(0.019)	(0.019)
Being a team player		0.019	0.017	0.016
		(0.021)	(0.021)	(0.021)
Confidence: Ability				
Quantitative expectations			0.019	0.018
			(0.017)	(0.017)
Verbal expectations			-0.002	-0.001
			(0.017)	(0.017)
Work/Life Preferences				
Family important				0.032
				(0.037)
Career important				0.006
				(0.022)
Wealth important				0.028
				(0.029)
Relatives/friends important				-0.001
				(0.022)
R-Square	0.25	0.27	0.27	0.27

continued

Appendix Table 2 *continued*, **Pooled OLS Estimates of Gender Wage Gap**

Variable	(5)	(6)	(7)	(8)	(9)
Female	**-0.051****	**-0.044***	**-0.043***	**-0.032**	**-0.033**
	(0.025)	(0.025)	(0.025)	(0.025)	(0.025)
Confidence: Admissions	-0.002	-0.001	-0.001	-0.001	-0.001
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Confidence: Connections					
Knowing the right people -		0.029*	0.028*	0.034**	0.034**
managerial success		(0.016)	(0.016)	(0.016)	(0.015)
Managerial Goals					
High managerial responsibility			0.054	0.049	0.038
			(0.045)	(0.044)	(0.044)
Job Preferences					
Non-monetary job attributes				-0.008**	-0.009**
				(0.003)	(0.003)
Contributes to society				-0.143**	-0.106**
				(0.031)	(0.032)
Current Job: Hours and Characteristics					
Large firm					0.068*
					(0.036)
Non-profit					-0.094**
					(0.047)
Government					-0.144**
					(0.049)
Finance, insurance & real estate					0.112**
					(0.037)
Public administration					0.110*
					(0.057)
Percent female in occupation					-0.178**
					(0.082)
R-Squared	0.28	0.28	0.29	0.31	0.34

Notes: Dependent variable is log of hourly wage of current, full-time (>=35 hours/week) jobs reported in Wave IV (933 observations). Models (2)-(9) include ability to organize, to capitalize on change, to delegate tasks, understanding business in other cultures, and good intuition; (5)-(9) include all variables from Model (4); (6)-(9) include whether one had confidence in knowing the right people for admissions; (7)-(9) controls for medium managerial responsibility; (9) includes whether the individual was self-employed, employed at a medium sized firm and the following industries: agriculture, forestries & fisheries, manufacturing, service, and public administration. Statistical significance of the coefficient at the 5 and 10 percent level is indicated by ** and *.

Appendix Table 3
Multiple Decompositions of Gender Log Wage Gap: Explained Contributions of Full Model

Variable (group)	*Oaxaca-Blinder* *Using pooled coefficients* contribution	% of gap	*Oaxaca-Blinder* *Using male coefficients* contribution	% of gap	*Oaxaca-Blinder* *Using female coefficients* contribution	% of gap	*Gelbach* *Decomposition* contribution	% of gap
Demographic/Background	0.001	0.6%	-0.007	-5.6%	0.010	8.2%	0.000	-2.3%
Employment Experience	0.016**	12.7%	0.013	9.9%	0.015	11.7%	0.016*	12.4%
Family Variables	0.022**	17.3%	0.021**	16.3%	0.009	7.1%	0.020**	15.9%
Undergraduate Variables	0.015**	11.4%	0.015**	11.4%	0.010	7.5%	0.014**	11.1%
Undergraduate GPA	-0.008**	-6.4%	-0.010**	-7.9%	-0.005	-4.0%	-0.009**	-7.0%
Quantitative GMAT	0.006	4.6%	-0.007	-5.7%	0.030*	23.7%	0.004	3.3%
Verbal GMAT	0.004	3.0%	0.005	4.0%	0.002	1.5%	0.004	3.1%
MBA Variables	0.010	7.5%	0.009	7.1%	0.009	7.0%	0.009	6.8%
MBA GPA	0.000	0.1%	0.002	1.8%	-0.000	-0.1%	0.000	0.1%
Current Job Characteristics	0.011*	8.7%	0.003	2.0%	0.023**	17.7%	0.011*	8.4%
Noncognitive Skills	0.002	1.2%	0.001	0.4%	-0.004	-2.8%	0.000	0.0%
Confidence: Ability	0.006	4.8%	0.006	5.1%	-0.006	-5.0%	0.005	4.1%
Work/Life Preferences	0.001	0.5%	0.005	3.7%	-0.011	-8.3%	0.000	0.0%
Confidence: Admissions	0.000	0.0%	0.000	0.3%	0.001	0.7%	0.000	0.0%
Confidence: Connections	0.004	2.9%	0.004	2.8%	0.003	2.2%	0.004	2.8%
Managerial Goals	0.001	0.4%	0.000	0.0%	0.001	0.7%	0.001	0.4%
Job Preferences	0.016**	12.8%	0.014**	10.9%	0.019**	14.7%	0.016**	12.6%
Total	0.106	82.5%	0.070	54.9%	0.105**	82.4%	0.094	73.8%

Notes: For each variable or set of variables, reported are the net explained contribution of the raw wage gap and the percentage of the gap explained due to gender differences in values of each category of variables. Gelbach decomposition follows Gelbach (2009). Each specification includes all of the variables from Table 1, and includes 933 observations. ** and * indicate explained contribution is statistically significantly different from zero at the 5 and 10 percent level.

In addition to annual salary and hourly wages, we also use hours worked as our dependent variable, despite the relatively small hours gap of 1.32 hours per week (results available upon request). Oaxaca-Blinder decompositions using pooled coefficients of the gender gap in either hours or log hours result in a total explained contribution of 41 to 42 percent of the gap. With either hours or log hours under the full model, the categories of variables found to be statistically significant at the 5 percent level were job characteristics, work/life preferences and family variables, whereas noncognitive skills and undergraduate GPA were significant at the 10 percent level.

Second, although our sample is already fairly selective, including only recent MBAs working more than 35 hours per week, it may be possible that outliers with particularly high or low earnings affect our results. To test this, we dropped from the sample individuals with the top and bottom 2 percent of earnings for both males and females and repeated our analysis. The results were not meaningfully different (results available from authors upon request).

Finally, the amount of the gender gap explained by particular variables may vary across salary ranges. We use quantile regression to conduct this analysis. Specifically, we performed quantile (least absolute value) regressions at the 25th, 50th (median), and 75th percentile of earnings. Interestingly, both the raw gap and the remaining unexplained gap are affected by location within the earnings distribution. In particular, the largest raw gap, 18.7 percent, exists for ‘low earners’, those at the 25th percentile, compared with 15.5 and 13.5 percent, for the 50th and the 75th percentiles. After including our full set of covariates, the unexplained gap shrinks to 6.1 percent at the 25th percentile, 4.3 percent at the 50th percentile, and only 1.3 percent at the 75th percentile. Thus, the covariates do a better job of explaining earnings differences at the upper part of the distribution (about 96 percent of the raw gap). That said, however, the impact of respective groups of variables is quite similar across percentiles.[33]

2.VI Discussion

Three stark conclusions emerge from this study of how the gender earnings gap is affected by the inclusion of previously omitted variables, in a broad array of noncognitive skills, and in indicators of work/life preferences, using the GMAT Registrant Survey, a dataset especially rich in traditional human capital variables. First, statistically significant gender heterogeneity exists (at the 5 percent level) among 7 of 15 self-reported noncognitive skills, one confidence measure, and among five labor market taste variables.[34] Secondly, decomposition analysis reveals gender heterogeneity of factors significantly associated with the wage gap – with male coefficients used in Oaxaca-Blinder decompositions, the traditional human capital variables of employment experience, family variables, and undergraduate experiences[35] matter (but not with female coefficients), whereas current job characteristics matter

33. Notable exceptions are GMAT scores and MBA variables, which have a significant (decreasing) effect on the gap at the 75th percentile and very little effect at the 25th percentile.

34. Among noncognitive skills, women self-reported more initiative, ethical behavior, communication skills, better ability to organize, motivate others and work with diversity. Men reported greater shrewdness and ability to adapt theory to practice. Among the labor market taste variables, women put more importance on relatives/friends, non-monetary job characteristics, and a job that contributes to society, whereas men placed more value on wealth. In addition, men exhibited greater confidence in doing well on the quantitative part of the GMAT.

35. Notably, men's undergraduate experiences (institution quality, grades, and major among others), though not their MBA education, explain about 10 percent of the gender earnings gap, despite matriculating a decade earlier on average.

when female coefficients are used (but not with male coefficients).[36] Finally, beyond a rich set of human capital variables, the noncognitive skills and work/life preference variables in our specification account for a quarter of the "explained" gender wage gap, from 69 to 82 percent. Our results, along with the other work connecting personality traits and preferences to earnings and with the growing gender heterogeneity literature, attempt to more fully measure "individual abilities," as envisioned in the original human capital model by Becker (1964).

MBA women appear to incur penalties for "good citizen" behavior, according to our findings and those of three other noncognitive skills-wage gap studies. While we observe gender heterogeneity regarding numerous stereotyped variables, namely assertiveness, shrewdness, physical attractiveness, initiative, and the importance of wealth and friends, our decomposition results indicate that two novel variables with good citizen characteristics are associated with the male-female earnings gap: women's higher ethical standards and their priority for jobs that contribute to society.[37] Other noncognitive skills-wage gap studies provide evidence that might similarly be construed as penalties for "good citizen" behavior: wider gender wage gaps result from greater importance put on people and family (Fortin 2008)[38] and higher female levels of agreeableness (Mueller and Plug 2006; Braakmann 2009). Unlike Fortin's (2008) conclusion that men's greater priority of work and money helps account for the wage

36. This is akin to Semykina and Linz's (2007) findings that showed Russian women's, but not men's, personalities strongly affected their earnings.

37. Job attributes and a smaller self-reported ability to adapt theory to practice by females are also significantly related to the gap.

38. While we also find that women put significantly more importance on "family and friends" (see Table 1), those priorities are not significantly associated with the gender wage gap in our decomposition analysis.

gap, the MBA men and women in our sample place similar importance on career and although men place more importance on wealth that difference is not associated with the wage gap.

Human capital models typically explain gender wage gaps as the consequence of females' lower human capital investment and reduced labor market attachment (Polachek 2006). Although differences in MBA experiences do not help explain the earnings gap, the gap is importantly accounted for by males' college experiences and by their greater job tenure and work experience.[39] Reduced labor market attachment, most importantly due to the presence of children, influences male-female wage gaps among Harvard undergraduates (Goldin and Katz 2008), University of Michigan lawyers (Noonan, Corcoran and Courant 2005), and University of Chicago MBAs (Bertrand et al. 2009). In stark contrast with these three studies, married MBA women in our sample (who work at least 35 hours a week) suffer no wage penalties relative to MBA women without children. In addition, MBA fathers earn more than unmarried males.[40]

Why do our results differ? Since large gender disparities had already emerged by the third year after graduation for the University of Chicago MBAs (Bertrand et al. 2009), the effect of the presence of children is not accounted for by our analysis ending 3-4 years after obtaining the degree. We can only speculate that for MBA women with degrees from typical MBA programs, having such education increased their

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39. Females' lower tenure and experience explains 1.7 percentage points of the gap in our decompositions analysis, which is substantial and at least marginally significant (see Table 7).

40. In all decompositions, except the one where female coefficients are used, family variables significantly explain a nontrivial amount of the gap.

intra-household earnings beyond the typical imbalance which often led women to bear greater household responsibilities. So, despite the extraordinarily high mean female earnings of University of Chicago MBAs, those with less labor market attachment may have had husbands with even higher earnings. In addition, the Bertrand et al. (2009) analysis includes part-time workers (which were between two and five times more likely to be female, depending on the number of years since graduation), whereas our analysis focuses on full-time (35+ hours per week) workers.

As scholars investigating educational and labor market outcomes[41] continue to seek to remedy the call for missing data and unobserved heterogeneity with noncognitive variables, they face challenges. First, no consensus exists about what constitutes noncognitive skills or how to measure them (see Borghans et al. 2008). Next, compared with the stability of cognitive ability (as of late adolescence), various noncognitive skills appear to evolve into middle age. Thus, for example, it will be of great interest to determine the efficacy of the GRE's newly adopted noncognitive skills assessment ("Personal Potential Index") which the ETS thinks will make the test more relevant to business schools in predicting graduate school outcomes (De Vise 2009).

Particular limitations of our analysis include the fact that the last survey occurred less than four years, on average, after completing the MBA program, when women's average age was 34 and men's 35. Differences in lifetime returns by gender may vary substantially over a longer time frame, especially with the presence of children. We should reiterate that we report estimated relationships between our novel variables (various confidence measures, a variety of work/life preferences, managerial

41. Regarding educational outcomes, see, for example, Carneiro and Heckman (2003) and for labor market outcomes, see, for example, Murnane, Willett, Braatz and Duhaldeborde (2001), Heckman, Stixrud and Urzua (2006), and Groves (2005).

expectations, and fifteen noncognitive skills, such as physical attractiveness, assertiveness, and initiative) and the gender pay gap, not causal links. Regarding the quality and reliability of our data, while we use actual rather than self-reported GMAT scores, several other variables are self-reported. Our data appropriately contains self-reported expectations and preferences (especially when they were reported prior to the observed earnings outcome). However, regarding the 15 noncognitive managerial skills and attributes, it would be desirable to have both self-reported data, since self-perception matters, and external assessments.

CHAPTER 3

A TAX AMNESTY IN THE CONTEXT OF A DEVELOPING ECONOMY

3. I. Introduction

While tax amnesties have been used as a policy tool to increase revenue collection by many governments, they have generated mixed results: some have failed while others have succeeded.[1] Why would a rational individual accept an amnesty and pay past dues? Answers hitherto provided in the literature have focused on behavioral aspects of the delinquent taxpayer.[2]

This paper takes a different and empirically relevant approach. Following the observation that often successful amnesties have taken place in times of transition to prosperity, we provide a theoretical justification of this link.[3] While the empirical connection has to be researched more carefully, we submit that, besides being based on evidence (albeit perhaps anecdotal), our analysis raises the possibility that economic liberalization is an important factor to consider when determining the timing of a tax

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[1] European (Belgium, Denmark, France, Germany, Ireland, Italy, the Netherlands, Norway, Sweden, and Switzerland among others) as well as South American countries (Argentina, Colombia, Ecuador, and Peru among others), India, and the majority of US states have used tax amnesties of some form to increase tax revenue.

[2] For example unanticipated regret (Malik and Schwab; 1991) or risk aversion (Andreoni; 1991).

[3] For example, Uchitelle (1989) mentions, Ireland (in 1988) and Colombia (in 1988) as cases of successful amnesties – in each case these took place in times of growth and trade liberalization. The same connection holds for the Indian tax amnesties of 1975 and 1997 that are generally considered to be successful (see Das-Gupta et. al (1995) regarding the 1975 amnesty). From 1975 to 1976 India improved its trade balance from -286 Million to +787 Million US-Dollars, showing a drastic change in economic conditions. 1997 is well known to be a period of liberalization (see http://indiabudget.nic.in/es97-98/chap22.pdf for an overview of the Voluntary Disclosure of Income Scheme (VDIS '97)).

amnesty. Specifically, we show that such an amnesty will generate response, even if enforcement activities remain unchanged, and develop conditions under which the amnesty results in higher tax collection.

3. II Tax Compliance without Amnesty

Consider risk-neutral agents, each with an identical project that has a two period life, and yields the net income Y in each period.[4] An agent is required to register her business with the appropriate Tax Authority (TA) and pay an income tax. We assume, for simplicity, that any tax evasion by a registered project is detected by the TA with probability 1. In other words, registration results in subsequent ``visibility`` that compels all registered projects to be legal; agents that choose to evade taxes also do not register. The legal or formal sector is the collection of all registered and tax-compliant businesses. The unregistered agents function in the underground or informal sector and are more difficult to trace. Let m denote the probability of detecting an agent's present period violations in the informal sector.

Suppose an agent is apprehended for non-compliance in period 2. The investigation may uncover her past period violations (if any). We denote μ (where $0 < \mu < 1$) to be the probability of revelation of an agent's past violation, given her detection in the informal sector in the present period. In a similar vein, we also assume that past violations of a currently legal (and registered) agent may be detected with the same

[4] We avoid incorporating risk aversion, or other psychological/behavioral aspects, such as feelings of guilt, so as not to confuse our analysis with factors that earlier papers have demonstrated to have positive effects on the success of a tax amnesty.

probability μ.[5] Since past violations may be easier to detect once an agent is already under inspection (or registered and visible, in terms of her record), it is reasonable to assume that $\mu > m$. For ease of exposition, we assume the tax and the fine to be proportional to Y. If caught, an agent is forced to pay the fine fY in addition to her outstanding taxes, tY.

Suppose that an agent has not paid her taxes in period 1. We assume, reasonably, that detection in period 1 implies mandatory registration (and therefore compliance) in period 2, [6] If the agent escapes detection, her expected payoff in period 2 is $Y - m(1 + \mu)(t + f)Y$ if she evades taxes a second time.[7] If she decides to be compliant in period 2, and moves to the formal sector, her expected payoff is $(1 - t)Y - \mu(t + f)Y$.

We make the following assumptions for the rest of the paper:

$$m < \frac{t}{(1+\mu)(t+f)} \qquad \text{(A.1)}$$

[5] Thus the joint probability of detection of prior period tax evasion is mμ for an informal sector agent. For a formal sector agent, this probability is simply μ, since her probability of detection of present offences is 1(in a sense, the registered agent is always under observation). Assuming a different probability of detection of prior offences for the registered agent does not change the nature of results, and only complicates the algebra.

[6] Relaxing this assumption to one where an agent penalized for period 1 violation, can become incognito in period 2, and thus able to violate again, makes no difference to our analysis other than complicating the algebra presented in the appendix. Also see footnote 14 in this context.

[7] With probability m she is penalized for her present violations; mμ is the joint probability of detection of her past violations.

$$\mu \geq \frac{t}{t+f} \tag{A.2}$$

As the appendix demonstrates, (A.1) is both necessary and sufficient to ensure tax evasion as the benchmark case. That this is predominantly the characteristic feature of the informal (or illegal) sector, and that the purpose of the amnesty is to encourage businesses to register and emerge out of the underground economy, is an observable fact abundantly borne out by journalistic and anecdotal observations. As the next section will show, (A.2) is necessary to ensure the acceptability of a tax amnesty in period 2.

Proposition 1: *Given (A.1), agents choose to be in the informal sector (or the underground economy) in period 1 and, if undetected, remain so and non-compliant in period 2. Agents are compliant in period 2 only if detected and compelled to register in period 1.*

Proof: See appendix.

//

3.III Tax Amnesty in Times of Prosperity

Suppose that an agent's income increases to $Y + \theta$ at the beginning of period 2 due to the positive effects of liberalization, and that, simultaneously, the regulator declares an amnesty. Agents who take the amnesty only need to pay outstanding taxes, and register their business in period 2. We further suppose that benefits from liberalization are available only in the formal or legal sector of the economy. Such an assumption is quite reasonable. The import and purchase of new and productive technology, or access to improved infrastructure may only be possible through legal and visible channels; foreign direct investments may not want to operate in the informal sector because of problems of enforceability of contracts. The increment θ, as well as the amnesty, is assumed to be completely unanticipated (or unexpected) in period 1.[8]

It is easy to see that, in the absence of non-linearities, partial compliance is never optimal in our model: the agent will either pay no taxes at all or pay them in full. With complete lack of anticipation of either the increase in income, or the amnesty, the agent's period 1 decision is the same as before, that is she decides not to pay taxes. Her optimal decision in period 2 depends on the relative magnitudes of three alternative payoffs:

Accepting the amnesty earns

$$(1-t)(Y+\theta)-tY \tag{1}$$

[8] Our results are robust to assuming that, in period 1, an agent expects a period 2 increment of θ with probability p. The additional algebra that verifies this is available upon request from the authors.

If the agent remains in the informal sector in period 2, her expected income is

$$Y - m(1+\mu)(t+f)Y \qquad (2)$$

The agent, however, may decide to move to the formal sector and earn $Y + \theta$. Then, given μ, the probability of discovery of her past tax evasion, she earns

$$(1 - t)(Y + \theta) - \mu(t + f)Y \qquad (3)$$

Comparing (1) to (3) we see that (A.2) implies that accepting the amnesty is superior to moving to the legal sector without making use of the amnesty offer. A comparison of (1) and (2) then reveals that it is strictly optimal to accept the amnesty *if* $\theta > \theta_1$, where[9]

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[9] $\theta_1 > 0$ as $2t > m(1+\mu)(t+f)$ given (A.1).

$$\theta_1 = Y\,\frac{2t - m(1+\mu)(t+f)}{1-t} \qquad (4)$$

Thus, the availability of new and enhanced opportunities in the formal sector must be significant enough to make a tax amnesty viable. Note that, for this outcome to hold, the probability of detection of past violations, at least in the formal sector, should be "sufficiently high". However, the detection probabilities need not be high enough to ensure compliance in the absence of amnesty, as is the case in our model.

Proposition 2: *Given (A.2), an unanticipated tax amnesty, declared at a time of liberalization and rising productivity, is successful only if liberalization has a positive and significant impact on the income of taxpayers.*[10]

Proof: Follows from the above analysis. //

3.IV Amnesty and the Tax Authority's Revenue

In the absence of an amnesty, but with the gains from liberalization, the payoff (1) is no longer available to the agent. Comparing (2) and (3), it is easy to show that an agent finds it optimal to move to the formal sector, post liberalization, if $\theta \geq \theta_2$, where

[10] Thus, the absence of liberalization, equivalent to assuming $\theta = 0$, implies that a tax amnesty is ineffective.

$$\theta_2 = Y \frac{t+\mu(t+f)-m(1+\mu)(t+f)}{1-t} \qquad (5)$$

Otherwise, she remains in the informal sector. Note that (A.2) implies that $\theta_2 > \theta_1$. If $\theta \in (\theta_1, \theta_2)$, agents who were not apprehended in period 1 remain in the informal sector in period 2, and forego the gains from liberalization if no amnesty is offered. In this case, a tax amnesty increases the revenue collected by the TA: (A.1) implies that $t > m(1+\mu)(t+f)$, when

$$m(1+\mu)(t+f)Y < 2tY + t\theta \qquad (6)$$

The L.H.S. of (6) represents the revenue from fines collected in the absence of the tax amnesty, while the R.H.S. is the revenue generated from those who accept the amnesty.

If $\theta \geq \theta_2$, the TA`s expected revenue *is* $t(Y + \theta) + \mu(t + f)Y$ if no amnesty is offered. Since $\mu(t + f) \geq t$ by (A.2)

$$t(Y + \theta) + \mu(t + f)Y \geq \quad 2tY + t\theta \tag{7}$$

and declaration of amnesty does not lead to higher revenues. Consequently, as we demonstrate in the appendix, the success of a tax amnesty - in terms of revenue for the TA - depends on the proportion of the two types of agents in the population.[11]

Proposition 3: *From the TA's point of view, an amnesty is successful (results in higher revenue) only if the proportion of low type agents (those who benefit moderately from liberalization) is high enough relative to the high type agents (those who gain substantially from liberalization*.

Proof: See appendix.

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3.IV Conclusions

The above sections demonstrate that a tax amnesty that is timed to coincide with liberalization and rising incomes can be successful, both in terms of participation and revenues collected, if the gains from liberalization are within an appropriate range. This success is despite the fact that the enforcement efforts by the Tax Authority remain

[11] Overall welfare increases with a tax amnesty if at least 1 low type agent is present, since the low type agent(s) will be able to benefit from liberalization.

unchanged for the previous levels that were inadequate to generate compliance. Our findings have important implications for the timing of tax amnesties as a policy tool.

CHAPTER 4

THE EFFECTS OF WAGE VOLATILITY ON GROWTH

4.I Introduction

Why do some countries grow faster than others? Over the last decades, it became clear that there is not one standardized answer to this question. An economy needs a combination of factors and for different countries and regions a different set of conditions may have to hold in order to foster growth.[1] However, the benchmark list of growth determinants, shared by most growing economies, is rather short. According to Mirestean and Tsangarides (2010), it consists only of debt, openness, inflation, initial income, investment, life expectancy, and population growth.

This paper examines the impact of another candidate of growth determinants: volatility in wages. To my knowledge, no paper has tackled this issue before and currently, there exists no clear consensus regarding the effect of various sorts of volatility on growth. Posch and Waelde (2009) argue that no causality at all runs from volatility to growth. Turnovsky and Chattopadhyay (2003) analyze developing economies and find that both monetary and terms of trade volatility affect growth negatively in small stochastic open economies. Similarly, Ramey and Ramey (1995) find negative effects of growth volatility itself on growth, mainly stemming from the volatility of innovations to growth, which they interpret as reflecting uncertainty. In contrast to these findings, Devereux and Smith (1994) suggest that international risk

[1] For a discussion of various possible sources of growth see, for instance, Barro and Lee (1994), Alesina et al. (1996), Barro (1996, 1997), or Frankel and Romer (1999) among many others. For good summaries, although a bit dated, refer to Temple (1999), Durlauf and Quah (1999) or Sala-i-Martin (2004).

sharing – which means a lower volatility -- in terms of portfolio choices reduces precautionary savings, which in turn lowers growth. Thus, arguments for both negative and positive effects of different kinds of volatility on growth can be found in the literature.

In a related context, Rodrik (1998) concludes that external risk, measured as the volatility of income associated with fluctuations in the external terms of trade, encourages people to call for a stronger public safety net and/or seek a job with the government, which is considered a safer source of income. Hence, private sector wage risk could be a determinant of government size and -- following previous literature such as Barro and Lee (1994) -- government size in turn affects growth.[2]

This paper merges the literatures on the connections from volatility to growth and to government size. I develop a model that first determines the number of people working in the public sector (as opposed to the riskier private sector) and then analyzes how volatility of private sector wages affects growth. The model suggests that volatility has both a direct (positive) effect on growth, but also an indirect (negative) effect on growth through the mediating role of government size. Intuitively, the direct effect is a result of precautionary savings, whereas the indirect effect works through the composition of the labor market. More risk in the private market leads workers to switch to public jobs, therefore increasing the size of government.

Following the model is the empirical analysis on a panel of 19 countries, which tests for the existence of both the direct and the indirect effect. I use a 3SLS approach to determine growth and government size simultaneously, thus controlling for the

[2] Regarding determinants of government size, see for instance Alesina and Wacziarg (1997), Ram (2009) or Iversen and Cusack (2001) among many others.

suggested endogeneity between growth and government size and a possible correlation of the error terms. The results provide strong evidence for my theoretical implications as both the direct and the indirect effect remain significant for various sets of controls. In addition, the results remain robust to different detrending methods and alternative measures of government size.

The next Section develops the theoretical model, pointing out the opposing direct and indirect effects of wage volatility on growth. Section 3 discusses the empirical analysis, consisting of methodology, a description of the data, the main results, and various robustness tests. Finally, Section 4 concludes the paper with a brief summary of results and possible implications.

4.II The Model

4.II.A The Economy

Imagine an economy where time is continuous consisting of 2 sectors: the public sector produces the public good, and the private sector produces the private good. The public good only requires labor as an input in production, whereas the private good requires labor and capital. As in Rodrik (1998), the technology in the public sector is riskless, as opposed to the technology needed to produce the private good, which is subject to uncertainty. Let the population consist of a continuum of agents of total size 1 with each agent having an infinite planning horizon. The fraction of workers employed in the public sector, λ, is determined endogenously. Consequently, $1-\lambda$ is the fraction of private sector workers. At the beginning of time, workers commit to working in either sector with their decision depending on the comparison of projected lifetime utilities from working in either sector -- a decision which in part depends on the wage in the stochastic private sector, in comparison to the riskless public sector wage.

4.II.B Production and Wages

Starting with the government, let the production function for the public good be

$$Y_G = \lambda^{\gamma} \tag{1}$$

where I assume diminishing marginal returns, $0 < \gamma < 1$. Public sector wages are determined by the marginal product

$$w_G = \gamma\lambda^{\gamma-1} \tag{2}$$

As for the production of the private good, I assume an AK-technology:[3]

$$Y_P = AK + b(1 - \lambda) \tag{3}$$

where $b = w_P$, the private sector wage, which follows a Brownian motion with a standard deviation σ:

$$db = \sigma dz \tag{4}$$

where z stands for a normal Wiener process.[4]

[3] Rodrik (1998) employs a general production function of which this is a special case. Even though allowing capital to perfectly substitute for labor is not necessarily realistic, it is convenient for calculations. It produces a constant rate of return to capital, but allows a stochastic wage.

[4] This production function is a stochastic version of famous works in growth theory, like Romer (1986) or Jones and Manuelli (1990). Similar to Smith (1998), the stochastic variable follows a Brownian motion. A drawback here is the theoretical possibility of the wage becoming negative -- a problem which is well-known in the literature. For a good discussion of this problem, please see for instance Waelde (2009).

4.II.C Growth

Workers are assumed to be identical and own the same initial wealth, $v_i(0)$, with $i \in \{G, P\}$, and $v_G(0) = v_P(0)$. Consequently, total societal wealth consists of $K(t) = \lambda v_G(t) + (1 - \lambda)v_P(t)$ at any point in time.[5] Further, denote c_G as the consumption of one public worker and similarly c_P as a private worker's consumption. Finally, with capital depreciating at the rate δ, the capital stock develops over time as follows:

$$\frac{dK}{dt} = Y_P - \delta K - \lambda c_G - (1 - \lambda)c_P \tag{5}$$

Notice that the government remains unproductive, as is common in most growth models -- only production of the private good contributes to growth. One could see the public good as spent by the government to maintain the infrastructure, as in Turnovsky (2000) for example.

[5] Unless it is essential, I will omit time notation in the remainder of the model.

4.II.D The Workers' Decisions

In this simple model, workers exhibit constant absolute risk aversion (CARA) and make their decision about where to work irreversibly at the beginning of time.[6] In particular, every worker faces the following maximization problem:

$$\max_{c_i} E \int_{t=0}^{\infty} -\frac{e^{-\theta t - a c_i}}{a} dt \tag{6}$$

subject to

$$\frac{dv_i}{dt} = r v_i + w_i - c_i \tag{7}$$

with $i \in \{G, P\}$. θ stands for the agents' rate of time preference and a represents absolute risk aversion. To conclude with assumptions, workers are able to

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[6] If wage is random, this is a classic problem in precautionary savings. It is well known that the only utility function allowing for a closed-form solution for consumption is CARA.

borrow and lend at a riskless rate, r, in this economy. Now, I turn to the endogenous determination of the optimal consumption in both sectors, calculate the equilibrium in the labor market, and finally analyze how volatility affects growth.

4.II.D.1 Working for the Government

The maximization problem for an agent considering a job in the public sector becomes

$$\max_{c_G} E \int_{t=0}^{\infty} -\frac{e^{-\theta t - a c_G}}{a} dt \tag{8}$$

subject to

$$\frac{dv_G}{dt} = r v_G + w_G - c_G. \tag{9}$$

Notice that the agent contemplating a government position only faces one state variable, wealth v_G. In the appendix, I show detailed derivations of the Bellman equation, leading to the optimal consumption from working in the public sector:[7]

$$c_G^* = \frac{\theta - r}{ar} + rv_G + w_G \tag{10}$$

Hence, consumption of a public sector worker is a linear function of wealth and wage, with an intercept determined by her rate of time preference in combination with the return to capital and her value of risk aversion. To assess the overall benefit from working for the government, I calculate the worker's value function evaluated at time zero:

$$J[v_G(0)] = -\frac{e^{\frac{r-\theta}{r} - arv_G(0) - aw_G(0)}}{ar}. \tag{11}$$

[7] To solve the maximization problems in both sectors, I use the concept of dynamic programming (Merton, 1971), which allows us to analyze optimal continuous-time dynamic models under uncertainty. For detailed derivations of the following results plus the transversality conditions for both sectors, please see the appendix.

(11) measures the expected future utility of pursuing the optimal savings path, evaluated at time zero. As we will see, the value function will become important for the determination of the equilibrium in the labor market.

4.II.D.2 Working in the Private Sector

The consideration of a job in the private market is slightly more complicated, since, in addition to wealth v_P, the agent also faces a stochastic private wage, w_P, as a state variable. In particular, an agent contemplating a private sector job faces the following maximization problem

$$\max_{c_P} E \int_{t=0}^{\infty} -\frac{e^{-\theta t - a c_P}}{a} dt \qquad (12)$$

subject to

$$\frac{dv_P}{dt} = r v_P + w_P - c_P \qquad (13)$$

which is a standard precautionary savings model in continuous time. Using the same method as above makes it possible to solve for the optimal consumption:

$$c_P^* = \frac{\theta - r}{ar} - \frac{a\sigma^2}{2r} + rv_P + w_P \tag{14}$$

with consumption being a linear function of wealth and wage, equivalent to the public sector wage. Only the intercept behaves differently compared to the public sector: the entire consumption profile shifts down by a risk premium for working in the stochastic private sector, $\frac{a\sigma^2}{2r}$. Thus, uncertainty causes consumers to save more at any point in time.

Again, the expected lifetime benefit of working in the private sector is given by the value function:

$$J[v_P(0), w_P(0)] = -\frac{e^{\frac{r-\theta}{r} + \frac{a^2\sigma^2}{2r} - arv_P(0) - aw_P(0)}}{ar} \tag{15}$$

4.II.E Equilibrium in the Labor Market

At time zero, workers compare the lifetime utility from working in either sector. Naturally, an agent moves to the sector which gives her the highest expected lifetime utility. Hence, workers allocate themselves in both sectors, just until the value functions are equalized:[8]

$$J[v_G(0)] = J[v_P(0), w_P(0)] \tag{16}$$

Using this condition in combination with the value functions (11) and (15) allows me to solve for the equilibrium in the labor market. The equilibrium share of people working for the government becomes[9]

$$\lambda^* = \left(\frac{\gamma}{b(0) - \frac{a\sigma^2}{2A}}\right)^{\frac{1}{1-\gamma}} \tag{17}$$

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[8] In equilibrium, wages equal the marginal product. Similarly, the interest rate is equal to the marginal product of capital when the bond market is in equilibrium: $r = A$.

[9] Note that the difference between the private and the public wage is exactly the volatility term, a risk premium for working in the private sector: $w_P = w_G + \frac{a\sigma^2}{2A}$.

In fact, 2 possible equilibria spring from (2.5)[10]:

• If $\gamma \geq b(0) - \frac{a\sigma^2}{2A}$, then $\lambda^* = 1$. If the public wage is very high and/or the volatility of private wages is very high, then everybody works for the government.

• If $\gamma < b(0) - \frac{a\sigma^2}{2A}$, then $0 < \lambda^* < 1$. This is the diversified equilibrium stemming from incomplete specialization.

Since the first equilibrium presents a relatively unrealistic corner solution (in practice, people work in both sectors), the following analysis focuses on the diversified equilibrium. Notice from (17) that λ^* is an increasing function of $\frac{a\sigma^2}{2A}$, as risk aversion induces people to value the safer public sector more, when uncertainty in the private market increases. Similarly, $\frac{\partial\lambda^*}{\partial\gamma} > 0$ since a higher production parameter for the public good, γ, increases the public wage and therefore the public workforce. Finally, (17) is decreasing in $b(0)$, asserting that a higher starting wage in the private sector decreases the public sector workforce.

PROPOSITION 1. A higher volatility of private sector wages increases the share of people working for the government.

Given the mixed equilibrium in the labor market, I now examine how volatility in the private sector affects growth.

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[10] $\lambda = 0$ is excluded by the assumption of diminishing marginal returns in the public sector, $0 < \gamma < 1$. Similarly, the fact that wages have to be positive is implied: $b(0) > \frac{a\sigma^2}{2A}$.

4.II.F The Effects of Wage Volatility on Growth

Given $c_G{}^*$, $c_P{}^*$, and λ^* from (10), (14), and (17), it is now easy to determine the equilibrium growth rate, as specified in (5). Simplifying and rearranging gives:

$$\frac{dK}{dt} = -\frac{\theta - A}{aA} - \lambda^*[w_G(t)] + (1-\lambda^*)\left[\frac{a\sigma^2}{2A}\right] - \delta K \qquad (18)$$

From here, how does an increase in σ^2 affect growth? Differentiating (18) with respect to σ^2 provides the answer:

$$\frac{\partial(\frac{dK}{dt})}{\partial\sigma^2} = (1-\lambda^*)\frac{a}{2A} - \frac{\partial\lambda^*}{\partial\sigma^2}\left(w_G(t) + \frac{a\sigma^2}{2A}\right). \qquad (19)$$

The first term indicates the positive direct effect on growth caused by lower consumption of private sector workers: the higher volatility of their wage encourages them to save more. The second term summarizes both components of the negative indirect effect on growth, coming from the change in the composition of the labor market: (1) $[-\frac{\partial\lambda^*}{\partial\sigma^2} w_G(t)]$ is the wage for workers switching from the productive private sector to the unproductive public job. (2) Since these job-switching workers now earn a riskless wage, there is no incentive for precautionary savings anymore $[-\frac{\partial\lambda^*}{\partial\sigma^2}\frac{a\sigma^2}{2A}]$.

PROPOSITION 2. A higher volatility of private sector wages has both a direct (positive) and an indirect (negative) effect on growth. The direct effect is caused by lower consumption of private sector workers, whereas the indirect effect comes from a change in the composition of the labor market: some workers switch to the unproductive -- but safe -- public sector, making precautionary savings obsolete for them.

Overall, this model predicts an ambiguous net effect of private wage volatility on growth since the direct and indirect effect point in opposite directions. The empirical part of the paper will now try to determine the validity of the above predictions.

4.III Empirical Analysis

4.III.A Methodology

Following the implications from (19), I expect private wage volatility to have direct and indirect effects on growth, where the indirect channel works through the size of the public sector. The direct effect is relatively easy to measure by regressing growth on wage variance, controlling for other growth determinants. The indirect effect is slightly more complex to analyze: First, I regress government size on wage variance to see if and how risk affects the size of the public sector, controlling for other determinants of government size. Second, I add government size as a covariate in the growth regression to see whether government size affects growth, too. Empirically, the two regressions for country i at time t are:

$$Growth_{i,t} = \alpha_1 + \alpha_2(\widetilde{w}^2)\ _{i,t-1} + \alpha_3(Gov)_{i,t} + \alpha_4(Growth)_{i,t-1} + \alpha_5(Growth)_{i,t-2} + \alpha_6(X)_{i,t-1}\alpha_7(Z)_{i,t} + \alpha_8(Unempl)_{i,t-1} + \delta_{i,t} \tag{20}$$

and

$$Gov_{i,t} = \beta_1 + \beta_2(\widetilde{w}^2)\ _{i,t-1} + \beta_3(Gov)_{i,t} + \beta_4(Gov)_{i,t-2} + \beta_5(Growth)_{i,t} + \beta_6(Z)_{i,t} + \beta_7(Unempl)_{i,t-1} + \epsilon_{i,t} \tag{21}$$

where $(\widetilde{w}^2)$, $(Growth)$, (Gov), and $(Unempl)$ represent the excess volatility of private sector wages, the growth rate, government size, and the unemployment rate. $\delta_{i,t}$ and $\varepsilon_{i,t}$ constitute the respective error terms. The direct effect of wage variance on growth is captured by α_2, whereas the indirect effect is expressed by the combination of β_2, the impact of wage variance on government size, and α_3, the effect of government size on growth. Hence, the indirect effect exists only if I can reject the Null Hypothesis of $H_0: (\beta_2)(\alpha_3) = 0$. $(X)_{i,t-1}$ contains notorious growth determinants: life expectancy, fertility, openness, GDP per capita, investment per capita, and inflation.[11] $(Z)_{i,t}$, the vector of controls shared by both equations, contains country fixed effects, time fixed effects, a linear and a quadratic time trend, and a country-specific time trend. Each of them will be included in turn as controls in various specifications. As mentioned in the introduction, different countries may react differently to potential growth determinants (but also to potential determinants of government size). Similarly, different years in my sample may experience exogenous shocks (for instance a global recession). Hence, fixed effects are intended to pick up any time- and country-invariant aspects. Finally, although not necessarily part of a usual growth equation, the unemployment rate may be of specific interest here: as the labor market is a driving part of the model, I want to ensure that wage volatility does not pick up effects resulting from the unemployment rate.[12]

The simultaneous nature of the equations -- (Gov) appears on the RHS in (20),

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[11] Following recommendations from Temple (1999) and others, I use lagged values of the explanatory variables in order to deal with a simultaneity problem prevalent in the growth literature. Durlauf et al. (2004) give a good summary of instrumental variables in their appendices 3 and 4, where lagged values for (i) investment from Bond et al. (2004), (ii) inflation from Li and Zou (2002), (iii) trade as share of GDP (openness) from Edwards (1998) and Amable(2000), and (iv) GDP from Rousseau (2002) among others are mentioned. Finally, due to data availability, a few notable growth determinants are absent in my analysis: the real exchange rate, debt, rule of law, economic freedom, democracy vs. autocracy, and a measurement for schooling. As my data contains mostly developed countries, most of these variables may not be too relevant; country- and time-fixed effects should pick up most of their contribution to growth here.

[12] I thank Sanjeev Kumar for pointing this out during a University of Memphis seminar.

while $(Growth)$ enters the RHS of (21) -- prevents me from applying an OLS framework. However, both equations are identified as there exist unique dependent variables for either regression: $(X)_{i,t-1}$, $(Growth)_{i,t-1}$, and $(Growth)_{i,t-2}$ predict $(Growth)_{i,t}$, but are not determinants of government size; similarly, $(Gov)_{i,t-1}$ and $(Gov)_{i,t-2}$ are significant predictors of (Gov), but not growth.[13] Those additional controls implicitly serve as instruments for the corresponding equations, that could be estimated in a 2SLS framework. Finally, I suspect that omitted variables could affect both equations, leading to a possible correlation of the error terms $\delta_{i,t}$ and $\varepsilon_{i,t}$. Thus, in order to control for correlation of the error terms, I incorporate the seemingly unrelated regression equations model (SUR) to extend the 2SLS to a 3SLS model.

4.III.B Data Sources and Descriptive Statistics

Table 8 summarizes the initial data set of 608 observations from 19 countries. Most of them were considered developed economies at the time of observation, setting this data set apart from others such as Turnovsky et al. (2003), who specifically analyze developing countries.[14] Table 9 provides a summary of all variables used and their method of computation. The most important variable of my analysis is also the most difficult one to compute: private sector wage volatility. I detrend time series of wages for each individual country, using the Hodrick-Prescott filter.

[13] Correlation coefficients indicate that this choice is reasonable (not displayed here, but coefficients are available at request). Lagged values of government size are highly correlated with current government size, but not with growth; the respective argument holds for lagged values of growth.

[14] The availability of reliable wage data plays a major role in the composition of this data set.

Table 8: Country Statistics

Country	Time Period	Observations
Australia	1984 – 2008	25
Austria	1976 – 2009	34
Belgium	1970 – 2009	40
Canada	1970 – 2006	37
Denmark	1970 – 2009	40
Finland	1970 – 2009	40
France	1970 – 2008	39
Germany	1970 – 2009	40
Italy	1970 – 2009	40
Japan	1970 – 2008	39
Korea	1985 – 2008	24
Netherlands	1970 – 2009	40
Norway	1970 – 2009	40
Poland	1992 – 2008	17
Slovak Republic	1994 – 2009	16
Spain	1980 – 2009	30
Sweden	1993 – 2009	17
United Kingdom	1970 – 2009	40
United States	1970 – 2009	40
N		608

Several steps are necessary in order to obtain a final measurement of private sector wage volatility:

1. The OECD statistics provide an index of ``Business Sector Labor Compensation per employee, excluding Agriculture", which I choose as a measurement

of private sector wages (w_P).[15] In order to prepare this data for the Hodrick-Prescott decomposition, I apply the natural logarithm to each observation.

2. The Hodrick-Prescott filter decomposes each country's time series (w_P) into a trend ($\bar{w}_P$) and a cycle ($\tilde{w}_P$).[16] Squaring the cycle term provides a measurement for the volatility of private sector wages ($\tilde{w}^2{}_P$) for each observation.

3. Since public sector wages may not always be an entirely riskless source of income (as assumed in the theoretical part), one needs to control for the volatility of public sector wages. In the absence of exact data on public sector wages, I choose an index of ``Total Economy Labor Compensation per Employee'' as a proxy for public sector wages (w_G).[17] With this data, steps 1 and 2 are repeated in order to obtain a measurement for public sector wage volatility ($\tilde{w}^2{}_G$).

4. The difference between the volatility of private sector wages ($\tilde{w}^2{}_P$) and the volatility of public sector wages ($\tilde{w}^2{}_G$) results in a measurement for the excess wage volatility in the private sector: $\tilde{w}^2{}_P - \tilde{w}^2{}_G = \tilde{w}^2$ in (20) and (21).

The growth rate (Growth Rate of Real GDP Laspeyres per capita), government size (Government Share of Real GDP per capita), openness, GDP (Laspeyres per

[15] One shortcoming of this analysis is the exclusion of the agricultural sector in private wages. However, country- and time-fixed effects should be able to control for this shortcoming for the most part.

[16] I use a value of $\lambda_{HP} = 100$ for the Hodrick-Prescott filter, as is common in the literature. One main concern of decomposing time series is the end-of-sample problem: observations close to the end (the beginning) of each series might be biased as data is only available for the past (the future). Following Watson (2007), I use an AR(1) growth rate model and extend each series by 4 data points in both directions before applying the filter.

[17] Even though private compensation is included here as well, it constitutes only a part of this index. Hence, a change in the volatility of private wages, holding everything else constant, will have a bigger effect on business sector labor compensation. The volatility of public wages on the other hand will only be captured in total economy wages.

capita), and investment (Investment Share of Real GDP per capita) are taken from the Penn World Table 6.3. In my main specifications, I convert government *share* per capita to government *expenditure* per capita as a measurement for government size. The same rationale applies to investment.[18] The fertility rate (births per woman) and life expectancy at birth are part of the World Development Indicators from the World Bank, whereas the inflation rate (CPI percentage change from the previous period) and the unemployment rate come from the OECD statistics. Due to the use of 2 lags in government size and growth and the occasional missing data point for various control variables, the final number of observations varies between 513 and 586.

[18] For the mathematical derivation of both variables, please refer to Table 1.

Table 9: Summary Statistics

Variable	Mean (Std. Dev.)	Min Max	N	Computation of Variable
Wage Volatility ($\tilde{w}^2$)	0 (0.04)	-0.344 0.223	618	1. Ln(Business Sector Wages) 2. Decomposition of Wages (λ_{HP} = 100) for each country time series separately 3. Repeating steps 1 and 2 for total wages 4. Squared cycle term from step 2 ($\tilde{w}^2$) – squared cycle term from step 3 ($\tilde{w}^2$) = excess volatility of private sector wages ($\tilde{w}^2$)
Growth Rate (Growth)	0.025 (0.021)	-0.098 0.103	605	(Growth Rate Laspeyres per capita)/100
Government Size (Gov)	8.082 (0.323)	6.728 8.731	605	Ln[(Gov't Share per capita/100)∗(GDP per capita)]
Life Expectancy	4.332 (0.036)	4.227 4.413	599	Ln(Life Expectancy)
Fertility	1.69 (0.285)	1.08 2.748	628	Fertility Rate
Openness	3.823 (0.599)	2.256 5.25	623	Ln(Openness)
GDP	10.003 (0.323)	8.861 10.787	623	Ln(GDP per capita)
Investment	8.737 (0.375)	7.007 9.688	623	Ln[(Investment Share per capita/100)∗(GDP
Inflation	0.051 (0.056)	-0.009 0.768	637	(Inflation Rate)/100
Unemployment Rate (Unempl)	0.072 (0.038)	0.01 0.2	550	(Unemployment Rate)/100

4.III.C 3SLS Results

Table 10 displays the main results, where control variables are added subsequently moving from left to right. The main rows of interest are the first 2 of the growth regression (the direct effect of volatility on growth and the second part of the indirect effect: the effect of government size on growth) and the first row of the regression predicting government size (the first part of the indirect effect: the effect of wage volatility on government size). Column (1) shows the basic 3SLS system of equations with only lagged values of growth and government size and country fixed effects as control variables. The direct effect is confirmed as volatility positively affects growth -- a result that is significant at the 5 percent level. Also, the indirect effect receives support -- even at the 1 percent level -- as both stages are significant: wage volatility has a positive effect on government size and government size affects growth in a negative way. Specification (2) adds life expectancy and fertility as controls into the growth equation, but both effects of volatility on growth remain significant. Column (3) adds time fixed effects, which again does not change the significance of both the direct and indirect effect. Next, the addition of both a linear and a quadratic time trend in specification (4) leaves the coefficients of interest untouched in terms of significance. Column (5) then includes more growth determinants (openness, GDP, investment, and inflation) and, after removing time trends, a country-specific time trend is added. Here again, the results support the theory: both the direct and the indirect effect remain significant. Finally, column (6) adds the unemployment rate to the previous specification.

Table 10: 3SLS Results	(1)	(2)	(3)	(4)	(5)	(6)

Dependent Variable: $Growth_t$						
Wage Volatility$_{t-1}$	0.04**	0.05**	0.05**	0.04**	0.03*	0.04**
	(0.019)	(0.019)	(0.016)	(0.019)	(0.018)	(0.017)
Government Size$_t$	-0.02**	-0.01*	-0.03**	-0.03**	-0.04*	-0.05*
	(0.004)	(0.009)	(0.009)	(0.010)	(0.024)	(0.028)
Growth Rate$_{t-1}$	0.30**	0.37**	0.37**	0.36**	0.31**	0.39**
	(0.041)	(0.043)	(0.043)	(0.043)	(0.037)	(0.040)
Growth Rate$_{t-2}$	-0.08**	-0.11**	-0.06	-0.14**	-0.03	-0.02
	(0.039)	(0.040)	(0.040)	(0.040)	(0.037)	(0.041)
Life Expectancy$_{t-1}$		-0.01	-0.20**	-0.25**		
		(0.059)	(0.085)	(0.101)		
Fertility$_{t-1}$		-0.00	-0.01	-0.01		
		(0.005)	(0.005)	(0.005)		
Openness$_{t-1}$					0.01	0.00
					(0.014)	(0.016)
GDP$_{t-1}$					-0.08**	-0.10**
					(0.037)	(0.038)
Investment$_{t-1}$					-0.03**	-0.04**
					(0.012)	(0.014)
Inflation$_{t-1}$					-0.14**	-0.18**
					(0.027)	(0.031)
Unemployment Rate$_{t-1}$						-0.10*
						(0.056)
R^2	0.267	0.274	0.516	0.286	0.423	0.451
Dependent Variable : Government Size$_t$						
Wage Volatility$_{t-1}$	0.06**	0.06**	0.04**	0.05**	0.06**	0.06**
	(0.017)	(0.018)	(0.017)	(0.017)	(0.017)	(0.017)
Government Size$_{t-1}$	1.19**	1.18**	1.15**	1.16**	1.05**	1.02**
	(0.036)	(0.038)	(0.038)	(0.038)	(0.036)	(0.040)
Government Size$_{t-2}$	-0.21**	-0.21**	-0.18**	-0.19**	-0.18**	-0.16**
	(0.036)	(0.038)	(0.038)	(0.038)	(0.034)	(0.039)
Growth Rate$_t$	0.17	0.13	0.30**	0.11	-0.11	-0.02
	(0.119)	(0.105)	(0.110)	(0.102)	(0.072)	(0.082)
Unemployment Rate$_{t-1}$						-0.06
						(0.043)
R^2	0.998	0.997	0.998	0.998	0.998	0.998
Country Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Time Fixed Effects	No	No	Yes	No	No	No
Time Trend	No	No	No	Yes	No	No
Country-Specific Time Trend	No	No	No	No	Yes	Yes
Observations	586	544	544	544	586	513

Notes: Standard errors are given in parentheses. ** and * indicate statistically significant at the 5 and 10 percent level. Time trend includes a linear and a quadratic time trend.

The unemployment rate is a significantly negative predictor of growth, but does not affect the main coefficients of interest: both the direct and the indirect effect of wage volatility on growth remain significant.

In summary, the empirical analysis provides strong evidence for the existence of both effects of wage volatility on growth: the positive direct effect and the negative indirect effect remain significant throughout all specifications. The upcoming robustness section specifically analyzes whether any of the results are driven by either the method chosen to decompose wages or the specific measurement used for government size.

4.III.D Robustness Tests

Table 11 displays a variety of robustness tests to see whether the obtained results are owed to either the choice of λ_{HP} for the Hodrick-Prescott filter, the method of decomposing wages, or the specific measurement of government size. Again, the first 2 rows in the growth regression and the first row of the regression estimating government size show the main coefficients of interest for the direct and the indirect effect of wage volatility on growth. In all 3 robustness tests, specifications (5) and (6) from Table 10 are replicated.

Table 11: Robustness Checks

	λ_{HP} = 6.25		Quadratic Detrending		Gov't Size and Investment in Shares	
	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable: $Growth_t$						
Wage $Volatility_{t-1}$	0.07*	0.07	0.02*	0.02**	0.03*	0.03**
	(0.042)	(0.042)	(0.009)	(0.009)	(0.016)	(0.016)
Government $Size_t$	-0.05*	-0.05**	-0.05*	-0.06**	-0.06**	-0.06**
	(0.024)	(0.028)	(0.024)	(0.028)	(0.022)	(0.024)
Growth $Rate_{t-1}$	0.31**	0.39**	0.31**	0.39**	0.32**	0.37**
	(0.037)	(0.040)	(0.037)	(0.040)	(0.038)	(0.040)
Growth $Rate_{t-2}$	-0.03	-0.02	-0.03	-0.02	0.03	0.03
	(0.037)	(0.041)	(0.037)	(0.040)	(0.036)	(0.038)
$Openness_{t-1}$	0.01	0.00	0.01	0.00	-0.01	-0.01
	(0.014)	(0.016)	(0.014)	(0.016)	(0.013)	(0.015)
GDP_{t-1}	-0.07**	-0.10**	-0.07*	-0.10**	-0.14**	-0.18**
	(0.037)	(0.038)	(0.037)	(0.038)	(0.021)	(0.025)
$Investment_{t-1}$	-0.03**	-0.04**	-0.03**	-0.04**	-0.04**	-0.04**
	(0.012)	(0.014)	(0.012)	(0.014)	(0.011)	(0.013)
$Inflation_{t-1}$	-0.14**	-0.18**	-0.14**	-0.18**	-0.13**	-0.16**
	(0.027)	(0.031)	(0.027)	(0.030)	(0.026)	(0.029)
Unemployment $Rate_{t-1}$		-0.10*		-0.12**		-0.07
		(0.056)		(0.056)		(0.052)
R^2	0.422	0.448	0.422	0.451	0.499	0.531
Dependent Variable: Government $Size_t$						
Wage $Volatility_{t-1}$	0.09**	0.09**	0.01*	0.02**	0.04**	0.05**
	(0.039)	(0.040)	(0.008)	(0.008)	(0.019)	(0.019)
Government $Size_{t-1}$	1.04**	1.01**	1.04**	1.01**	0.95**	0.94**
	(0.037)	(0.040)	(0.037)	(0.040)	(0.027)	(0.031)
Government $Size_{t-2}$	-0.17**	-0.15**	-0.17**	-0.15**	-0.11**	-0.11**
	(0.034)	(0.040)	(0.034)	(0.040)	(0.027)	(0.030)
Growth $Rate_t$	-0.11	-0.01	-0.11	-0.02	-0.88**	-0.85**
	(0.072)	(0.082)	(0.072)	(0.082)	(0.077)	(0.082)
Unemployment $Rate_{t-1}$		-0.06		-0.06		0.01
		(0.044)		(0.044)		(0.055)
R^2	0.998	0.998	0.998	0.998	0.994	0.994
Observations	586	513	586	513	586	513

Notes: Standard errors are given in parentheses. ** and * indicate statistically significant at the 5 and 10 percent level. Specifications (1) and (2): a value of $\lambda_{HP} = 6.25$ for the Hodrick-Prescott filter is used. In (3) and (4), quadratic detrending is used to decompose wages. Specifications (5) and (6) use the natural log of Government Share per capita and Investment Share per capita to generate the variables Government Size and Investment, respectively. All specifications include country fixed effects and country-specific time trends.

First, as different authors suggest different values of λ_{HP} for the

Hodrick-Prescott filter when dealing with annual data, it may be interesting to see whether using another value for λ_{HP} to detrend wages generates the same results in terms of significance. The main results from Table 2 use the most common value of $\lambda_{HP} = 100$ for annual data (for instance Backus and Kehoe (1992)), but Ravn and Uhlig (2002) suggest $\lambda_{HP} = 6.25$. Thus, specification (1) shows the main result from column (5) in Table 3 for $\lambda_{HP} = 6.25$, confirming the significance of both the direct and the indirect effect. Specification (2) adds the unemployment rate and is the only regression returning one barely insignificant coefficient: the direct effect slips out of the ten-percent significance range here. Second, the Hodrick-Prescott filter in general has been the subject of debate.[19] In order to control for the specific method of detrending wages, specifications (3) and (4) display regression results from using quadratic detrending on the wage data at hand. Still, the difference between the squared cycle terms of business sector and total economy wages represents the measurement of private sector wage volatility -- only with the difference that instead of the Hodrick-Prescott filter, I use quadratic detrending. All results tell the same story as before: both the direct and the indirect effect remain significant in their determination of growth. Here, the addition of the unemployment rate as a control in both equations even strengthens both effects.

Third, in my main results I define (Gov) as government expenditure per capita (and similarly investment per capita as investment) which may be driving results. Do results also hold with (Gov) defined as government *share* of GDP per capita? Specifications (5) and (6) display results when using the natural logarithm of

[19] See, for instance, Cogley and Nason (1995).

government share of GDP per capita (and also the investment share of GDP per capita as a control variable in the growth regression). Here again, all necessary coefficients carry the expected signs and are significant.

In summary, the main results in table 10 do not appear to be driven by (1) the specific value of λ_{HP}, (2) the method of detrending or (3) the measurement of government size. Only a different choice of λ_{HP} makes the direct effect of wage volatility on growth barely insignificant in one specification.

4.IV Conclusions

This paper (1) provides an explanation for the question how wage volatility affects growth and (2) suggests an answer to the question why previous research did not find a clear consensus regarding the effect of volatility on growth.

My theoretical model predicts two channels in which wage volatility affects growth: a positive direct and a negative indirect effect. Intuitively, the direct effect stems from increased precautionary savings (equivalent to less consumption) by workers in response to more income risk. The indirect effect comes from a change in the composition of the labor market: some workers move to the unproductive public sector after private sector wages become more volatile. In the second half of the paper, the analysis of 608 observations across 19 countries provides strong empirical evidence for both the direct and the indirect effect of private sector wage volatility on growth. Thus, if an analysis does not recognize both opposing effects, but rather tests only a direct effect of wage volatility on growth, the net result is ambiguous: depending on which effect dominates, a positive or negative net effect of wage volatility on growth may be observed. Although specific to *wage* volatility, this analysis may inspire further research to take a closer look at various sorts of volatility and their effects on growth.

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APPENDICES

Chapter 3

Proof of proposition 1: Comparing the payoffs $Y - m(1 + \mu)(t + f)Y$ and $(1 - t)Y - \mu(t + f)Y$, it is easy to see that, if the agent has been undetected in period 1, she will not comply in period 2 if

$$m < 1 - \frac{f}{(1+\mu)(t+f)} \tag{1.A}$$

Next, suppose that the agent is compliant in period 1. In period 2, compliance yields a payoff of (1 – t)Y, while violation gives Y – m(t + f)Y. If

$$m < \frac{t}{t+f} \tag{2.A}$$

the agent will be a violator in period 2. Note that the R.H.S. of (1.A) is strictly greater than that of (2.A). Thus, if (2.A) is satisfied, an agent will always be a tax evader in period 2, irrespective of her decisions in period 1.

Suppose that (2) holds. Then, the agent chooses to be non-compliant in period 1 if[1]

$$Y + m[-(t+f)Y + (1-t)Y] + (1-m)[Y - m(1+\mu)(t+f)Y] >$$

$$(1-t)Y + Y - m(t+f)Y \tag{3.A}$$

The L.H.S. of the above inequality represents the expected payoff from non-compliance in period 1. If she is non-compliant, then, with probability m she will be audited, and is subsequently compliant in period 2. With probability (1 – m) on the other hand, she avoids detection in period 1, and finds it optimal to remain non-compliant in period 2. It is easy to see that, if

$$m < \frac{t}{(1+\mu)(t+f)} \tag{4.A}$$

[1] If we do not assume that a violator apprehended in period 1 has to be registered and compliant in period 2, given (2.A), the only change in the above proof is that (3.A) changes to $Y + m[-(t+f)Y + Y - m(t+f)Y] + (1-m)[Y - m(1+\mu)(t+f)Y] > (1-t)Y + Y - m(t+f)Y$

It is easy to check that (4.A) is sufficient for satisfaction of the above inequality.

both (3.A) and (2.A) are satisfied, and the agent will be a tax evader in period 1, and, if not detected, remains so in period 2.

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Proof of proposition 3: Assume that there are two types of agents distinguished by their gains from liberalization. Specifically, we assume that n_i is the number of the type θ_i, with i = L or H, and that

$$\theta_1 < \theta_L < \theta_2 < \theta_H \tag{5.A}$$

Then, a tax amnesty increases the revenue collected from each type L, and lowers the revenue from each type H agent. For an overall increase in revenue to the TA from the amnesty, the following condition must hold:

$$n_L[2tY + t\theta_L] + n_H[2tY + t\theta_H] \geq n_L m(1+\mu)(t+f)Y + n_H[\mu(t+f)Y + (Y+\theta_H)t] \tag{6.A}$$

which implies that the relative populations of the two types need to satisfy

$$\frac{n_L}{n_H} \geq \frac{\mu(t+f)-t}{t[2+\frac{\theta_L}{Y}]-m(1+\mu)(t+f)} \tag{7.A}$$

As the above conditions imply, the proportion of low types need to be "appropriately high" for the amnesty to result in higher revenues for the TA.

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Chapter 4

Working for the Government

To solve the agents' maximization problem, the Bellman equation presents a common method to address dynamic programming problems. In the public sector, the agent faces the following problem, where wealth v_G represents her only state variable:

$$\max_{c_G} -\frac{e^{-ac_G}}{a} - \theta J(v_G) + J^{'}(v_G)(rv_G + w_G - c_G) \tag{8.A}$$

Taking the first derivative gives

$$c_G = -\frac{lnJ^{'}(c_G)}{a}. \tag{9.A}$$

As a next step, an 'educated guess' (in this case one might assume that the state variable v_G exhibits similar properties than the choice variable c_G) provides a possible solution to the value function, $J(v_G)$:

$$J(v_G) = -\frac{e^{-\beta_0 - \beta_1 v_G}}{\beta_1}. \tag{10.A}$$

Taking the first derivative

$$J^{'}(v_G) = e^{-\beta_0 - \beta_1 v_G} \tag{11.A}$$

allows me to rewrite the Bellman equation as

$$0 = -\frac{e^{-\beta_0-\beta_1 v_G}}{a} + \frac{\theta}{\beta_1} e^{-\beta_0-\beta_1 v_G} + e^{-\beta_0-\beta_1 v_G}(r v_G + w_G - \frac{\beta_0+\beta_1 v_G}{a}). \quad (12.A)$$

Dividing by $e^{-\beta_0-\beta_1 v_G}$ gives

$$0 = -\frac{1}{a} + \frac{\theta}{\beta_1} + r v_G + w_G - \frac{\beta_0+\beta_1 v_G}{a} \qquad (13.A)$$

From here, I collect terms to conclude

$$\beta_1 = ar \qquad (14.A)$$

and

$$\beta_0 = \frac{\theta - r}{r} + a w_G. \tag{15.A}$$

Using the above results for the optimal consumption and the value function leads to the results presented in the main text.

Transversality Condition for the Public Sector

In any infinite horizon dynamic optimization problem, the present value of the state variables is required to converge to zero as the planning horizon recedes towards infinity. From (7.A):

$$-\frac{\theta}{J} J + \frac{J^{'}}{J}\left(r v_G + w_G - \frac{\theta - r}{a r} - r v_G - w_G\right) < 0 \tag{16.A}$$

Using results for J and J' and simplifying gives a straight forward solution:

$$r > 0 \tag{17.A}$$

Hence, a positive interest rate is sufficient to fulfill the Transversality Condition for working in the public sector.

Working in the Private Sector

The agents' Bellman equation in the private sector becomes slightly more busy, as she faces two state variables - wealth v_P and the stochastic private sector wage w_P:

$$\max_{c_P} -\frac{e^{-ac_P}}{a} - \theta J(v_P) + J'_{v_P}(rv_P + w_P - c_P) + J''_{w_P}\frac{\sigma^2}{2}. \tag{18.A}$$

Taking the first derivative then gives

$$c_P = -\frac{lnJ'(c_P)}{a} \tag{19.A}$$

Similar to the above exercise, I conjecture

$$J(v_P) = -\frac{e^{-\beta_0 - \beta_1 v_P - \beta_2 w_P}}{\beta_1}. \qquad (20.A)$$

Taking the first derivative with respect to v_P becomes

$$J'_{v_P} = e^{-\beta_0 - \beta_1 v_P - \beta_2 w_P} \qquad (21.A)$$

Similarly,

$$J'_{w_P} = \frac{\beta_2}{\beta_1} e^{-\beta_0 - \beta_1 v_P - \beta_2 w_P} \qquad (22.A)$$

and

$$J''_{w_P} = \frac{\beta_2^2}{\beta_1} e^{-\beta_0-\beta_1 v_P-\beta_2 w_P} \qquad (23.A)$$

constitute the respective derivatives with respect to w_P. Bringing these results back to the Bellman equation gives

$$0 = -\frac{e^{-\beta_0-\beta_1 v_P-\beta_2 w_P}}{a} + \frac{\theta}{\beta_1} e^{-\beta_0-\beta_1 v_P-\beta_2 w_P} + e^{-\beta_0-\beta_1 v_P-\beta_2 w_P}\left(r v_P + w_P - \frac{e^{-\beta_0-\beta_1 v_P-\beta_2 w_P}}{a}\right) - \frac{\sigma^2 \beta_2^2}{2\beta_1} e^{-\beta_0-\beta_1 v_P-\beta_2 w_P}. \qquad (24.A)$$

Dividing by $e^{-\beta_0-\beta_1 v_P-\beta_2 w_P}$ gives

$$0 = -\frac{1}{a} + \frac{\theta}{\beta_1} + rv_P + w_P - \frac{\beta_0 + \beta_1 v_P + \beta_2 w_P}{a} - \frac{\sigma^2 \beta_2^2}{2\beta_1} \tag{25.A}$$

Then

$$\beta_1 = ar, \tag{26.A}$$

$$\beta_2 = a \tag{27.A}$$

and

$$\beta_0 = \frac{\theta - r}{r} - \frac{a^2 \sigma^2}{2r} \tag{28.A}$$

These results allow me to solve for the optimal consumption and the value function presented in the main text.

Transversality Condition for the Private Sector

Similarly to the public sector, but slightly busier, the following condition needs to hold in order to satisfy the Transversality Condition in the private sector:

$$-\frac{\theta}{J}J + \frac{J'_{v_P}}{J}\left(rv_P + w_P - \frac{\theta - r}{ar} - rv_P - w_P\right) + \frac{J''_{w_P}\frac{\sigma^2}{2}}{J} < 0 \qquad (29.A)$$

Using results for J, and ${J_{w_P}}''$ plus an algebraic simplification gives the same result as in the public sector:

$$r > 0. \qquad (30.A)$$

Again, a positive interest rate is enough to satisfy the Transversality Condition in the private sector.