ESSAYS ON THE LABOR MARKET IMPACT OF TRADE POLICY

by

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ABSTRACT

The first two chapters of this dissertation evaluate the dynamic response of human capital investment and wage inequality to trade liberalization. The first chapter develops a structural, dynamic, general equilibrium model of an economy in which forward-looking individuals optimally choose their levels of human capital and sector of employment each period. The model is estimated with pseudo-panel methods using data from Sri Lanka and then used to test the impact of a reduction in manufacturing tariffs. The results show that the transition takes 40 years to complete and that 22% of the potential long-run welfare gains are lost due to costly adjustment of human capital. Balanced-budget government subsidies that directly encourage skill investment speed up the economy's transition and can improve welfare, while employment subsidies do not. Importantly, skill premia (wage inequality) and education investment evolve *non-monotonically*. These results highlight the shortcomings of reduced-form studies that correlate wage changes and trade policy changes across different points in time: First, by ignoring labor market dynamics, these studies may erronously conclude a one-directional change in wage inequality. This is especially problematic if the transition is not yet complete. Second, comparing only wage changes — rather than utility changes — fails to capture the true welfare losses/gains experienced by different groups of individuals and the aggregate economy.

The second chapter develops a tractable version of the general equilibrium model of the first chapter to demonstrate analytically the impact of trade liberalization. Solving the model shows that trade liberalization can lead to rising wage inequality in developing countries even in the absence of technology spillovers. Moreover, the greater the persistence of older generations' human capital over time, the longer the time frame in which wage inequality monotonically rises. This may explain why reduced-form empirical studies find that wage inequality increased in post-liberalization developing countries, contradicting the predictions of classical trade theory. This paper shows that while the long-run implications of classical theory still hold, the *transitions* of wage inequality and human capital investment are clearly non-monotonic. When technology spillovers occur, the type of technology determines the relative outcomes for high-skill and low-skill labor.

The third chapter documents rising wage polarization in Sri Lanka during the 1992-2009 period and finds that these changes occurred at the level of occupations. Decomposing these wage changes shows that occupational tasks associated with technology spillovers and outsourcing have played a key role in this polarization. In particular, returns have increased to routine mechanized tasks linked to low-wage occupations, and to information and communication tasks linked to high-wage occupations. Both sets of tasks are highly conducive to technology growth and outsourcing. These results highlight the importance of considering occupation-specific skills — in addition to the traditional human capital measures of schooling and work experience — when assessing the labor market impacts of greater international competition.

READERS/ADVISERS

This dissertation was supervised by Pravin Krishna and Robert Moffitt. Helpful comments were provided by Richard Spady, Elena Krasnokutskaya, and seminar partcipants at the Johns Hopkins University Department of Economics and School of Advanced International Studies (SAIS).

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Endogenous Human Capital Investment: Adjustments to Trade Policy

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Abstract

Contrary to the predictions of classical trade theory, human capital investment and the wage-skill premium did not decline in many post-liberalization developing countries. This paper contributes to the structural trade literature by allowing for endogenous human capital investment within a dynamic, multi-sector, overlapping-generations equilibrium framework. The model is estimated using pseudo-panel methods with labor force data from Sri Lanka and is then used to simulate a trade shock in the manufacturing sector. The model yields rich dynamics for wage-skill premia, education investment, labor supply, and output following the trade shock. The results show that the direction of change in wage-skill premia and human capital investment varies across the economy's transition path. This can be reconciled with the model's overlapping generations structure and the equilibrium feedback effects between human capital quantity and skill price. Shutting off endogenous education investment results in larger welfare losses during the adjustment period. Balanced-budget subsidies that directly encourage skill investment speed up the economy's transition and can improve welfare, while switching subsidies do not. Overall, the results suggest that the *endogenous* adjustment of skill is a key determinant of post-liberalization outcomes in developing countries, and that policies targeting skill investment in the expanding sectors can help capture a greater share of the potential long-run gains to trade.

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1 Introduction

1.1 Overview

The Stolper-Samuelson theorem predicts that skill premia will decrease in developing countries following trade liberalization. However, empirical evidence has been mixed; skill premia either increased or evolved non-monotonically in a number of developing countries that liberalized trade (Goldberg and Pavcnik, 2007; Robbins, 1996; Wood, 1997; Michaely et al., 1997; Zhu and Trefler, 2001). Moreover, the Stolper-Samuelson theorem implies that skill downgrading will occur in developing countries following trade liberalization. Yet, evidence is also mixed with regard to the impact of trade on schooling enrollment (Edmonds and Pavcnik, 2004; Lai, 2010). A large body of empirical and theoretical studies offer several explanations for these phenomena; e.g. differences across countries in the pre-liberalization tariff structure, the historical timing of liberalization, skill-biased technological change, foreign direct investment (FDI), and heterogeneous firms.

However, these explanations do not account for two key aspects of an economy's response to a structural change. First, human capital is costly to acquire and is endogenously determined based on market conditions. Second, the dynamics of an economy's human capital stock — and thus output and income — depends on the time horizon studied since different birth cohorts may experience different adjustment costs. The model developed in this paper has finitely-lived overlapping generations. Thus, private human capital investment is costly in the form of foregone wages. Moreover, different generations face different future wage paths. This means that the incentive for private human capital investment — which in turn determines the economy-wide skill stock and skill premia — may depend on the post-liberalization time horizon chosen for study.

While endogenous human capital accumulation has been previously addressed in the trade literature, most of these studies model 'skill' as a binary variable within a two-sector framework. However, recent work suggests that this parsimonious approach oversimplifies both the skill investment process and the labor market outcomes of trade liberalization. For example, examining cross-country data on literacy and trade openness, Lai (2010) concludes that the skill intensity of a country's comparative advantage sector coupled with the level of literacy determines whether skill investment increases or decreases in a developing countries following trade liberalization. Using a dynamic framework, Hall (2010) determines that differences in the returns to education — in terms

of the efficacy of technology adoption — determines whether income inequality takes a U-shaped or inverted U-shaped transition following trade liberalization. Using a model of costly skill acquisition and a continuum of sectors/skills, Blanchard and Willmann (2013) conclude that differences in countries' educational cost structures can give rise to diverse post-liberalization outcomes in human capital investment and wage inequality.

These studies suggest that models with multiple skill levels and/or multiple sectors allows for a richer set of labor market outcomes that better conform to empirical observations. The model developed in this paper allows individuals to optimally invest in one of several skill levels (modeled as years of schooling) and choose employment in one of three sectors each period.

Understanding the trade-induced dynamics of human capital investment is of particular relevance to policymakers. A country's ability to absorb the potential long-run gains to trade is positively correlated with its stock of human capital (Grossman and Helpman, 1994; Tybout, 2000). Thus, reduced human capital investment in the short run following trade liberalization could diminish the potential long-run gains in real output and welfare.

This paper develops a structural, dynamic, general equilibrium framework of the labor market to quantify the short-, medium- and long-run impact of trade liberalization on human capital investment. The model explicitly links individual education and employment decisions with the aggregate human capital stock, output, wages, and welfare. The model is adapted from Keane and Wolpin (1997) and Lee (2005), and includes multiple sectors, overlapping generations, heterogeneous and forward-looking individuals, switching costs, and self selection. Individuals choose among five mutually exclusive alternatives: employment in one of three sectors, school attendance, and home production. Individuals' choices determine the evolution of their human capital stock, which comprises education and sector-specific work experience. This, in turn, determines equilibrium labor supply, wages, and output each period. Individuals are assumed to form rational expectations about the future path of equilibrium wages. The model parameters govern the utility derived from each labor-market alternative as well as switching costs.

The model parameters are identified by variation across birth cohorts in the time profiles of labor market choices, education levels, demographic characteristics (e.g. age, gender, number of children), and wages. The data set comprises successive cross sections of the Sri Lanka Labour Force Survey (LFS). The choice of Sri Lanka is particularly suitable to the analysis as it is a small,

open, developing economy which maintains high tariff rates in its tradeables sectors relative to its developed country trading partners. The LFS covers approximately 20,000 nationally representative households each year and spans 18 years. Thus, the data set contains a large sample size and tracks several generations of individuals over a significant portion of their lifetimes. Since the LFS is a repeated cross section, pseudo-panel methods — as in Browning et al. (1985) — are used in the estimation of the model parameters.

The estimated model is then used to simulate a one-time, permanent decline in the manufacturing output price. The impact of this policy change is evaluated for human capital investment, output, wages, and welfare. The labor market's transition between the initial and final 'steady states' is driven by several key features of the model. First, individuals can optimally alter the composition of their human capital stock by attending school or choosing where to work. Second, the overlapping generations feature means that older individuals retire each year to be replaced by younger individuals. Third, individuals can choose home production as a labor market alternative, allowing them to temporarily exit the labor market in the event of an unfavorable wage draw. Fourth, switching into one sector from another alternative incurs a cost.

At the aggregate level, the economy's transition is driven primarily by sector-specific returns to human capital — i.e. 'skill' prices. Because skill prices adjust in equilibrium, a one-time trade liberalization in one sector will affect current and future skill prices in all three sectors. This in turn affects the relative returns to education across sectors, and thus, the incentives for private human capital investment during the transition period.

The results from the trade policy simulation reveals that both education investment and the skill premium evolve non-monotonically during the transition, which takes several years. The initial downward pressure on the skill premium is gradually reversed as workers move out of manufacturing. Over time, new generations enter the labor market, sorting into the low-skill agriculture sector and a larger proportion into the high-skill non-tradeables sector; thus, new generations sort into greater skill extremes. Both physical capital and high-skill labor move into the two remaining sectors, but the high-skill non-tradebles sector absorbs a larger proportion of this reallocation. This raises skill investment once again, but eventually narrows the skill premium. However, as a result of this sorting into skill extremes, the new stead-state skill premium exceeds the old. The time-consuming transition results in a 22% loss of the long-run potential welfare gains from trade; i.e. if

the transition were instantaenous, this loss would not occur. Shutting off the possibility of *endogenous* education investment consumes an additional 8% of potential long-run gains and results in a less volatile transition of the skill premium over time.

While individuals employed in manufacturing at the time of the tariff reduction experience large welfare losses, the *average* individual enjoys a welfare gain. A balanced-budget subsidy that targets enrollment in school or vocational training in the non-tradeables sector speeds up the transition, increases aggregate welfare, and reduces welfare losses of manufacturing workers. In contrast, a switching subsidy that assists manufacturing workers improves welfare for those particular workers and speeds up the transition, but decreases aggregate welfare. This suggests that governments should implement policies that *directly* target skill investment if the goal is to mitigate as much as possible the adjustment costs of trade liberalization.

Overall, these results suggest that the *endogenous* adjustment of skill is an important determinant of post-liberalization outcomes in developing countries, and that policies targeting skill investment in the expanding sector can harness a greater share of potential long-run gains.

1.2 Literature Review

This paper contributes to the diverse and growing body of literature on the labor market impact of trade policy. One branch of this research examines correlations between industry-specific wages and industry-specific measures of trade such as import prices (Revenga, 1992), tariffs (Pavcnik et al., 2004a), and import shares (Kletzer, 2002; Pavcnik et al., 2004b). Another branch of research focuses on the labor demand side, examining the impact of trade on industry-specific employment (Trefler, 2004), on income inequality and unemployment under search-and-matching frictions (Helpman and Itskhoki, 2009), on wages paid by importing versus exporting firms (Amiti and Davis, 2012), and on job turnover (Davidson and Matusz, 2005). The impact of trade on labor supply supply decisions is examined in (Edmonds and Pavcnik, 2004). The within-country local labor markets effects of national trade policies are studied in McLaren and Hakobyan (2010) and Kovak (2013).

Several recent studies have examined the *dynamics* of the labor market's repones to trade reform, both from a labor demand perspective (Melitz, 2003; Helpman et al., 2011) and a labor supply perspective (Artuc, 2009; Artuc et al., 2010; Cosar, 2013; Dix-Carneiro, 2013). This paper fits in with the latter body of literature. The dynamic approach permits individual welfare to be measured

in terms of lifetime utility instead of static wage changes. Moreover, the dynamic approach permits a richer analysis since it tracks the economy's adjustment over several years as well as provides a setting for counterfactual experiments.

Artuc et al. (2010) study the inter-sectoral movement of labor in a structural dynamic framework with switching costs and homogenous workers with infinite lives. They find that, although the mean and variance of switching costs is high and results in slow adjustment, trade liberalization leads to welfare gains. This paper differs from their approach in a number of important ways. Firstly, workers are heterogeneous in multiple dimensions, allowing for an analysis of how trade reform affects multiple types of individuals and providing a framework for targeting labor market policies at specific groups. Secondly, individuals endogenously accumulate human capital, where the 'endogenous' aspect facilitates adjustment while the 'accumulate' aspect can act as a barrier to adjustment. Thirdly, individuals can choose to temporarily exit the labor market, which conforms to findings in previous studies that wage shocks affect labor supply decisions (Edmonds and Pavcnik, 2004).

Cosar (2013) develops an overlapping generations model with ex-ante homogeneous workers, sector-specific human capital accumulation, search-and-matching frictions, and wage bargaining. He finds that sector-specific human capital interacted with search-and-matching frictions generates an externality than explains a very slow labor-market adjustment to trade shocks. Two key features distinguish this paper from his. Firstly, the labor market is assumed to be perfectly competitive, so labor market frictions do not come into play. Instead, barriers to mobility come from the interaction between sector-specific human capital and finite horizon life-cycle effects, as well as switching costs. Secondly, sector-specific work experience is allowed to transfer across sectors, albeit imperfectly.[1] This results in higher mobility and faster adjustment than Cosar's paper, while capturing the more realistic scenario that individuals are rewarded for general skills (acquired from *total* work experience) in addition to sector-specific skills.

Artuc (2009) and Dix-Carneiro (2013) adapt the same discrete-choice framework of Keane and Wolpin (1997) used in this paper. Both papers feature multiple sectors, overlapping generations, heterogeneous workers, and switching costs. They find that the welfare impact of trade reform differs significantly between younger versus older workers. In addition, Artuc (2009) finds that

[1] Cosar (2013) assumes all accumulated work eperience is lost when a worker switches out of his current sector.

the welfare impact depends on the individual's sector of employment at the time of reform. Both studies also find that switching costs are large and are the primary reason for slow adjustment. This paper differs from theirs in two important ways. Firstly, it allows for investment in education, which also means that the decision process starts at a younger age (15 as opposed to 25). This allows for early-life human capital investments to persist throughout the lifetime, as has been found in the labor literature (Keane and Wolpin, 1997; Cunha et al., 2010). Persistence of early choices has implications for inter-sectoral mobility and adjustment costs. More importantly, one of the main motivations of this study is to evaluate the impact of trade liberalization on human capital formation, of which schooling is a key component. Inclusion of a schooling choice also allows for policy experiments explicitly targeting schooling incentives, such as an education subsidy. Thus far, the literature has focused almost exclusively on testing unemployment insurance and re-employment subsidies. Secondly, this paper imposes rational expectations on individuals. The counterfactual experiments show that, compared to adaptive expectations, rational expectations leads to smaller inter-sectoral labor reallocation in the short run as individuals correctly anticipate that short-term changes in skill prices are partially undone in the long-run as the economy settles to a new steady state. Moreover, individual welfare losses are smaller under rational expectations, a result which has implications for the structure and magnitude of different labor market policies that assist the economy's transition.

2 Model

The model is adapted from the dynamic, discrete choice framework of Keane and Wolpin (1997) and Lee (2005). In any given time period, the economy is populated with individuals aged 15 through 65. At each age, individuals maximize expected lifetime utility by choosing among five mutually exclusive and exhaustive labor market alternatives: 1. Employment in the agricultural sector, 2. Employment in the manufacturing sector, 3. Employment in the services sector, 4. Attend school, 5. Engage in home production.

2.1 Flow Utilities

The individual's flow utility from working in sector $j = 1, 2, 3$ in year t is the wage earned, w_j. The wage equals the sector-specific equilibrium price of human capital (skill price), r_{jt}, multiplied by the individual's human capital in that sector, h_{jt}:

$$U_{jt}(a) = w_{jt} = r_{jt} \cdot h_{jt} \tag{1}$$

The agent's stock of human capital in sector $j = 1, 2, 3$ is defined as:

$$\begin{aligned} h_{jt} &= exp(\beta_{j1} \cdot (a-14) + \beta_{j2} \cdot (a-14)^2 + \beta_{j3} \cdot Educ + \beta_{j4} \cdot Male \\ &\quad + \beta_{j5} \cdot Exp_1 + \beta_{j6} \cdot Exp_2 + \beta_{j7} \cdot Exp_3 + \epsilon_{jt}) \end{aligned} \tag{2}$$

where $Educ$ is years of schooling, Exp_j is total years of work experience in secror $j = 1, 2, 3$, $Male$ is a dummy variable for gender, and ϵ_{jt} is an idiosyncratic shock to human capital in sector j at time t. The specification allows for work experience accumulated in one sector to be transferred to all other sectors, with the degree of transferability governed by the coefficients β_{j5}, β_{j6} and β_{j7}. The intercepts of the human capital production function have been normalized to zero since they cannot be separately identified from the sector-specific skill price, r_{jt}. If the individual chooses to work in sector $j = 1, 2, 3$ at age a, he will enter age $a+1$ with an additional year of work experience in that sector: $Exp_j(a+1) = Exp_j(a) + 1$.

The flow utility from attending school is:

$$\begin{aligned} U_{4t}(a) &= exp(\beta_{40} + \beta_{41} \cdot (a-14) + \beta_{42} \cdot (a-14)^2 + \beta_{43} \cdot Educ \\ &\quad + \beta_{44} \cdot Male + \beta_{45} \cdot \mathbf{I}\{s \geq O'Level\} + \beta_{46} \cdot \mathbf{I}\{s \geq A'Level\} + \epsilon_{4t}) \end{aligned} \tag{3}$$

where $O'Level$ and $A'Level$ stand for the *Ordinary Level* (O'Level) and *Advanced Level* (A'Level) educational qualifications, respectively, and I is an indicator variable for whether that particular schooling milestone has been reached. [2] The coefficient β_{43} allows for the possibility that agents

[2] The O'Level and A'Level are two examinations administered nationwide each year by the Sri Lankan government in

with more years of schooling derive greater utility from attending school. The coefficient β_{45} captures any pecuniary and non-pecuniary costs to attending school beyond the O'Level qualification, while β_{46} captures any additional costs to attending school beyond the A'Level.[3]

The schooling utility specification attempts to capture the life-cycle pattern of school attendance and educational attainment observed in the data; attendance declines rapidly with age, the number of years of schooling is clustered around 11 and 13 (when the O'Level and A'Level, respectively, are completed), and the percentage of people who have passed the O'Level far exceeds that for the A'Level. The term ϵ_{4t} is an idiosyncratic shock to schooling utility at time t. If the individual chooses to attend school at age a, he will enter age $a+1$ with an additional year of schooling: $Educ(a+1) = Educ(a) + 1$.

The flow utility from home production is:

$$\begin{aligned} U_{5t}(a) &= exp(\beta_{50} + \beta_{51} \cdot (a-14) + \beta_{52} \cdot (a-14)^2 + \beta_{53} \cdot Educ \\ &\quad + \beta_{54} \cdot Male + \beta_{55} \cdot Kids + \epsilon_{5t}) \end{aligned} \tag{4}$$

where $Kids$ is the number of children below age six who reside in the household.[4] The coefficient β_{55} captures any impact of young children on home production utility. For simplicity, the variable $Kids$ is assumed to take on the values $\{0, 1, 2\}$. In addition, $Kids$ is assumed to follow an exogenous Markov process that is known to all agents, and depends on age, year, gender, and education level. If the individual chooses home production at age a, his sector-specific work experience and

accordance with the country's British-patterned education system. Typically, the O'Level exams are taken at age 16 after two years of coursework, and passing grades in key subjects are a requirement to qualify for A'Level coursework. The A'Level (or collegiate) examinations are taken at age 18 or 19 after three years of coursework and high passing grades are required for entrance to the country's public universities.

[3] In the labor literature, the key educational milestones are usually *high school* graduation and *college* graduation. However, due to the small number of places available each year in Sri Lanka's higher education institutions, only 1.42 of the total population has obtained any form of college/university education. In comparison, 15.79 and 7.73, respectively, have an O'Level and A'Level qualification. Moreover, O'Level coursework in Sri Lanka is considered to be on par with high school coursework in the United States, and A'Level coursework on par with the first two years of college. This is supported by the fact that students who have passed the O'Level exams are eligible to apply to US colleges, while those who have passed the A'Level exams are given two college courses worth of academic credit for each subject passed with at least a grade of C. Thus, in this model, an agent who has obtained at least an O'Level qualification should be viewed as having earned the equivalent of a US high school degree or more, while an agent with at least an A'Level qualification has obtained the equivalent of two years of US college coursework or more.

[4] Note that the agent need not be the children's parent. Given the extended family structure of a typical Sri Lankan household, the presence of very young children could affect the labor market choices of parents and non-parents (e.g. older siblings, aunts, grandparents) alike.

years of schooling remains unchanged when he enters age $a+1$.

The 5x1 vector of idiosyncratic flow utility shocks, $\epsilon_t = [\epsilon_{1t}, \epsilon_{2t}, \epsilon_{3t}, \epsilon_{4t}, \epsilon_{5t}]$, is drawn from a normal distribution that is independent across individuals, alternatives and time:

$$\epsilon_t \sim \mathcal{N}(0, \Sigma)$$

where Σ is a diagonal variance-covariance matrix.

2.2 Switching Costs

An individual who enters sector $j' = 1, 2, 3$ at time t from sector $j = 1, ..., 5$ at time $t-1$ incurs a switching cost that is a function of his age, gender, and the sector into which he is switching:

$$C_{j't}(a) = \begin{cases} exp(\gamma_{j0} + \gamma_{j1} \cdot a + \gamma_{j2} \cdot a^2 + \gamma_{j3} \cdot Male) & j' \neq j, j' = 1, 2, 3 \\ 0 & j' = j, j' = 1, ..., 5 \end{cases} \tag{5}$$

Note that switching into school or home production does not incur a cost. The switching cost can be interpreted as capturing all unobserved pecuniary and non-pecuniary costs associated with finding a job in a new sector. Pecuniary costs can include expenses associated with job search and geographic relocation. Non-pecuniary costs can include the psychological costs to switching, such as reluctance to change the status quo.

2.3 Aggregate Production

Production in sector $j = 1, 2, 3$ at time t takes the following Cobb-Douglas specification:

$$Y_{jt} = p_{jt} A_{jt} H_{jt}^{\alpha_{jt}} K_{jt}^{1-\alpha_{jt}} \tag{6}$$

where p_{jt} is the market price of sector j output, A_{jt} is the Hicks-neutral technology parameter, H_{jt} is the aggregate quantity of human capital, K_{jt} is the physical capital stock, and α_{jt} is the labor share of output. All of these variables are time dependent.

The aggregate quantity of human capital, H_{jt}, is the sum of sector-specific human capital over all individuals who chose sector j at time t:

$$H_{jt}^S = \sum_i d_i h_{ijt} \tag{7}$$

where h_{ijt} is the sector-specific human capital of agent i, and d_i is an indicator for whether the agent chose to work in sector j ($d_i = 1$) or not ($d_i = 0$).

The labor market is assumed to be perfectly competitive. Thus, the skill price, r_{jt}, equals the marginal product of human capital in each sector:

$$r_{jt} = \frac{\alpha_{jt} Y_{jt}}{H_{jt}}$$

Rearranging the above equation yields the demand for human capital in sector j at time t:

$$H_{jt}^D = \frac{\alpha_{jt} Y_{jt}}{r_{jt}} \tag{8}$$

The *equilibrium* skill price in sector j at time t is the skill price that clears the labor market:

$$H_{jt}^S = H_{jt}^D \Longrightarrow \sum_i d_i h_{ijt} = \frac{\alpha_{jt} Y_{jt}}{r_{jt}^*} \tag{9}$$

where the * subscript for r_{jt} indicates that this is an equilibrium quantity.

2.4 Expectations

An individual's choice at age a and time t depends on his expectations about future utility. Recall that utility in sector $j = 1, 2, 3$ is a function of the individual's sector-specific human capital and equilibrium skill price:

$$U_{jt}(a) = r_{jt}^* \cdot h_{jt}.$$

Thus, to compute expected future wages, the individual must form expectations about future equilibrium skill prices. Agents are assumed to form rational expectations about the current and future path of equilibrium skill prices. A rational expectations equilibrium skill price series, $\{r_{jt}^*\}_{t=1}^T$, where T is the terminal period, satisfies the following conditions:

1. Agents have perfect foresight about future skill prices, $\{r_t^*\}_{t=1}^T$, and make current decisions based on that knowledge.

2. The labor market clears in each time period.

2.5 State Transitions

At any age a, the individual's state vector is the set of variables whose quantities are known and which determine the present value of expected lifetime utility. Given the flow utility functions and the rational expectations assumption for skill prices, the individual's state vector at age a is:

$$\Omega_a = \{Exp_1, Exp_2, Exp_3, Educ, Kids(a), Choice, \bar{\epsilon}_a, \bar{r}(a)^*\}$$

where $\bar{\epsilon}_a$ is the $5x1$ vector of idiosyncratic shocks to flow utility at age a, and $r(\bar{a})^*$ is the vector of current *and* future equilibrium skill prices from age a through 65 for all sectors $j = 1, 2, 3$. The agent's state vector evolves from age a to $a + 1$ depending on the choice he makes at age a. For each of the five possible choices, the state vector evolves as follows (the individual state variable that changes with each choice is shown in red):

$$\begin{aligned}
\Omega_{a+1} &= \{Exp_1 + 1, Exp_2, Exp_3, Educ, Kids(a+1), \bar{\epsilon}_{a+1}, \bar{r}(a+1)^*\} \\
\Omega_{a+1} &= \{Exp_1, Exp_2 + 1, Exp_3, Educ, Kids(a+1), \bar{\epsilon}_{a+1}, \bar{r}(a+1)^*\} \\
\Omega_{a+1} &= \{Exp_1, Exp_2, Exp_3 + 1, Educ, Kids(a+1), \bar{\epsilon}_{a+1}, \bar{r}(a+1)^*\} \\
\Omega_{a+1} &= \{Exp_1, Exp_2, Exp_3, Educ + 1, Kids(a+1), \bar{\epsilon}_{a+1}, \bar{r}(a+1)^*\} \\
\Omega_{a+1} &= \{Exp_1, Exp_2, Exp_3, Educ, Kids(a+1), \bar{\epsilon}_{a+1}, \bar{r}(a+1)^*\}
\end{aligned}$$

It is assumed that individuals have zero years of work experience at age 15: $Exp_j = 0$ for $a = 15$ and $j = 1, 2, 3$. Note that work experience and years of schooling remain unchanged if the agent chooses home production.

2.6 Individual Maximization Problem

At any age a, the individual's problem is to choose the alternative $j = 1, ..., 5$ that maximizes present expected lifetime utility net of switching costs:

$$\max_{j\in 1,...,5} E\left[\sum_{\tau=a}^{A} \delta^{\tau-1} U(a) \Big| \Omega(a)\right] \tag{10}$$

$$U(a) = \sum_{j\in 1,...,5} \left[U^j(a) - C^j(a)\right] d^j(a) \tag{11}$$

where $d^j(a) = 1$ when alternative j is chosen at age a and $d^j(a) = 0$ otherwise. The term δ is the time discount factor.

The solution to the individual's decision problem is obtained recursively. Define $V(\Omega(a))$ as the value function at age a given the state vector $\Omega(a)$. Define $V^j(\Omega(a))$ as the expected present value from choosing alternative $j = 1, ..., 5$. Then, the value function at age a is:

$$V\Omega(a) = \max_{j\in 1,...,5} \left[V^j(\Omega(a))\right] \tag{12}$$

where $V^j(\Omega(a))$ can be written in Bellman form:

$$V^j(\Omega(a)) = \begin{cases} U^j(a) + \delta E V^j(\Omega(a+1)) & if a < 65 \\ U^j(a) & if a = 65 \end{cases} \tag{13}$$

The term E indicates that $V^j(\Omega(a+1))$ is an expected value. Given the assumption of rational expectations for equilibrium skill prices, the only source of uncertainty for agents is the realization of their idiosyncratic utility shocks. (All agents are assumed to know the distribution from which the utility shocks are drawn.)

The multi-dimensional nature of the choice problem leads to a very large number of feasible state vectors; for example, there are 5.6 milllion possible states that a 65-year-old individual can achieve, 4.5 million possible states that a 64-year-old can achieve, and so on. Appendix A describes the methods used to circumvent this problem in solving the choice model.

2.7 Equilibrium Skill Prices

The model assumes no aggregate shocks. Therefore, the only source of uncertainty in the model is the realization of future idiosyncratic utility shocks. However, because a large number of individuals populate the economy at any given time, these idiosyncratic shocks are averaged out. Thus, the

time path of equilibrium skill prices is deterministic, and is assumed to be deterministic from an individual perspective as well. This means that the future skill prices upon which individuals base their current decisions are also the skill prices that are eventually realized; that is, individuals have rational expectations. Because different birth cohorts are alive during different time spans, each cohort faces a different path of equilibrium skill prices from age 15 through age 65.

To compute the rational expectations equilibrium skill price path, the method developed in Lee (2005) is adapted to make the estimation routine run much faster. First, one complete estimation routine is conducted under adaptive expectations only. That is, for a given parameter set Θ, individuals at time t solve the choice problem by assuming that the current period's equilibrium skill prices will persist forever: $r^*_{jt} = r_{j,t+1} = ... = r_{jT}$ for each $j = 1, 2, 3$. When the economy moves forward to time $t + 1$ and the equilibrium skill price is updated to $r^*_{j,t+1}$ (which is not necessarily equal to r^*_{jt}), individuals assume that $r^*_{j,t+1}$ persists forever. Thus, the skill price path obtained in this manner is an equilirbium path, though not a rational expectations path; this is because the assumption of adaptive expectations is violated each period.

Once the optimal parameter set, $\hat{\Theta}_A$, is obtained under *adaptive* expectations, a second estimation routine is conducted under *rational* expectations with $\hat{\Theta}_A$ as the initial parameter set. Individuals are now assumed to perfectly forecast the year-on-year *ratio* of future skill prices. This time series of ratios is computed as:

$$\frac{r_{j,t+1}}{r_{jt}} = \frac{r^{*A}_{j,t+1}}{r^{*A}_{jt}}, \forall t$$

where $\{r^{*A}_{jt}\}^T_{t=1}$ is the equilibrium skill price sequence obtained under the optimal parameter set, $\hat{\Theta}_A$, with adaptive expectations. This equation yields a sequence of skill prices that can be written in terms of r_{j1}. Once r_{j1} is determined in equilibrium in period 1, the economy moves forward to period 2 and a new sequence of skill prices written in terms of r_{j2} is obtained. This process is repeated thought time T, yielding a second sequence of equilibrium skill prices, $\{r^{*R1}_{jt}\}^T_{t=1}$ (where $R1$ signifies iteration 1 of the rational expectations computation routine.) This process is repeated to obtain several skill prices sequences $\{r^{*R2}_{jt}\}^T_{t=1}$, $\{r^{*R3}_{jt}\}^T_{t=1}$, ..., $\{r^{*Rn}_{jt}\}^T_{t=1}$ until the sequences converge under a pre-determined criterion. The parameter set is then updated to Θ_{R1} via an optimization algorithm and the rational expectations iterations are repeated as above. The 'true' deterministic

path of skill prices, $\{r_{jt}^{*R}\}_{t=1}^{T}$, is the one obtained from the optimal parameter set determined under rational expectations, $\hat{\Theta}_R$.

Note that the rational expectations computation routine requires generating several skill price sequences for a single parameter set. This means that the model must be solved and the economy's time path simulated multiple times for every tested parameter set in the estimation, a time-consuming process. [5] This paper improves on the method of Lee (2005) by testing several parameter sets first under adaptive expectations only, which takes about 10% of the time required for a rational expectations run. The resulting optimal parameter set, $\hat{\Theta}_A$, then acts as a very 'good' initial guess for the rational expectations run. As it turned out, $\hat{\Theta}_A$ is very close to $\hat{\Theta}_R$, which means that the number of parameter searches required under rational expectations is very small. This considerably reduces the estimation time compared to the original method of Lee (2005).

3 Data

3.1 Sri Lanka Labour Force Survey

The model is estimated using data from the Sri Lanka Labour Force Survey (LFS), a repeated cross section of approximately 20,000 households surveyed each year since 1992. Each quarter, the Department of Census and Statistics (DCS) samples approximately 5,000 nationally representative households to be interviewed during a home visit. Respondents are asked to report their age, gender, number of years of schooling completed, whether the O'Level or A'Level qualifications have been obtained, and whether the individual currently works, attends school or stays at home. For individuals who are employed, the four-digit ISIC industry classification is recorded.[6] Because the data is recorded by household, the number of children — and their ages — in each household is visible. The data spans 18 survey years, from 1992 through 2009. For the estimation, observations are restricted to individuals aged 15 through 65 who have reported that they are either employed, attending school, or staying at home, and whose household structure (i.e. number of children) is visible. This leaves approximately 890,000 individual observations across 18 years.

[5] In Lee (2005), for a given parameter set, Θ, the choice problem is first solved under adaptive expectations. The resulting skill price ratios are then used to start off the first iteration of the rational expectations computation routine, under the same parameter set, Θ. Thus, the model's solution and simulation must be conducted many times for each and every parameter set tested in the estimation routine.

[6] ISIC - International System of Industry Classification

The model assumes that employment, schooling and home production choices are mutually exclusive. However, the data shows that some individuals engage in several of these activities during the year. Thus, each individual is assigned to just one of the five alternatives based on the information he reported. An individual is considered to been employed if he reported that he worked for either a wage, profit (self-employment) or family gain during the previous week, or he had a job but did not work the previous week due to other reasons.[7] The sector of employment — agriculture, manufacturing, services — is determined from the 4-digit ISIC code assigned to each employed person. For individuals who worked at multiple jobs, the job reported as the main economic activity is selected. An individual is considered to have attended school if he reported that he attended school and was not employed the previous week. An individual is considered to have engaged in home production if he neither attended school nor was employed.

Since the model assumes that all employment is full time, the wage parameters are estimated using hourly wages rather than annual wages. This prevents having to distinguish between full-time and part-time workers. For employed individuals, the LFS reports the monthly wage and the number of hours usually worked per *week*. Number of hours worked per *month* is computed by scaling weekly hours upwards by $\frac{30.4167}{7} = 4.3452$, where 30.4167 is the average number of days in a month and 7 is the number of days in a week. The hourly wage is then obtained by dividing the monthly wage by the number of hours worked per month.

Employed individuals report the number of years and months in their current job. Those who have been employed in the current job for less than 12 months are assumed to have switched into that sector from either another sector, school or home in the previous period. Those who have been employed in the current job for at least 12 months are assumed to have worked in that sector during the previous year, and therefore, did not switch.

The model is estimated via simulated method of moments (SMM), which matches sample moments from the LFS data to moments generated from simulating the model. The model parameters are estimated to minimize the weighted distance between the sample moments and simulated moments. Four main types of moments are used:

[7] According to the LFS, an individual with a job may not have worked the previous week due to vacation, off-season activity, a labor dispute, bad weather, mechanical failure or fuel shortage.

1. Choice Probabilities: The proportion of people who are employed in agriculture, employed in manufacturing, employed in services, attending school, and staying at home

2. Wages: The mean and standard deviation of hourly wages in agriculture, manufacturing and services

3. Schooling: The proportion of people with completed schooling categorized into four main education levels

4. Switching Probabilities: The proportion of new entrants (i.e. with less than 12 consecutive months in the current job) into agriculture, manufacturing and srvices

All moments are conditioned on age, year and gender. The choice, wage and schooling moments are also conditioned on education level, while the choice moments are further conditioned on whether at least one child aged 6 or below is part of the household. Education is categorized into four levels: less than secondary school (0-8 years), lower secondary school (9-10 years), O'Level completion but not A'Level completion (11-12 years), and A'Level completion and above (13 or more years). These cutoffs are determined to match the data, which shows that individuals are clustered around these four education levels. The total number of conditional moments to be matched is 93,600.

3.2 Descriptive Statistics

Figure 1 shows the choice proportions for each gender from 1992 through 2009. The probability of attending school declines rapidly with age. Females are much more likely than males to remain at home, and the probability increases rapidly after about age 50. The percentage of males working in agriculture and services is much higher than that of females. However, the probabilities of working in manufacturing are almost identical for the two genders. This is likely because Sri Lanka's large textile and garment industry chiefly employs women.

The cohort-specific wage profiles are shown in Figure 2. These are constructed by plotting each birth cohort's mean wage at every age for the age range observed in the data for that particular cohort. For example, the 1977 birth cohort's mean wage profile is observed from age 15 (in 1992) through age 32 (in 2009). The 1976 cohort's profile is observed from age 16 (in 1992) through age

33 (in 2009), and so on. As with an individual wage profile, the cohort wage profiles are concave with respect to age.

Figure 3 shows the mean log hourly real wage (in local currency) across time for each sector and gender. Wages are generally higher for males in all sectors, with the largest premium in manufacturing.

Figure 4 plots, for each gender and age, the average number of children aged 6 and below residing in the household. Average number of children peaks at age 30 for females and age 34 for males, and then increases again after age 50. The latter phenomenon is likely due to the extended family structure common in Sri Lanka where live-in grandparents often help raise young children.

3.3 Population Data

To generate the simulated moments required in the SMM estimation procedure, the economy must be simulated forward year by year all the way through 2009. Therefore, a starting distribution of individuals is needed. The starting distribution must include each individual's sector-specific work experience, completed schooling, previous year's choice, age, gender, and number of children; these are the individual state variables that determine choices. However, the LFS being a repeated cross section, individuals' lifetime sector-specific work experience is not recorded. Therefore, following the method of Lee (2005) and Lee and Wolpin (2006), the missing variable is generated by starting the economy several years *prior* to the first data year; in this case, 1920. Without any information on Sri Lanka's 1920 population, the 1920 starting distribution is created arbitrarily. All individuals are assumed to have exactly five years of schooling. Work experience in agriculture, manufacturing and services is randomly chosen based on the individual's age. The distribution of gender in 1920 is assumed to be evenly split between males and females, as it is for the 1992-2009 period. Starting from 1991 and working backwards, the number of children age 6 and under is assumed to be progressively higher to account for higher birth rates in the past. Note that while the economy is simulated from 1920 through 2009, only the simulated moments from 1992 onwards are matched with the sample moments.

The economy evolves forward each year with the retirement of the oldest cohort (those aged 65) and the entry of the youngest cohort (those aged 15). Thus, a distribution of incoming 15-year-olds is needed for every year from 1921 through 2009. The incoming distributions for 1992 through

2009 are obtained directly from the LFS data. The distributions for 1921 through 1991 are based upon the 1992 incoming distribution. Starting from 1991 and working backwards, each distribution is assumed to be progressively less educated and have more young children living in the household. The rate at which this progression takes place is chosen arbitrarily.

Recall that r^*_{jt}, the equilibrium skill price in sector j at time t, is the skill price at which sector-specific aggregate labor demand equals aggregate labor supply. Labor demand is computed directly from national accounts data, while labor supply is computed from simulating the model. In the SMM estimation procedure, $N = 800$ individuals from each cohort are simulated. Aggregate labor supply is computed as the sum of these individuals' human capital stocks weighted by their relative cohort sizes:

$$H^S_{jt} = \sum_i \frac{C_i}{N} d_i h_{ijt} \tag{14}$$

The term C_i is individual i's cohort size. Thus, cohort sizes are required for all ages 15 through 65 and all years 1920 through 2009. For the 1992-2009 period, cohort sizes are obtained from the LFS by summing population weights across all individuals surveyed in that cohort. For the 1940-1991 period, cohort sizes are obtained from the United Nations Demographic Yearbooks (UNDY). For the 1920-1944 period, only data on total population is available. Cohort sizes for this time period are computed by extrapolation, using cohort size information from later years.

3.4 Markov Process for Number of Children

The exogenous Markov process for the variable $Kids$ (the number of children age 6 and under) is computed directly from LFS data by backcasting household members' ages. Consider, for example, the transition probability from 0 to 1 child for an individual aged 25 in year 1992. The backcasting procedure is as follows: First, use the 1992 LFS cross section to count the number of 25-year-old individuals in 1992 with 1 child; call this value N^1_{1992}. Second, reduce the ages of all individuals in 1992 by one year; this gives the same 1992 households as they would have been in 1991. From this, count the number of 24-year-olds with 0 children; call this value N^0_{1992-1}. The 0 to 1 transition probability in 1992 is then defined as $\frac{N^1_{1992}}{N^0_{1992-1}}$.

In addition to age, these year-by-year transition probabilities are also conditioned on year, gender, and education level. Since $Kids$ takes on values of only 0, 1 or 2 in the model, individuals in the data with 3 or more children are assumed to have only 2. Due to a lack of detailed household data, the transition probabilities for 1920-1991 are assumed to be identical to that of 1992.

3.5 Aggregate Data

Agents make their decisions based, in part, on current and future equilibrium sector-specific skill prices. Recall that the equilibrium skill price in sector $j = 1, 2, 3$ is determined by equating labor supply with labor demand in that sector:

$$H_{jt}^S = H_{jt}^D \Longrightarrow \sum_i d_i h_{ijt} = \frac{\alpha_{jt} Y_{jt}}{r_{jt}^*}$$

Rearranging yields the following equation:

$$r_{jt}^* \cdot \sum_i d_i h_{ijt} = \alpha_{jt} Y_{jt}$$

The left-hand side of this equation is the sum of wages earned by all individuals who optimally chose to work in sector j at time t; it is the equilibrium skill price multiplied by aggregate sector-specific human capital. This quantity must equal total labor compensation, $\alpha_{jt} Y_{jt}$, the right-hand side of the equation. Total labor compensation is computed directly from national accounts data. Thus, the equilibrium skill price is determined by imposing equality between aggregate wages (computed by simulating the model) and total labor compensation (national accounts data).

To compute total labor compensation, the quantities Y_{jt} and α_{jt} for each j and t must be obtained. In this model, Y_{jt} is sector-specific gross value added, which is computed as sector-specific gross domestic product minus subsidies plus taxes. The World Development Indicators (WDI) reports data on sector-specific gross value added for Sri Lanka going back to 1959. Since the economy starts in 1920 for the estimation, the value added time series is extrapolated back to 1920 via log regression.

The term α_{jt} is the labor share of sector-specific value added. The Central Bank of Sri Lanka (CBSL) reports data on compensation of employees, CE_{jt}, for each sector going back to 1983. For the years 1983-2009, the labor share is computed as the ratio between compensation of employees and value added:

$$\alpha_{jt} = \frac{CE_{jt}}{Y_{jt}}$$

For 1920-1982, the labor shares are assumed to be the same as in 1983.

The compensation data series, CE_{jt}, does not include the informal sector, which is expected to be large in a developing country. Moreover, the relative size of the informal sector is most likely to be largest in agriculture, and smallest in manufacturing. Thus, the values of α_{jt} are adjusted accordingly.[8]

4 Identification

4.1 Sector-Specific Work Experience

Recall that human capital is a function of total years of work experience, Exp_j, in each sector $j = 1, 2, 3$. With an adequately long panel data set, an individual's complete choice history starting from age 15 is observed, making it possible to track total years of work experience accumulated since age 15. The coefficients for work experience would then be identified by summing up the number of times each individual chose sector $j = 1, 2, 3$ during his lifetime. However, the LFS data is a repeated cross section (RCS), giving no information about individual choice histories. Thus, it is not possible to compute total years of work experience, Exp_j.[9] Another identification strategy must therefore be implemented.

Even though individual choice histories are unavailable, the choice histories of distinct birth cohorts are observed. [10] Specifically, the proportion of individuals aged a in survey year t who chose each alternative j can be computed from the data. The same birth cohort is then followed into the next survey year, $t + 1$, where the proportion of individuals aged $a + 1$ who chose alternative j is observed. In this manner, the choice probability profiles of a single birth cohort can be tracked over time.

[8] Gollin (2002) finds that Sri Lanka's economy-wide labor share must be inflated from 0.493 to 0.575 to account for the informal sector. Accordingly, this paper computes sector-specific employee compensation to match an economy-wide labor share of 0.6, under the assumption that the informal sector is twice as large in agriculture and 1.5 times as large in services compared to manufacturing.

[9] While the choice history of school attendance is also not observed, the LFS records every individual's completed years of schooling to date. Thus, the state variable $Educ$ is directly available in the data for each individual.

[10] A birth cohort is identified by age and time period. For example, individuals aged 15 in year 1992 belong to the birth cohort born in 1977. Individuals aged 16 in year 1993 belong to the same 1977 birth cohort.

The idea behind identification of dynamic models with RCS data is that if there exists a 'best' set of parameters that governs the observed *individual* outcomes, then it is also the best set of parameters that governs the outcomes of appropriately aggregated *groups of individuals*. This identification strategy theory goes back to Browning et al. (1985) [11] and Deaton (1985), and was motivated by the dearth of panel data along with the availability of high-quality RCS data in many countries.[12] The theory was expanded upon by Moffitt (1993) who demonstrated that, under certain restrictions, models that are both linear and non-linear in parameters are identified and can be consistently estimated with group aggregated RCS data as long as a full set of cohort and age dummies are used.

In this model, an individual accumulates work experience over time by the choices he makes each period. To see how cohort choice profiles identify the work experience parameters, consider a hypothetical birth cohort, c, who are aged 15 in year t. Recall that agents are assumed to enter the decision-making period with zero work experience; i.e. $Exp^c_{jt}(15) = 0$ for all $j = 1, 2, 3$. Suppose that 25%, 20% and 15% of individuals in cohort c chose to work in sector 1, 2 and 3, respectively, at age 15 and time t. Then, cohort c enters age 16 at time $t + 1$ with $Exp^c_{1,t+1}(16) = 0.25$, $Exp^c_{2,t+1}(16) = 0.2$ and $Exp^c_{3,t+1}(16) = 0.15$. This cumulation proceeds through age 65. Thus, as with the choice histories of different *individuals* in a panel data set, the choice probability profiles of different birth *cohorts* in a RCS data set identify the work experience parameters.

4.2 Switching Costs

The switching cost parameters are identified by the proportion of currently employed individuals who worked in the same sector in the previous year. Due to the RCS nature of the data, prior choices are not directly observed. Instead, they are proxied from current job tenure, which is recorded in the LFS in years and months. An individual who has worked more than 12 months in his current job in sector $j = 1, 2, 3$ is assumed to have worked in sector j during the previous year, and therefore did not switch sectors. An individual with 12 months or less in his current job in sector j is assumed to have switched from another alternative $j' \neq j$ in the previous year.

However, many individuals likely change jobs while remaining in the same sector. Lee and Wolpin (2006) find that the cost of switching occupations *between* sectors is 1.3-3.1 and 1.4-7 times

[11] Browning et al. (1985) use the British Family Expenditure Survey, a repeated cross section, to estimate a dynamic model of consumption and saving.

[12] In fact, Deaton (1985) cites Sri Lanka as an example of a developing country with good-quality RCS data.

larger for males and females, respectively, than switching occupations *within* sectors. Therefore, the switching costs estimated in this paper should be interpreted as a lower bound. This implies that the economy's adjustment to trade liberalization will be faster than it otherwise would be, meaning that the adjustment costs should also be thought of as a lower bound. Fortunately, despite the likely mismeasurement of switching costs, the simulated data from the SMM estimation matches well with the true data. This implies that the assumptions made about switching may not be significantly misleading.

4.3 Selection Bias

The model has endogenous selection into the five labor-market alternatives, giving rise to the possibility of selection bias in the estimated parameters. Correct identification of the parameters is achieved from a combination of exclusion restrictions and distributional assumptions.

Wages in sector $j = 1, 2, 3$ are observed in the data only for individuals who chose to work in that sector. Since it is unlikely that these individuals are a random sample of the population, conventional OLS wage regressions would result in biased estimates. Instead, the wage parameters are correctly identified from assuming a standard normal error term distribution and from including variables in the utility functions that determine choices but not wages; e.g. number of children, switching costs. Similarly, the parameters for school and home production utility are correctly identified from the standard normal assumption for the error term distribution and from including variables that do not enter these utility functions but do affect choices; e.g. work experience in sectors $j = 1, 2, 3$.

Thus, the solution to the individual optimization problem serves the same purpose as a two-step bias correction procedure in a reduced-form model, in that it provides the required sample selection rules for identification.

4.4 Data Moments and Parameters

While it is difficult to mathematically prove identification of each individual parameter, it is possible to provide an intuitive argument for how each distinct set of moments helps identify a distinct set of parameters.

Choice probabilities and mean sector-specific wages help identify the wage parameters for each sector $j = 1, 2, 3$. All three sets of moments are conditioned on age, year, and gender, while the wage and choice moments are also conditioned on level of schooling. As mentioned above, conditioning the choice probabilities on age and year provides the birth cohort instrument that identifies the coefficients for sector-specific experience, while conditioning on gender and schooling level identifies the coefficients for the gender dummy and years of schooling. The mean standard deviation of sector-specific wages — conditioned on age, year, and sex — help identify the wage variance parameters.

Choice probabilities and schooling level probabilities help identify the school utility parameters and the school error variance parameter. Both sets of moments are conditioned on age, year, and gender. Two of the four schooling levels are O'Level completion and A'Level completion, which help identify the coefficients on the O'Level and A'Level dummies in the school utility function. Choice probabilities also help identify the home production utility parameters and the home error variance term. The choice probabilities for each alternative is conditioned on whether children aged 6 and below reside in the household, which helps identify the parameter for number of children in the home utility function. In addition, the cohort choice probability profiles for sectors $j = 1, 2, 3$, which tracks cohort sector-specific experience over time, provide an exclusion restriction for the school and home utility parameters since sector-specific experience determines choices without affecting school and home utility.

The switching probability moments for each sector $j = 1, 2, 3$ help identify the sector-specific switching cost parameters. This set of moments is conditioned on age, year, gender, and education level. In addition, the switching probability moments provide an exclusion restriction to help identify the wage, school and home parameters since prior choices affect current choices (because of switching costs) without affecting any of the five utility functions.

5 Estimation

5.1 Simulated Method of Moments

The parameters of the five utility functions are estimated via simulated method of moments (SMM). Specifically, the weighted sum of the squared differences between sample moments and moments

simulated by the model is minimized with respect to the parameters. The moment weights are the inverse values of the estimated variances of the moments, thus assigning smaller weights to moments with a higher variance. The time discount factor is set to $\delta = 0.97$. The steps of the estimation procedure are as follows:

1. Set up the starting distribution of individuals in 1920: This consists of a joint distribution of age, gender, years of schooling, and sector-specific experience constructed to reflect a population that is less educated than the 1992 distribution. Each birth cohort is represented by 800 individuals weighted according to their cohort size.

2. Set up the entering distributions of 15-year-olds for each year in 1921-2009: This consists of a joint distribution of gender, years of schooling, and number of children in the household. Each entering distribution is progressively more educated with time.

3. Obtain the pre-determined time series of aggregate variables for 1920-2009: sector-specific value added, labor income shares, and the Markov process for number of children

4. Guess an initial vector of parameters, Θ, for the utility and switching cost functions: To obtain a 'good' initial guess, a reduced-form, two-step version of the discrete-choice model is estimated (see Appendix C).[13]

5. Run the adaptive expectations estimation routine:

   (a) For a given parameter vector, Θ, solve the Bellman equations for the choice problem, imposing that individuals believe current skill prices persist forever.

   (b) Simulate the economy forward from 1920 through 2009, replacing the oldest cohort with a distribution of 15-year-olds, updating individual choices and state variables, and computing the market-clearing skill prices, r^*_{jt}.

   (c) Compute the SMM criterion function, which is the weighted distance between simulated and true data moments:

[13] Although the reduced-form estimation can neither include sector-specific work experience nor capture the utilities derived from school and home production, it still provides a useful guideline as to the magnitudes and signs of the structural utility function parameters.

$$L(\Theta) = (m(\Theta) - m)' W^{-1} (m(\Theta) - m) \tag{15}$$

where $m(\Theta)$ is the vector of simulated moments, m is the vector of true moments, and W is a weighting matrix that consists of the diagonal elements of the empirical variance-covariance matrix of the data moments. There are many more moments (93,600) than parameters (54), so the model is over-identified. Standard chi-square tests for model fit are conducted.

(d) Update the parameter vector using the parallel Nelder-Mead optimization algorithm of Wiswall and Donghoon (2007). Then repeat steps 1 through 4 until a set of parameters, $\hat{\Theta}_A$, is found that minimizes $L(\cdot)$.

6. Compute the sequence of equilibrium skill price ratios, $\{\frac{r_{j,t+1}}{r_{j,t}}\}_{t=1920}^{2008}$, from the economy governed by the parameter set $\hat{\Theta}_A$.

7. Run the rational expectations estimation routine:

   (a) For a given parameter vector, Θ, and skill price ratio sequence, $\{\frac{r_{j,t+1}}{r_{j,t}}\}_{t=1920}^{2008}$, do the following for each time period t from 1920 through 2009:

      i. Solve the Bellman equations for period t, imposing that individuals believe the sequence of future skill price ratios is fixed at $\{\frac{r_{j,t+1}}{r_{j,t}}\}_{t=1920}^{2008}$.

      ii. Simulate the economy for period t, replacing the oldest cohort with a distribution of 15-year-olds, updating individual choices and state variables, and computing the market-clearing skill prices, r_{jt}^*.

      iii. Move the economy forward one year and repeat steps 1 through 3.

   (b) Update the sequence of equilibrium skill price ratios and repeat steps 1 and 2 until the price ratio converges.

   (c) Compute the SMM criterion function.

   (d) Update the parameter vector using the parallel Nelder-Mead algorithm. Then repeat steps 1 through 4 until a set of parameters, $\hat{\Theta}_R$, is found that minimizes $L(\cdot)$.

5.2 Results

The parameter estimates and their standard errors are given in Tables 1, 2 and 3. The computation method for the standard errors is described in Appendix B.

The human capital production function parameter estimates (Table 1) show that the returns to schooling in manufacturing is higher than in agriculture and slightly lower than in services. This implies that a permanent decline in manufacturing wages could reduce aggregate schooling investment, depending on the proportion of the workforce that moves into agriculture versus services.

The coefficients for work experience indicate that sector-specific experience accumulated in one sector is transferable to other sectors, but only partially. Thus, switching sectors results in a wage decline, creating a barrier to inter-sectoral mobility. The results also show that experience in both agriculture and manufacturing are both more transferable to services. This perhaps reflects the very broad range of industries and occupations that comprise the services sector. Thus, a permanent negative wage shock in manufacturing may result in a greater expansion of services than of agriculture.

As expected, human capital increases with age in all three sectors, reflecting the rewards to overall labor market experience or general human capital. Male workers earn more than females, receiving the highest premium in manufacturing and the lowest in services. This last result most likely reflects the fact that many service sector industries employ a disproportionately large number of women.[14]

The school utility parameters, given in Table 2, indicate that the utility from attending school drops rapidly with age. While the finite horizon lifetime contributes to declining school attendance with age, the strict age-structured pattern of the national schooling system is also a likely factor. Obtaining an O'Level qualification, usually at age 15 or 16, is costly, as given by the negative coefficient for the O'Level dummy. An A'Level qualification, usually obtained at age 18 or 19, imposes an additional cost. These costs conform to the pattern of schooling achievement seen in the data, with smaller proportions of people at higher levels of schooling.[15] Utility increases with education level, possibly capturing permanent and unobservable characteristics of the individuals who persistently self-select into school.

[14]For example, the vast majority of nurses and teachers are women.

[15]The Sri Lankan education system has been criticized for its emphasis on primary education at the expense of higher education.

The utility attached to home production increases with age, is higher for women than for men, and rises with the number of young children in the household. The larger utility value for women helps explain the significant difference in labor force participation rates between men and women at lower levels of schooling. More educated individuals derive higher utility from home production. This may capture unobserved household or family characteristics; for example, individuals with more education may have families with more wealth, and thus, have lower costs associated with not working.

5.3 Model Fit

Tables 4 and 5 show that the model fits well with the data in terms of matching choice proportions and mean wages. An additional test of the model is whether it can match features of the data that were *not* utilized in the estimation. Three types of moments are evaluated here; the proportion of individuals observed each year who have never been employed (Figure 5), the reservation wages of the non-employed (Figure 6), and average wages by number of children in the household (Figure 7). As the figures indicate, the model performs well in matching these additional moments.

6 Policy Experiments

6.1 Initial Steady State

Before any policy experiments are conducted, the economy's initial steady state is generated. This ensures that the results of the policy experiments are independent of cohort-specific effects or other unobserved time trends in the data. Once this initial steady state has been reached, the economy is subjected to a trade policy "shock" and its transition to the new steady state is tracked. The computations for long-run gains/losses and welfare are conducted from these transitional dynamics. The estimated utility and switching parameters, $\hat{\Theta}_R$, are fixed for all policy experiments.

The transition to the initial steady state begins from 2009, the last year of the data. Recall that the estimation utilized available real value added data to determine equilibrium skill prices. However, for the steady-state simulation, real value added and skill prices must now be computed simultaneously in equilibrium along the economy's transition path. Thus, some additional informa-

tion is needed for 2009: the capital rental rate, r_K, the sector-specific productivity parameters, A_j, and the domestic consumption shares in agriculture, manufacturing and services.

The capital rental rate, r_K, is be computed using value added and the aggregate physical capital stock. Data on the capital stock for 2009 is not available for Sri Lanka. However, data on annual gross fixed capital formation (GFCF) is available for 1963-2009 from the World Bank Indicators, the United Nations Statistical Division, and the Central Bank of Sri Lanka. Using the perpetual inventory method, the aggregate capital stock for 2009, K_{2009}, is computed using the GFCF time series and an annual depreciation rate of 4% as given in Nehru and Dhareshwar (1993). Using K_{2009}, the economy-wide capital rental rate is computed as $r_K = \frac{(1-0.6)Y_{2009}}{K_{2009}}$, where 0.6 is the economy-wide labor income share. The sector-specific capital rental rates, r_{jK}, are all assumed to equal the economy-wide rental rate r_K, which implies perfect capital mobility across sectors. The rental rate is kept fixed at r_K for the initial steady state simulation, and the sector-specific physical capital stocks are determined in equilibrium such that $r_{jK} = r_K$.

Real value added is computed as output scaled by the inverse of the consumer price index:

$$Y_t = \frac{\sum_{j=1}^{3} Y_{jt}}{CPI_t} \tag{16}$$

where $CPI_t = \prod_{j=1}^{3} p_j^{\mu_j}$ and μ_j is the share of domestic consumption on sector j output. For all policy experiments, consumption shares are imposed as $\mu_1 = 0.2$, $\mu_2 = 0.25$, and $\mu_3 = 0.55$.[16]

Normalizing the 2009 output prices to unity, $p_{j,2009} = 1$ for $j = 1, 2, 3$, the sector-specific productivity parameters are computed as $A_{j,2009} = \frac{Y_{j,2009}}{H_{j,2009}^{\alpha_{j,2009}} K_{j,2009}^{1-\alpha_{j,2009}}}$. For the simulation, the productivity parameters are fixed at the 2009 values, while the agriculture and manufacturing output prices, p_1 and p_2, are fixed throughout at unity. The output price of the non-tradeables (services) sector, p_3, adjusts in equilibrium.

To start off the simulation, the state variables of the 2009 population distribution is updated to reflect the optimal choices made in 2009 during the estimation. As the economy evolves forward, each entering generation is assumed to be identical to the distribution of 15-year-olds from 2009.

[16]Data on sector consumption shares is not available for Sri Lanka. Devereux and Lane (2006) calculate that the share of non-tradeables in CPI in a developing country is around 0.55. The same is assumed for Sri Lanka in setting $\mu_3 = 0.55$. The share of tradeables in CPI is then 0.45. It is assumed that the agriculture share is lower than the manufacturing share. Thus, $\mu_1 = 0.2$ and $\mu_2 = 0.25$.

This ensures that the results of the policy experiments are not dependent on any cohort-specific features. Labor income shares, α_j, are fixed at their 2009 values. The model is simulated long enough until sector-specific value added, the physical and human capital stocks, and the equilibrium skill prices are unvarying.

The initial steady state is generated in the following steps:

1. Move the economy forward by one year, replacing the oldest cohort with the distribution of 15-year-olds from 2009.

2. Solve the individual choice problem at the equilibrium values of sector-specific physical capital, K_{jt}, skill prices, r_{jt}, and the services output price, p_{3t}. Equilibrium is determined by the following seven equations:

   (a) The physical stocks are allocated in each sector such that the sector-specific rental rates all equal the imposed value of r_K:

   $$r_K = \frac{(1-\alpha_j)Y_{jt}}{K_{jt}^{(1-\alpha_j)}}, j = 1, 2, 3 \tag{17}$$

   (b) The skill prices equate labor demand with labor supply:

   $$H_{jt} = \frac{\alpha_j Y_{jt}}{r_{jt}}, j = 1, 2, 3 \tag{18}$$

   (c) The non-tradeables output price is determined such that a fixed fraction, $\mu_3 = 0.55$, of aggregate income is spent on non-tradeables output (which, by definition, must all be consumed domestically):

   $$\mu \sum_{j=1}^{3} Y_{jt}(\bar{p}) = Y_{3t} \tag{19}$$

   where $\bar{p} = [p_1, p_2, p_3]$.

3. Record real value added, aggregate human capital, and physical capital for each sector. Repeat steps 1 through 3 until these aggregate variables converge.

Once the initial steady state is computed, the non-tradeables output price, p_3, is reset to unity and the productivity parameter, A_3 is readjusted according to $A_3 = \frac{Y_3}{H_3^{\alpha_3} K_3^{1-\alpha_3}}$, and is fixed at this level for all policy experiments. The aggregate capital stock at the initial steady state, $\bar{K}$, is also fixed at that level for all policy experiments. Instead, the economy-wide rental rate, r_K, is allowed to adjust in equilibrium such that $r_{jK} = r_K$, $j = 1, 2, 3$ (i.e. capital is perfectly mobile across sectors).

6.2 Trade Shock

The initial steady state is now shocked with a one-time 30% decline in the manufacturing output price, from $p_2 = 1$ to $p_2 = 0.7$, that persists forever. The agriculture output price is fixed at $p_1 = 1$, while the non-tradeables output price is allowed to adjust in equilibrium. Figure 8 shows the transition of output prices, skill prices, choice proportions, sector-specific capital stock, aggregate real output and real welfare from the initial to the final steady state.

The decline in p_2 is accompanied by a decline in the equilibrium manufacturing skill price, r_2^*. Since wages are a positive function of skill prices, $w_j = r_j h_j$, manufacturing wages also fall, resulting in a net outflow of labor from manufacturing. In contrast, employment in agriculture and services increase. Consequently, the capital rental price in manufacturing is pushed downwards in manufacturing and upwards in agriculture and services. Thus, physical capital reallocates away from manufacturing and into the remaining two sectors.

The services output price — which adjusts in equilibrium — also declines, causing the overall price level to fall. This is because the initial decline in manufacturing wages lowers aggregate demand, and thus, by equation 19, pushes down the non-tradeables price. Because of this decline in output prices — and thus wages — in manufacturing and services, a larger proportion of people opt into home production, reducing aggregate employment in the short-run. However, the fall in output prices dominates the decline in overall employment such that aggregate demand rises on net, increasing *real* output sharply in the short run. Because the return to schooling is relatively high in the adversely affected sector, enrollment in schooling declines initially.

Although the labor market's short-run response is large, the economy takes about 40 years to reach the new steady state. The short-run labor exodus from manufacturing raises the manufacturing skill price, causing manufacturing employment to rise again in the long run, though it remains well

below its pre-shock level. A similar incomplete reversal occurs in the other two sectors. The initial rise in the agriculture skill price is partially reversed as more people move into agriculture. This somewhat reverses the rise in agriculture employment, although it remains higher than its pre-shock level. As a result of the drop in the equilibrium services output price, the services skill price also falls initially, and continues to fall as labor moves from manufacturing into services. However, as the manufacturing skill price and employment level rises again, the movement of labor into the services sector halts and partially reverses itself, causing the services skill price to rise again in the long run, though never reverting to its pre-shock level. Thus, the labor market variables show non-monotonic transitions following the trade shock.

Figure 9 shows the evolution of skill premia computed for different pairs of the four major education levels. For all pairs expect the two lowest education levels, the skill premium falls at first, then takes on an inverted U shape before settling to a higher steady state level. For the two lowest education level pairs, the skill premium takes a U shape before converging to almost the same steady state level as before. These non-monotonicities can be reconciled with two aspects of the model acting in tandem. The first is that individuals optimally invest in human capital at the start of the lifetime. Thus, the initial decline in skill premia is because a disproportionately large number of *high-skill* workers suffered a wage loss since they had self-selected into the manufacturing sector *because* of their higher skill levels. As a result, the wage gap narrows at first. The second is that manufacturing is the 'middle-skill' sector. With the decline of the middle-skill sector, new generations sort into the low-skill agricultural sector and the high-skill service sector; in other words, they sort into greater skill extremes. This simultaneous up-and-down sorting widens the wage gap until the services output price and all skill prices converge to their new steady state levels. Figures 8 and 10 also show that the services sector absorbs a larger share of the economy's capital stock and highest skill workers.

Long-run Gains

The long-run aggregate gains/losses resulting from the trade policy can be computed in two ways. If the main policy target is output, then it suffices to compare the levels of real output at the initial and final steady states. However, if the policy target is welfare, then comparison of steady-state output levels is inadequate because it ignores the utilities of individuals who do not work as well as the

switching costs incurred by those who changed sectors. Aggregate welfare at any time t is defined as total income earned by all households in the economy, I_t, plus the utilities of all individuals attending school ($\sum_i U_{it}^{School}$) or staying at home ($\sum_i U_{it}^{Home}$), minus the switching costs incurred by individuals who switched sectors between $t-1$ and t, $\sum_i C_i^{Switch}$:

$$W_t = I_t + \sum_i U_{it}^{School} + \sum_i U_{it}^{Home} + \sum_i C_i^{Switch} \tag{20}$$

It is assumed that domestic households own the economy's capital stock. Thus, total income earned by households is the sum of labor income and capital income in each sector, which is simply aggregate output: $I_t = \sum_{j=1}^{3} \alpha_j Y_{jt} + \sum_{j=1}^{3} (1-\alpha_j) Y_{jt} = Y_t$.

Denote as W_F and W_I aggregate welfare at any given time period in the initial and final steady states, respectively. If the economy's response to the trade shock were instantaneous, then the economy jumps from the initial to the final steady state, the assumption of classical theory. If so, the present discounted value of the welfare gain from trade is:

$$\Delta WG_{SS} = \tfrac{1}{1-\delta}(W_F - W_I)$$

The welfare gain as a fraction of initial steady-state welfare is:

$$\Delta WG_{SS}\% = \frac{\frac{1}{1-\delta}(W_F - W_I)}{\frac{1}{1-\delta}(W_I)} * 100$$

The first column of Table 6 shows that aggregate real output and aggregate welfare increase by 6.36% and 9.16%, respectively. This is because the economy's price level is permanently lower after the tariff reduction, causing real output and real wages to increase. With more purchasing power for households, aggregate welfare is higher in the new steady state.

Adjustment Path

The above welfare calculations are based on the classical assumption that the economy adjusts instantly to the policy change. Therefore, these gains can be thought of *potential* gains. However, the economy requires a 40-year adjustment period before arriving at the new steady state. The present discounted value of aggregate welfare along this transition path is:

$$W_A = \sum_{t=0}^{\infty} \delta^t W_t \tag{21}$$

where W_t is defined as in equation 20. The *actual* long-run gain is thus $\frac{1}{1-\delta}(W_A - W_I)$. The total transition cost is therefore the difference between the long-run potential gain and the actual gain:

$$TC = \frac{1}{1-\delta}(W_F - W_I) - (W_A - \frac{1}{1-\delta}W_I) = \frac{1}{1-\delta}W_F - W_A \tag{22}$$

The transition cost as a percentage of the long-run gain is:

$$TC\% = \frac{\frac{1}{1-\delta}W_F - W_A}{\Delta WG_{SS}} * 100$$

The second column of Table 6 gives the transition cost in terms of both aggregate output and welfare, expressed as a percentage of the long-run potential gains. In terms of both output and welfare, transition costs eat up about 22% of the long-run gains to trade.

Welfare Gains without Endogenous Education

This experiment is geared to show the importance of endogenous education investment in determining the transition costs following trade liberalization. Education levels of agents are pre-determined, as assumed in the prior literature. Specifically, each year, all agents age 15 through 65 are assumed to have the same distribution of schooling as the 2009 population in the LFS. Note that in the computation of aggregate welfare, the schooling component of welfare is now zero: $\sum_i U_{it}^{School} = 0$.

Table 7 shows the long-run gains and transition costs. The first column shows that aggregate real output and aggregate welfare increase by 14.57% and 16.0%, respectively. However, the second column shows that transition costs consume 30% and 31% of the long-run gains in output and welfare, respectively; that is, the welfare loss is larger by about 8 percentage points compared to the case with education investment.

Why are the long-run *potential* welfare gains larger without education investment? It is because the trade-induced decline in human capital prices no longer has a negative impact on education investment. With a smaller human capital scarcity in the economy, the upward pressure on the wage-skill premium in the medium run is dampened as well. The education investment of new generations is no longer negatively affected by the rise in wage-skill premia, which means that the

'pecuniary' externality that generates an underinvestment of human capital is now smaller. Thus, the economy has a higher level of human capital in the new steady state compared to the situation with education investment. Higher human capital stocks translate to higher real output, and thus, welfare.

However, as discussed above, comparative statics analyses inflate the true gains from trade. Without education investment, a crucial margin of adjustment to the policy change is shut down. As a result, a larger percentage of the long-run potential gains is now lost during transition; this is shown in the second column of Table 7.[17] Thus, studies that disallow education investment are likely to significantly *overestimate* the actual gains from trade.

Finally, as noted above, the variation in the wage-skill premium during the transition is much smaller without education investment. This suggests that endogenous human capital might explain the mixed empirical evidence on wage-skill premia in developing countries. Given the long transition length calculated in this paper and others, the adjustment phase in response to trade policy may well be ongoing even for those countries that liberalized in the late 1970s (e.g. Sri Lanka) and early 1980s (e.g. Mexico). This suggests that the time periods chosen are crucial for the comparative statics analyses typically conducted to evaluate trade reforms. These results also highlight that comparative statics analyses fail to capture the non-monotonic dynamics of labor market variables, partcularly the skill premium.

Individual Welfare Changes

The lifetime welfare of any individual i is the present discount value of his utility, net of switching costs, from his current age a through age 65:

$$W_i = \sum_{\tau=a}^{65} \delta^{\tau-a}(U_i(\tau) - C_i(\tau)) \tag{23}$$

Denote as W_A^i and W_I^i the lifetime welfare with and without the trade shock, respectively, for an individual i who was alive in year $t = 0$ when the trade shock occurred. His welfare change from the trade shock is defined as $W_I^i - W_A^i$.

[17] Dix-Carneiro (2013) finds an analogous result for physical capital mobility. When he assumes zero capital mobility across sectors, he finds that the transition consumes a much larger share of long-run gains than under perfect capital mobility. This is because zero capital mobility shuts down one of the adjustment mechanisms of the economy in response to a policy change.

Table 8 gives the average welfare changes of individuals who were employed in manufacturing at the time of the trade shock. The welfare changes are expressed as a percentage of W_1^i, the pre-shock level of welfare. Overall, manufacturing workers experience a 13.2% loss of the lifetime welfare they would have enjoyed if the trade shock had not occurred. Welfare losses vary considerably across age and education level. Low-educated workers (less than a O'Level qualification) from the youngest age group, 15-29, experience the smallest welfare loss, while high-educated workers (at least a O'Level qualification) from the oldest age group, 45-65, experience the largest loss.

Overall, welfare losses are largest for older workers. This is because they have accumulated more sector-specific experience in manufacturing, thus experience greater wage losses when p_2 falls. The direct costs of switching sectors also increase with age, meaning that even without sector-specific experience, older workers are less mobile. Moreover, because of the finite horizon, older workers have less time in which to invest in new human capital.

Welfare losses are larger for high-educated workers. Because the returns to schooling are relatively high in manufacturing, high-educated manufacturing workers experience a larger drop in their wages. Moreover, while low-educated workers can switch into agriculture, high-educated workers would prefer to switch into services, whose schooling returns are higher than in manufacturing. However, while the agriculture output price remains fixed at its global level, the services output price decreases in equilibrium, pushing down the services skill price. Thus, high-educated manufacturing workers experience a larger drop in lifetime welfare since most of them switch into services.

Table 9 shows the welfare changes for all individuals who were alive at the time of the shock, not just those who were employed in manufacturing. Overall, individuals experience a welfare *gain* of 8.4%. Workers in the middle age range, 30-44, experience the largest gains, 20-21% for both low- and high-educated workers. Young workers (age 15-29) also experience a welfare gain, while the oldest workers (age 45-65) experience a welfare loss. That welfare gains are highest for the middle age group, instead of the youngest, may at first seem strange. However, note that real wages in the economy rise as a result of the decline in the price level. Middle-aged workers, who have accumulated more human capital than younger workers, experience a large increase in real wages. The welfare increase resulting from a higher real wage dominates the welfare loss resulting from lower inter-sectoral mobility for these middle-aged workers.

Low-educated individuals overall fare better than high-educated workers. Again, as explained above, this is because the adversely affected sector pays relatively high returns to schooling, while the sector with the highest rewards to schooling — services — experiences a large skill price decline.

6.3 Labor Market Policies

Three labor policies are evaluated: a schooling subsidy, an employment subsidy for the services sector, and a vocational training subsidy for the services sector. The individuals targeted are those who were employed in the manufacturing sector at the time of trade liberalization. The policies are evaluated for their impact on the speed of adjustment, and on aggregate and individual welfare.

All three policies are intended to encourage re-employment in the services sector. The services sector has been gradually expanding in Sri Lanka, while agriculture has been shrinking. Moreover, the transitional dynamics following the trade shock show that labor reallocation favors the services sector over agriculture. Thus, it is expected that further trade liberalization in Sri Lanka will expand the services sector even more, while agriculture continues to shrink. In addition, the vocational training programs implemented by Sri Lanka's central government are geared towards services sector employment.

Experiment I: Education Subsidy

Eligible workers receive a subsidy to invest in education for up to 10 years starting from the time of the trade shock. Only individuals who were employed in the manufacturing sector at the time of the shock are eligible.[18] The program's expiration is known to all individuals; i.e. the 10-year program duration is built into individuals' expectations when they solve their Bellman equations.

The subsidy is sponsored by a lump-sum income tax. Specifically, starting from $t = 0$ through $t = 9$, a fraction, ψ, of aggregate real output is transferred to eligible individuals who choose to attend school. Because real output is determined in equilibrium, the total transfer amount is also determined in equilibrium: $\Psi = \psi Y$. Each eligible individual who chooses schooling receives the

[18]The subsidy can be thought of as financial assistance to obtain a certificate, diploma or degree in information technology, management, business, marketing, accountancy, and similar programs that have been available in Sri Lanka since the 1990s. Most of these programs are run by local and foreign private institutions, and receive state accreditation. They typically target young adults who have completed O'Levels or A'Levels and are looking to hone a specific set of skills to find employment in Sri Lanka's growing services sectors. These programs also provide a key higher-education alternative to the state-run universities which are capacity constrained and often undermined by political unrest.

same subsidy amount, s. Thus, if n eligible individuals choose schooling, then $s = \frac{\Psi}{n} = \frac{\psi Y}{n}$. Therefore, s is also determined in equilibrium. The tax rate, ψ, is set to decrease over time. This is because the majority of eligible workers who choose the subsidy do so at the beginning of the program; that is, n falls over the 10 years of the program.[19] After some experimentation, ψ is set to 0.01% of output at $t = 0$ and declines linearly to zero by $t = 10$.

Figure 11 shows the transitions of aggregate output and welfare for all labor market policies. The education subsidy initially lowers output compared to the no-policy benchmark since some individuals who would have chosen to work are attending school instead. However, the resulting increase in human capital raises output after the subsidy programs ends. The economy reaches its new steady state faster than without the subsidy. Aggregate welfare is also higher with the subsidy than without.

Tables 11 and 12 give the welfare changes for low- and high-educated manufacturing workers. Compared to the no-policy benchmark, both low- and high-educated manufacturing workers in the youngest age group (15-29) experience a smaller welfare loss as a result of the subsidy. However, middle-aged and older workers do not benefit, and in fact, are slightly worse off. Because the utility from attending school falls rapidly with age, middle-aged and older workers do not find it optimal to enroll in an educational program. They are worse off because the lump-sum transfer of income, $\Psi = \psi Y$, benefits young individuals while taxing older workers.

Experiment II: Employment Subsidy

Under this program, eligible workers receive a subsidy, s, if they move directly into the services sector. Again, eligible workers are those who were employed in manufacturing at the time of the trade shock. The employment subsidy is sponsored by a lump-sum income tax with the same declining tax rate sequence as for the education subsidy. Total tax revenue, $\Psi = \psi Y$, and the individual subsidy amount, $s = \frac{\Psi}{n}$ are determined in equilibrium. The program lasts 10 years and its duration is known to all individuals.

The employment subsidy results in a larger reallocation of manufacturing workers into the services sector compared to the no-policy benchmark. Correspondingly, output increases relative to

[19] If ψ were kept constant over time, the individual subsidy amount, s, would be extremely large in the last few years of the program. This means the government is over-paying eligible individuals who would have otherwise accepted a lower subsidy.

the no-policy benchmark during the 10 years of the program (Figure 11). After the program expires, growth in aggregate output slows down initially because the utility from services employment is no longer as high, thus raising the relative value of other alternatives such as home production. However, output is still higher than in the no-policy benchmark and steady-state output is reached faster. The employment subsidy has a smaller positive impact on aggregate welfare than the education subsidy. This is because the latter directly increases the economy's human capital stock for up to 10 years, while the former only subsidizes a one-time switching of sectors.

Tables 11 and 12 show that the employment subsidy reduces the welfare loss incurred by manufacturing workers, even resulting in a gain for the youngest workers. Low-educated, middle-aged workers also experience a small welfare gain. Young, low-educated workers benefit the most from the subsidy. Overall, manufacturing workers are much better compensated by the employment subsidy than the education subsidy.

Experiment III: Vocational Training Subsidy

In this experiment, eligible workers face a sixth labor market alternative. They can now choose to obtain one year of vocational training in the services sector.[20] The skills thus obtained are equivalent to an additional three years of sector-specific experience in services. After completion of one year of training, individuals are no longer eligible for the program. The flow utility received from training is just 50% of the flow utility received from home production. Thus, the government offers a subsidy to compensate for this utility loss. As before, the subsidy is sponsored by a lump-sum income tax with the individual subsidy determined in equilibrium. The program is offered for 10 years and this duration is known to all workers.

Figure 11 shows that, as with the education subsidy, the vocational training program reduces output initially compared to the no-policy benchmark. This is because some individuals who would have otherwise worked are now engaged in training. The fall in output is *greater* than that for the education subsidy. While the education subsidy is used almost exclusively by young individuals, training is chosen by middle-aged and older individuals as well. Thus, more people overall choose vocational training, resulting in lower employment and output during the program's tenure. How-

[20]The Sri Lankan government began implementing vocational training programs in the 1990s, more than a decade after the country's initial trade reform. By the 1990s, it had become clear that workers did not have the required skills demanded in the post-liberalization economy in which the services sector had expanded considerably.

ever, once the program expires, output jumps up to a higher level than under the education subsidy, and remains higher until steady state is reached. This is both because more people undertake training than schooling, and because the return to sector-specific experience is higher ($\beta_{37} = 0.0954$) than the return to schooling ($\beta_{33} = 0.0726$) in the services sector. As for welfare, steady state is reached fastest under the vocational training program. In fact, welfare under vocational training is higher at every point in the transition period than for any of the other policies (including the no-policy benchmark).

Tables 11 and 12 show that the training program significantly reduces welfare losses incurred by manufacturing workers, even resulting in gains for young workers. Young, low-educated workers benefit the most from the training program since they already had relatively low mobility costs.

7 Conclusion

This paper evaluates the short-, medium- and long-run response of endogenous human capital investment in a small open economy that experiences a one-time, exogenous decline in the manufacturing output price, as would occur with a tariff reduction. The theoretical framework allows for an explicit link between private human capital investment decisions and equilibrium aggregate variables — labor supply, wages, output, and welfare — across time.

The experiment is conducted in several steps. First, a dynamic, multi-sector, general equilibrium model of the labor market is estimated with cross-sectional data from Sri Lanka, a small open economy. The model framework is adapted from Keane and Wolpin (1997) and Lee (2005), and features overlapping generations, heterogeneous and forward-looking individuals, switching costs, and self selection. Because the data set is a repeated cross section (RCS), pseudo-panel methods are used in the estimation, as in Browning et al. (1985) and Deaton (1985).

Second, the estimated model is used to simulate a trade 'shock', a permanent decline in the manufacturing output price. The results show that both education investment and the skill premium evolve non-monotonically during the transition. The manufacturing tariff cut puts downward pressure on skill investment and the skill premium. However, as workers start moving out of manufacturing in the short and medium run, the skill premium starts widening. Over time, new generations enter the labor market, some entering the low-skill agriculture sector and a larger proportion en-

tering the high-skill non-tradeables sector. Physical capital reallocates into agriculture and a larger proportion into non-tradeables.Because of worker self-selection into the two skill extremes of agriculture and services, the new steady state skill premium is higher than before the trade reform took place.

The potential long-run gains to aggregate output and welfare are 9% and 5%, respectively, but the time-consuming transition consumes about 22% of these potential gains. While individuals employed in manufacturing at the time of trade reform experience large welfare losses, the average individual enjoys a welfare gain. Shutting off endogenous education investment consumes an additional 8% of potential long-run gains, while the skill premium shows less variation over time.

A balanced-budget subsidy that targets education investment or vocational training in the non-tradeables sector speeds up the transition, increases aggregate welfare, and reduces the individual welfare losses of manufacturing workers. However, the education subsidy disproportionately benefits the youngest individuals. In contrast, a moving subsidy that assists manufacturing workers improves welfare for those workers and speeds up the transition, but decreases aggregate welfare.

Overall, these results yield two key observations. First, the endogenous adjustment of skill is an important determinant of post-liberalization outcomes in developing countries. Contrary to classical theory, both skill investment and the skill premium can rise or fall during different phases of the transition process, depending on the speed at which individuals switch sectors and invest in human capital. Second, short-run policies that directly encourage skill investment in the expanding (non-tradeables) sector can help capture a larger share of the potential long-run gains to trade.

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A Solving the Bellman Equations

At any age a, an individual chooses the alternative that maximizes the utility he expects to derive for the remainder of his lifetime, age $a+1$ through 64. That is, he must compute $EV\Omega(a+1)$. Thus, prior to simulating the model in the estimation routine and policy experiments, the choice problem must be solved for the heterogeneous individuals in the data. As described in section 2, the choice problem can be depicted in Bellman form and solved via backward recursion, starting from the terminal age, 65.

Two computational difficulties arise in solving the Bellman equations. First, because individuals must form expectations about future utility shocks, computing the value functions requires a five-dimensional integration over the joint distribution of shocks. This is accomplished via Monte Carlo integration. A random sample of $5x1$ vectors of utility shocks are drawn and the value $\max_{j\in 1,\ldots,5}\left[V^j(\Omega(a))\right]$ is computed for each shock vector, ϵ. Then, $EV\Omega(a)$ is approximated as the mean value of $\max_{j\in 1,\ldots,5}\left[V^j(\Omega(a))\right]$ across the utility shock draws.

The second computational difficulty arises from the large number of achievable states that the individual must consider when computing his value functions. Since computing $EV^j(\Omega(a)$ is not feasible for several million state space points, the interpolation method of Keane and Wolpin (1997) is employed. Specifically, for each age a, $EV^j(\Omega(a)$ is computed only for a subset of feasible state vectors, $\{\Omega(a)\}$. The resulting set of expected values, $\{EV^j(\Omega(a)\}$ values are then regressed on the corresponding state variables in $\{\Omega(a)\}$. The regression coefficients are used to approximate the expected values of the remaining states.

To describe the solution algorithm, first define as $\tilde{\Omega}_t(a)$ an individual's state vector at time t without utility shocks:

$$\tilde{\Omega}_t(a) = (Exp_1+1, Exp_2, Exp_3, Educ, Kids(a), Sector, \bar{r_t})$$

where $\bar{r_t}$ represents the sequence of current and future equilibrium sector-specific skill prices that the individual will face from now until age 65. As described in section 2, for the purpose of implementing the model, $\bar{r_t}$ is written solely in terms of the *current* sector-specific skill prices, r_jt, $j=1,2,3$. Thus, from a computational standpoint, $\bar{r_t}$ is actually a 3x1 vector.

The solution algorithm is run separately for each gender g as follows:

1. For $a = 65$, randomly select $N = 500$ feasible state vectors:

$$\{\tilde{\Omega}_t^n(a) = \{(Exp_1 + 1, Exp_2, Exp_3, Educ, Kids(a), Sector, \bar{r}_t)\}_{n=1}^N$$

2. For each state vector n, draw 200 utility shocks from the joint distribution $\bar{\epsilon}$ and compute $EV\Omega_t^n(a)$ using the Monte Carlo method described above.

3. Regress $\{EV\Omega_t^n(a)\}_{n=1}^N$ on a complete second-order polynomial function of $\{\tilde{\Omega}_t^n(a)\}$:

$$EV\Omega_t^n(a) =$$

$$exp(\delta_0 + \delta_1 Exp_1 + 1 + +\delta_2 Exp_2 + \delta_3 Exp_3 + \delta_4 Educ + \delta_5 Kids(a) + \delta_6 \bar{r}_t + \delta_7 Sector) + G$$

   where G is a set of square and cross terms. The coefficient estimates are then used to approximate $EV\Omega_t(a)$ for the remaining state vectors for age 65.

4. Use the Bellman equations specified in Section 2 to repeat steps 1 through 3 for all ages 64 through 16.

The interpolation regression provides a good fit of the value functions to the state variables; the R-squared values are 0.97 or above for each age and gender.

B Weighting Matrix and Standard Errors

The simulated method of moments (SMM) estimation procedure minimizes the weighted distance between the simulated and actual moments. Let X_{ik} be i^{th} observation of the k^{th} moment, and let N_k be the number of individuals that comprise the k^{th} moment. The sample moment is defined as:

$$m_k = \frac{\sum_{i=1}^{N_k} X_{ik}}{N_k}$$

which is the mean conditional moment computed from the LFS data. Denote the corresponding simulated moment as $m_k^s(\theta)$. The SMM estimation procedure finds the parameter vector, θ, that minimizes the distance between $m_k^s(\theta)$ and m_k. Each moment condition is computed as $g_k(\theta) = \frac{m_k^s(\theta) - m_k}{m_k}$. Note that each moment is scaled by $\frac{1}{m_k}$, the true moment. This ensures that all moments are within a narrow range of values.

The vector of moment conditions is:

$$g(\theta) = [g_1(\theta), g_2(\theta), ..., g_K(\theta)]$$

where K in the total number of moments used. The objective function to be minimized is:

$$L(\theta) = g(\theta)' W g(\theta)$$

Following Lee and Wolpin (2006), two assumptions are made with regard to the weighting matrix:

1. W is diagonal
2. $E\left[g_k(\theta)\right] = \frac{\sigma_k^2}{N_k}$

where σ_k^2 is the sample variance of the k^{th} moment.

As mentioned in Section 5, the estimation is conducted in two stages. Correspondingly, the weighting matrix W is computed twice:

1. In the first stage, which assumes adaptive expectations, it is assumed that $\sigma_k^2 = 1$ and each k sample moment is weighted by N_k. Thus, the diagonal elements of W consists of the K values of N_k. Let $\hat{\theta}_A$ be the first-stage estimate of θ.

2. In the second stage, which assumes rational expectations, σ_k^2 is updated as follows:

$$\sigma_k^2 = \left[g_k(\hat{\theta}_A)\right]^2$$

   Each k sample moment is weighted by $\frac{N_k}{\sigma_k^2}$. Thus, the diagonal elements of W consists of the K values of $\frac{N_k}{\sigma_k^2}$.

The variance covariance matrix of the parameter estimates is defined as $V = (D'WD)^{-1}$, where D is the matrix of partial derivatives of the moments with respect to each parameter and W is the weighting matrix computed in the second stage. The standard errors of the parameter estimates are the square roots of the diagonal elements of V.

C Reduced Form Estimation

To begin the SMM estimation procedure, an initial guess of the structural parameters must be tested. A good initial guess is important in preventing the parameter search algorithm from getting permanently 'stuck' near a 'bad' local minimum. To obtain a good starting guess, a simple reduced-form version of the structural choice model is estimated. While this simpler model fails to capture many of the aspects of the structural model, it nevertheless provides an idea of the magnitudes and signs of the structural parameters.

The reduced form model is adapted from Lee and Trost (1984) and is implemented in two stages. In the first stage, the utility attached to each of the $J = 5$ labor market alternatives is estimated. Just as in the structural model, the five alternatives are agriculture, manufacturing, services, school, and home production. In the second stage, the wage equations for each of the three sectors are estimated using a selection correction term computed in the first stage.

The utility derived by individual i in choosing alternative j is:

$$U_{ij} = \beta_j' X + \epsilon_{ij}$$

where X is a vector of individual characteristics and year dummies, β is a vector of coefficients, and ϵ_{ij} is an idiosyncratic shock that is iid and drawn from an extreme-value distribution (McFadden, 1974). The probability of choosing alternative $j = 1, ..., 5$ is:

$$P_j = \frac{exp(\beta_j' X)}{\sum_{k=1}^{J} exp(\beta_k' X)} \tag{24}$$

The coefficients β_j are estimated via maximum likelihood. The estimated coefficients are then used to compute the selection correction term, λ_j:

$$\lambda_j = \frac{\phi(G(\hat{\beta}_j' X))}{F(\hat{\beta}_j' X)}, s = 1, 2, 3$$

where ϕ is the standard normal density function, Φ is the standard normal distribution function, and $G(\hat{\beta}_j' X) = \Phi F(\hat{\beta}_j' X)$.

The selection correction term, λ_j, is inserted into the wage equation which is estimated via ordinary least squares:

$$W_j = \gamma_j Y + \delta_j \lambda_j + \xi_j, j = 1, 2, 3 \tag{25}$$

The estimation results for the choice and wage equations are given in Tables C.1 and C.2. The choice model was estimated with sector 1 (agriculture) as the base alternative. Therefore, the sector 1 utility parameters, β_1, are all normalized to 1. The remaining utility coefficients are measured relative to β_1.

D Capital Stock and Productivity Growth

The model can be used to conduct additional counterfactual experiments that measure the impact of trade-induced foreign direct investment (FDI) and productivity growth, both of which have been offered as explanations for rising skill premia in post-liberalization developing countries. In one experiment, the aggregate capital stock is allowed to grow starting from the time of the trade liberalization until it is 10% larger than its initial steady state value. As before, capital is perfectly mobile. Figure D.1 shows that this increased quantity of capital allocates into manufacturing and services, with agriculture experiencing capital outflow. The economy-wide skill premium — measured for education levels 3 and 4 versus 1 and 2 — is higher throughout the transition period and at the new steady state. This is not surprising since capital moved into the high-skill sectors and away from the low-skill sector.

In the second experiment, manufacturing productivity (A_2) is allowed to grow starting from the time of the trade reform until it is 10% larger than its initial steady state value. As shown in Figure D.1, the reallocation of capital favors manufacturing even more than in the first experiment. The skill premium shows a similarly large increase as in the previous experiment. Thus, the results conform to empirical evidence that trade liberalization combined with increases capital and technology results in greater wage inequality because these inputs disproportionately favor the high-skill sectors where capital has higher returns.

E The Role of Expectations

The above policy experiments were conducted assuming that individuals have rational expectations about future skill prices. This may have important implications for adjustment costs. Figure 8 shows that the manufacturing skill price gradually falls following the trade shock, and recovers slightly as the economy approaches steady state. This partial recovery occurs because the exodus of labor from manufacturing raises the return to human capital in that sector. Under rational expectations, individuals correctly predict that skill prices gradually fall and recover. Thus, some manufacturing workers who experience a wage decline after the trade shock may nevertheless opt to remain in manufacturing, because they build into their value functions the (correct) assumption that skill prices will rise again.

On the other hand, if individuals did not have perfect foresight, they will assume that the drop in the manufacturing skill price persists for some time. With static expectations, they will assume that the lower skill price will persist forever. This may compel more workers to exit manufacturing and incur switching costs at the beginning of the transition, and perhaps even re-enter at a later date once skill prices rise again. The implication is that without perfect foresight, movements in and out sectors may be higher, resulting in larger adjustment costs.

To test this conjecture, the economy's response to the trade policy shock is simulated under static expectations. Figure E.1 shows the evolution of output prices, sector choice proportions, and skill prices under static versus rational expectations. Under static expectations, the labor movement out of manufacturing overshoots at the start of the transition, with employment rising again after about 10 years. Consequently, employment in services and agriculture overshoots in the first 10 years. The variation in skill prices over time is larger as a result. The services output price shows a large decline before rising again to its new steady-state value.

Tables E.1, E.2 and E.3 show the aggregate and individual adjustment costs for the economy under adaptive expectations. Under adaptive expectations, adjustment costs consume over 27% of the long-run potential gains to trade, compared to 22% under rational expectations. Manufacturing workers experience a greater welfare decline under adaptive expectations: 18% compared to 13% under rational expectations. Taking all individuals in the economy, the lifetime welfare gain is 5.8% as opposed to 8.4% under rational expectations.

These results suggest that the efficacy of different labor market policies in reducing welfare losses and/or speeding up adjustment depends on whether expectations fall under perfect foresight, static, or something in between these two extremes. While the inter-sectoral movement out of manufacturing is too large at the beginning of the transition under static expectations, it also means that switchers incur large welfare losses. Therefore, a larger employment subsidy is needed to compensate the switchers, but is likely to increase aggregate adjustment costs since the subsidy encourages 'too much' switching.

F Tables

Table 1: Sector-specific Human Capital: parameter estimates

Variable	Agriculture	Manufacturing	Services
$(age-14)$	0.0430	0.0341	0.0242
	(0.00007)	(0.00034)	(0.00019)
$(age-14)^2$	-0.0009	-0.0010	-0.0011
	(0.000079)	(0.000074)	(0.000081)
$Educ$	0.0479	0.0703	0.0726
	(0.000012)	(0.000010)	(0.000002)
$Male$	0.1780	0.2303	0.1053
	(0.00155)	(0.00016)	(0.00026)
Exp_1	0.1073	0.0223	0.0349
	(0.00014)	(0.00035)	(0.00029)
Exp_2	0.0302	0.0978	0.0410
	(0.00051)	(0.000194)	(0.00011)
Exp_3	0.0340	0.0413	0.0954
	(0.00036)	(0.00045)	(0.000081)
SD of shock	0.5717	0.5523	0.7076
	(0.00028)	(0.00062)	(0.00063)

Table 2: School and Home Utility: parameter estimates

	School	Home
$Constant$	2.9918	3.62
	(0.0022)	(0.0014)
$(age-14)$	0.0003	0.0378
	(0.000018)	(0.000045)
$(age-14)^2$	-0.0630	-0.0002
	(0.0000122)	(0.0000737)
$Educ$	0.1439	0.0582
	(0.00024)	(0.0000471)
$Male$	0.2130	-0.2318
	(0.00016)	(0.00031)
$O'Level=1$	-0.5631	
	(0.0022)	
$A'Level=1$	-0.2422	
	(0.0010)	
$Kids$		0.1673
		(0.0092)
SD of shock	0.0597	20.41
	(0.00033)	(0.08998)

Table 3: Switching Costs: parameter estimates

Variable	Agriculture	Manufacturing	Services
$Constant$	1.85	1.47	1.21
	(0.0650)	(0.0096)	(0.0431)
$(age-14)$	0.0052	0.0023	0.0011
	(0.00088)	(0.00122)	(0.00065)
$(age-14)^2$	-0.00010	-0.00013	-0.00009
	(0.000019)	(0.000032)	(0.000011)
$Male$	-0.022	-0.041	-0.005
	(0.0011)	(0.0018)	(0.0008)

Table 4: Model vs. Data: choice proportions (%), 1992-2009

	Data	Reduced Form Model	Structural Model
$Agriculture$	19.27	19.02	19.44
$Manufacturing$	9.09	8.26	10.02
$Services$	25.66	26.13	26.02
$School$	10.58	10.78	10.08
$HomeProduction$	35.40	35.81	34.44

Table 5: Model vs. Data: mean log wages, 1992-2009

	Data	Reduced Form Model	Structural Model
$Agriculture$	2.964	3.067	3.058
$Manufacturing$	3.369	3.392	3.446
$Services$	3.645	3.444	3.707

Table 6: Long-run Welfare

	Long-run Gain (%)	% of Long-run Gain Lost
Welfare	9.16	22.38
GDP	6.36	22.06

Table 7: Long-run Welfare: without endogenous education

	Long-run Gain (%)	% of Long-run Gain Lost
Welfare	16.0	30.52
GDP	14.57	30.94

Table 8: Welfare Changes: Manufacturing Workers

All	13.2466	
	Low Educ	High Educ
Age 15-29	2.3165	13.0154
Age 30-44	5.8336	11.3714
Age 45-65	9.9713	21.8148

Table 9: Welfare Changes: All Individuals

All	-8.4335	
	Low Educ	High Educ
Age 15-29	-13.6596	-6.8692
Age 30-44	-21.1321	-20.4988
Age 45-65	1.4750	13.2613

Table 10: Long-run Welfare under Different Labor Market Policies

	Long-run gain	Adjustment Cost			
		No Policy	Education Subsidy	Employment Subsidy	Vocational Training
Output	8.96	22.06	22.22	20.66	22.53
Welfare	5.16	22.38	16.61	28.47	14.97

Table 11: Welfare Losses under Different Labor Market Policies: Manufacturing Workers, Low Educ

	No Policy	Education Subsidy	Employment Subsidy	Vocational Training
All	14.2466	11.7778	6.5196	-4.3435
Age 15-29	2.3165	-2.1573	-10.2378	-14.5649
Age 30-44	5.8336	7.1338	4.0833	-2.6283
Age 45-65	9.9713	9.4911	3.7877	-3.5483

Table 12: Welfare Losses under Different Labor Market Policies: Manufacturing Workers, High Educ

	No Policy	Education Subsidy	Employment Subsidy	Vocational Training
All	14.2466	11.7778	6.5196	-4.3435
Age 15-29	13.0154	8.9352	-8.1637	-10.3403
Age 30-44	11.3714	9.7574	7.4451	-4.6351
Age 45-65	21.8148	20.1205	18.6873	3.0167

Table C.1: Reduced-form Model: choice parameters:

	Manufacturing	Services	School	Home
age	-0.0140	0.1054	-1.2991	-0.2130
	(0.0029)	(0.0023)	(0.0057)	(0.0020)
age^2	-0.0001	-0.0012	0.0153	0.0029
	(0.0000)	(0.0000)	(0.0001)	(0.0000)
$Kids = 1$	0.0526	0.1956	0.0363	0.2952
	(0.0131)	(0.0098)	(0.0198)	(0.0096)
$Kids = 2$	-0.0824	0.2562	0.0146	0.4213
	(0.0194)	(0.0137)	(0.0334)	(0.0133)
$Educ$	0.1521	0.2374	0.6622	0.1245
	(0.0015)	(0.0012)	(0.0040)	(0.0011)
$Male$	-0.5601	0.6713	-1.1285	-1.7900
	(0.0120)	(0.0099)	(0.0147)	(0.0093)
Constant	0.9211	-2.1720	16.5807	5.9907
	(0.0593)	(0.0477)	(0.07904)	(0.04292)

Table C.2: Reduced-form Model: wage parameters:

Variable	Agriculture	Manufacturing	Services
age	0.0220	0.0512	0.0804
	(0.0020	(0.0017)	(0.0019)
age^2	-0.0003	-0.0006	-0.0008
	(0.0000	(0.0000)	(0.0000)
$Educ$	0.0265	0.0695	0.1113
	(0.0019	(0.0010)	(0.0010)
$Male$	0.1410	0.3176	0.1663
	(0.0112	(0.0056)	(0.0125)
Constant	2.3026	1.3262	0.4875
	(0.0747	(0.0502)	(0.0643)

Table E.1: Long-run Welfare under Adaptive Expectations:

	Long-run Gain (%)	Adjustment Cost (% of Long-run Gain)
Output	9.10	27.17
Welfare	5.19	27.76

Table E.2: Welfare Losses under Adaptive Expectations: Manufacturing Workers:

All	18.6157	
	Low Educ	High Educ
Age 15-29	6.8975	19.5197
Age 30-44	9.0066	18.4746
Age 45-65	14.1864	24.2922

Table E.3: Welfare Losses under Adaptive Expectations: All Individuals:

All	-5.8432	
	Low Educ	High Educ
Age 15-29	-7.9945	-2.4813
Age 30-44	-14.9265	-15.4935
Age 45-65	5.4662	19.7502

G Figures

Figure 1: Choice Proportions by Gender and Age

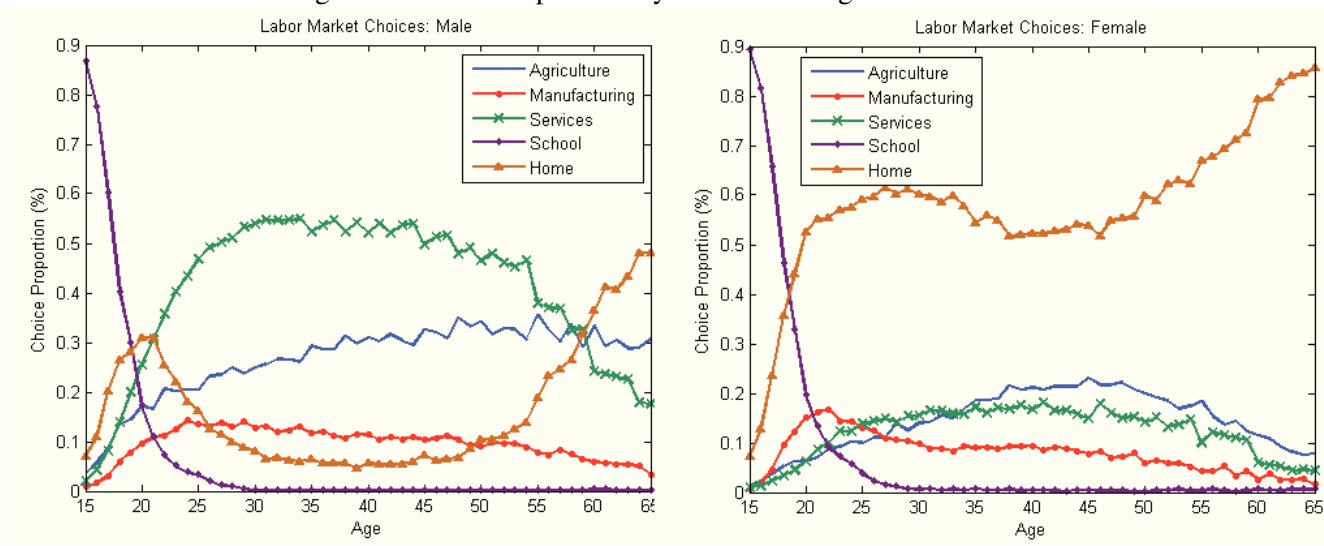


Figure 2: Age-Wage Profiles by Gender

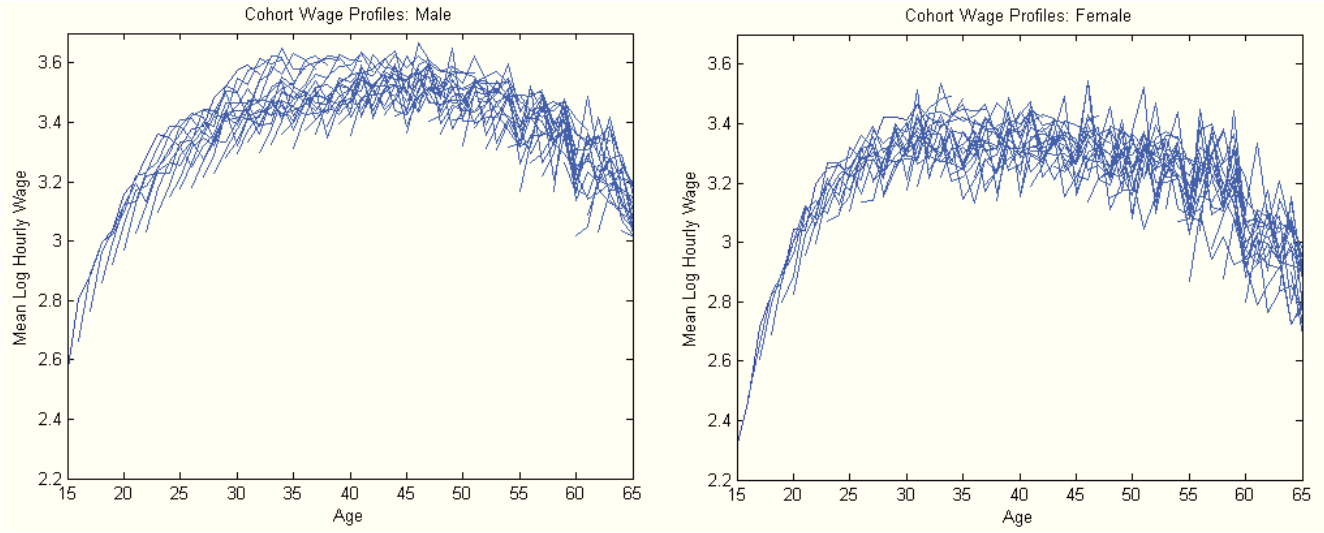


Figure 3: Mean Log Wages by Year, Sector and Gender

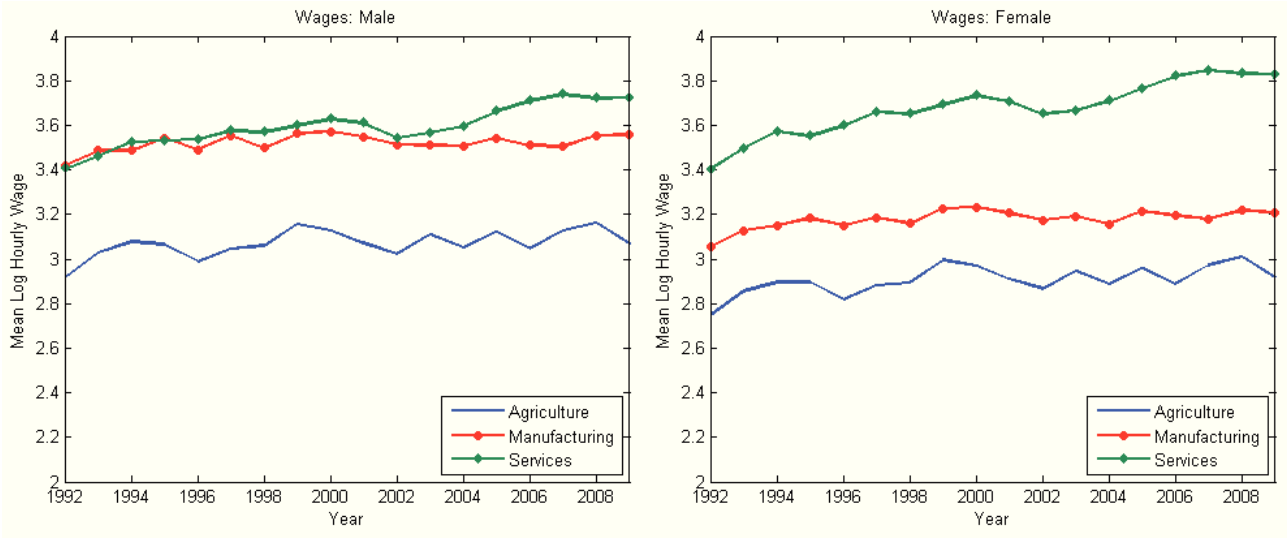


Figure 4: Average Number of Pre-School Children by Gender

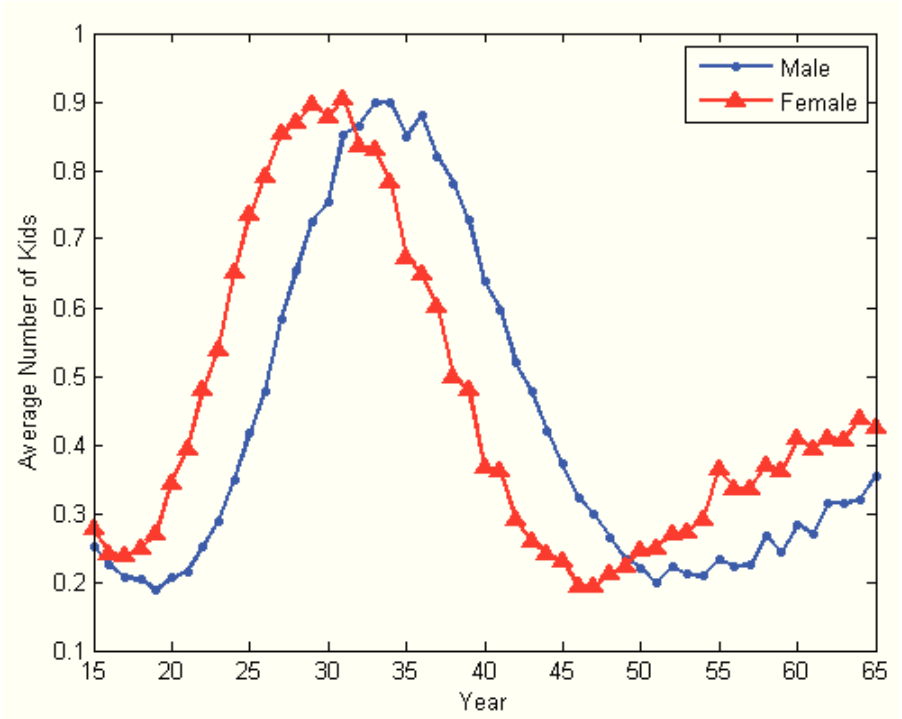


Figure 5: Proportion Who Have Never Worked, Ages 22-65

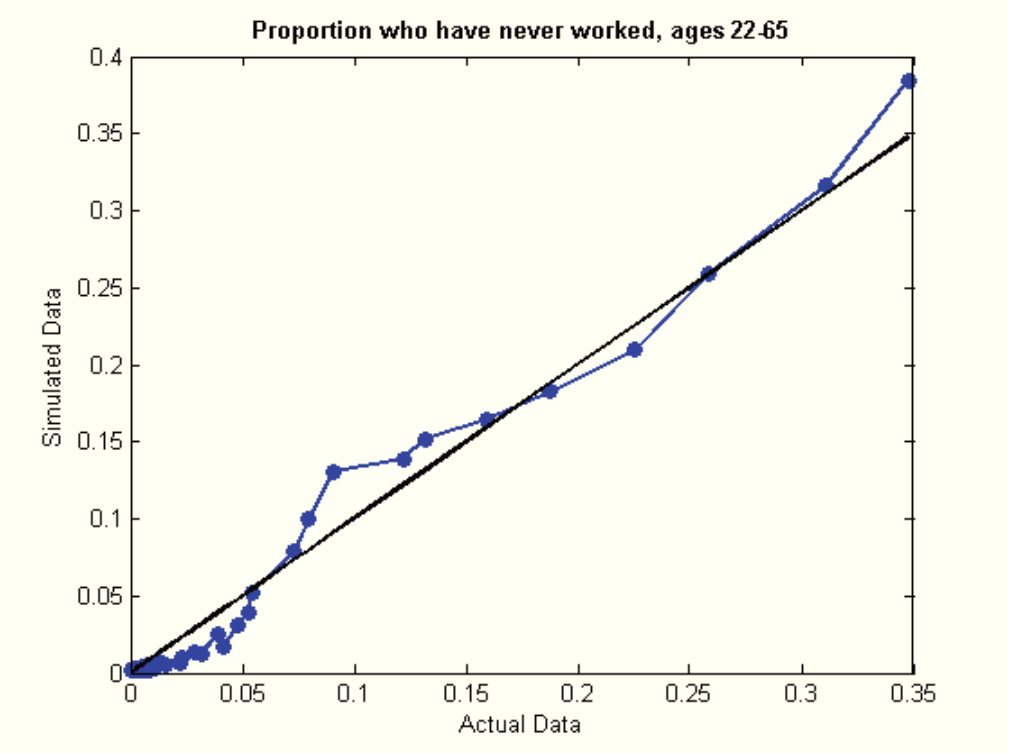


Figure 6: Reservation Wages

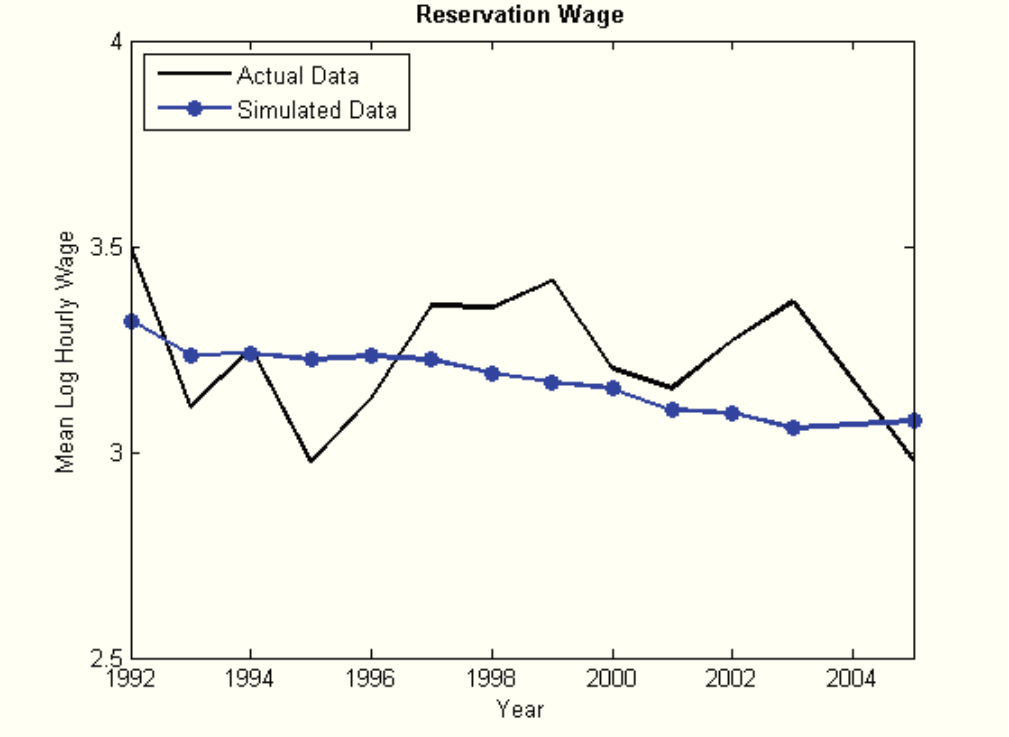


Figure 7: Wages by Number of Kids

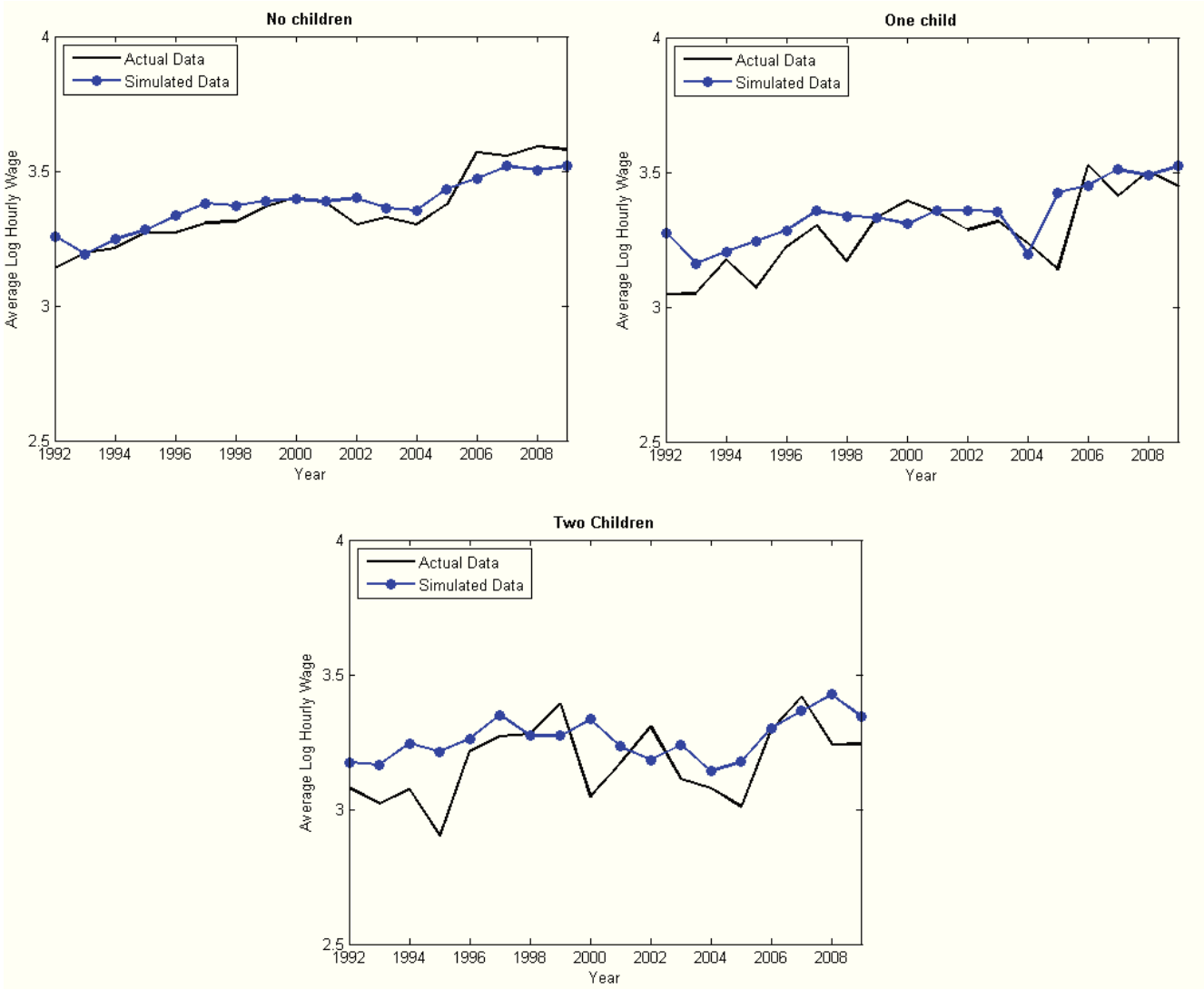


Figure 8: Transitions

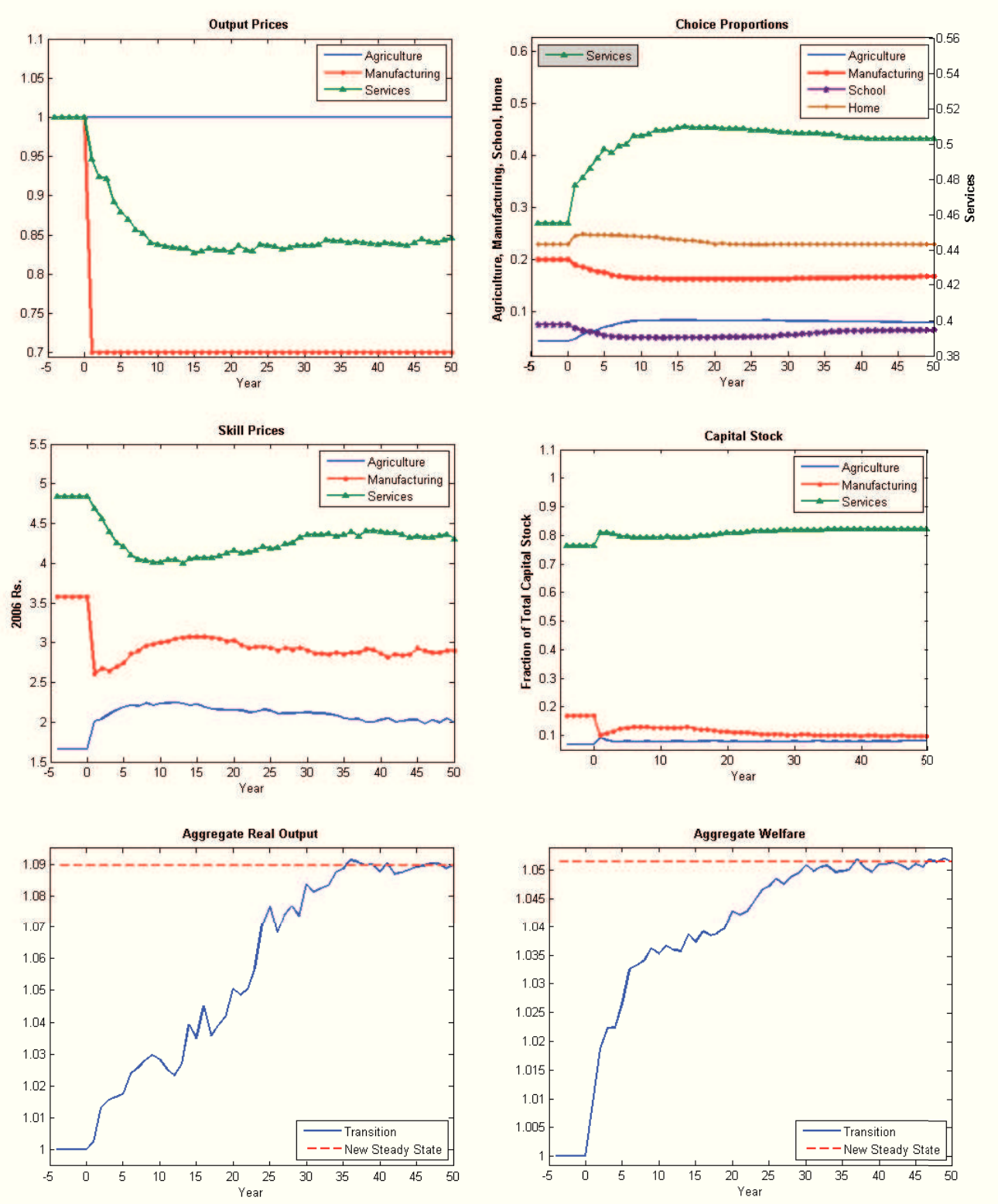


Figure 9:

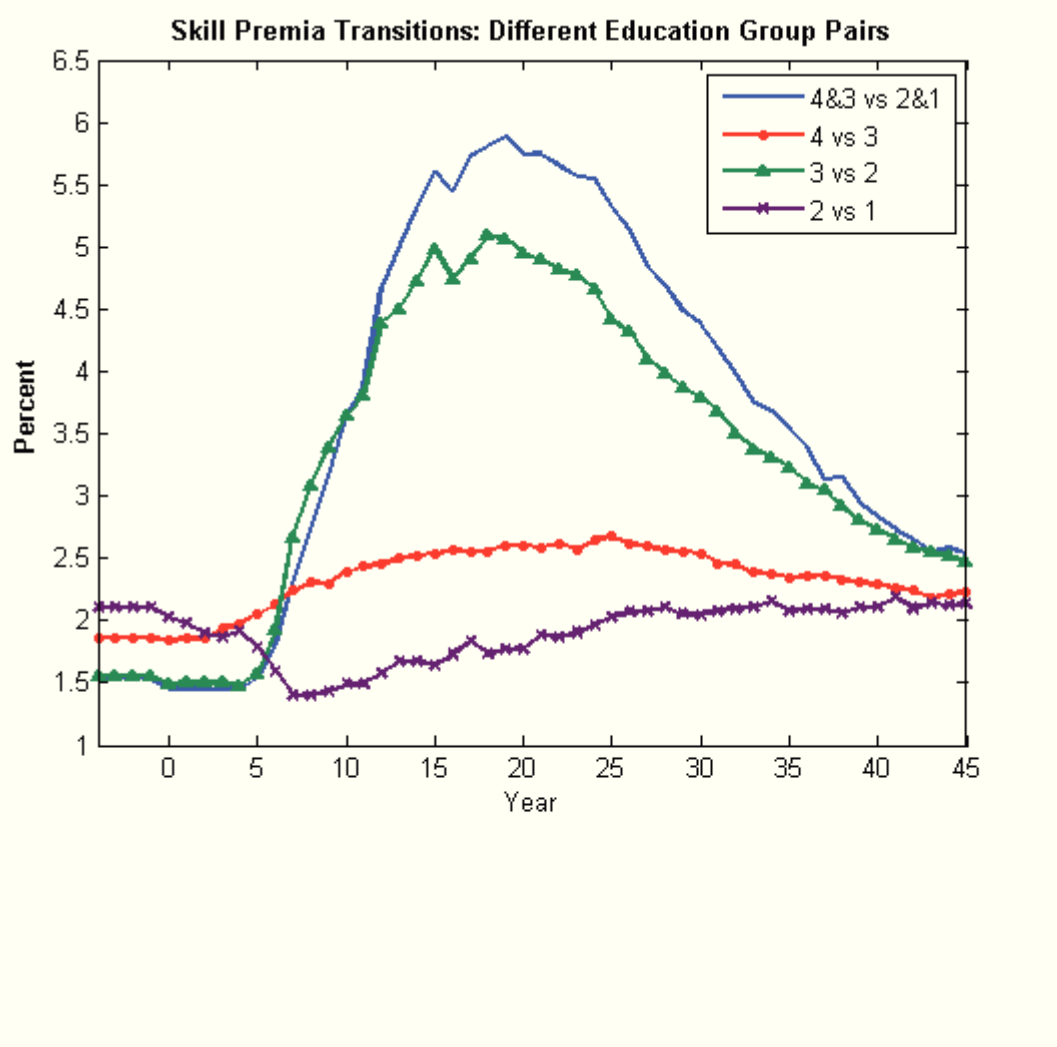

Skill Premia Transitions: Different Education Group Pairs
Percent
Year
4&3 vs 2&1
4 vs 3
3 vs 2
2 vs 1
6.5
6
5.5
5
4.5
4
3.5
3
2.5
2
1.5
1
0
5
10
15
20
25
30
35
40
45

Figure 10: Transitions: Proportion of Highest and Lowest Educated Workers by Sector

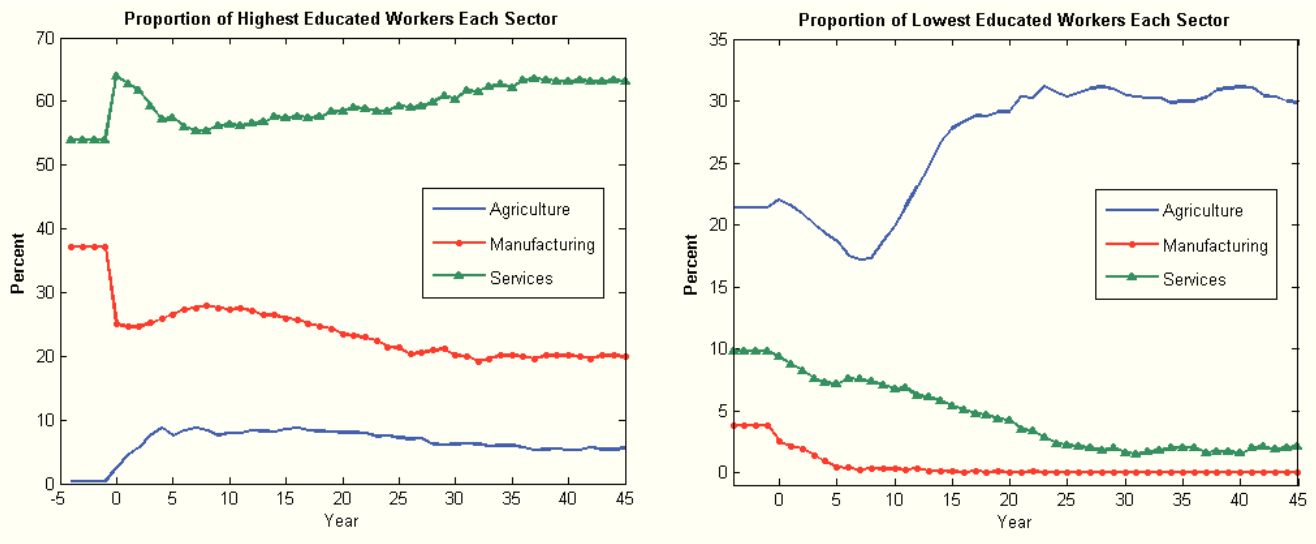


Figure 11: Transitions: Labor Market Policies

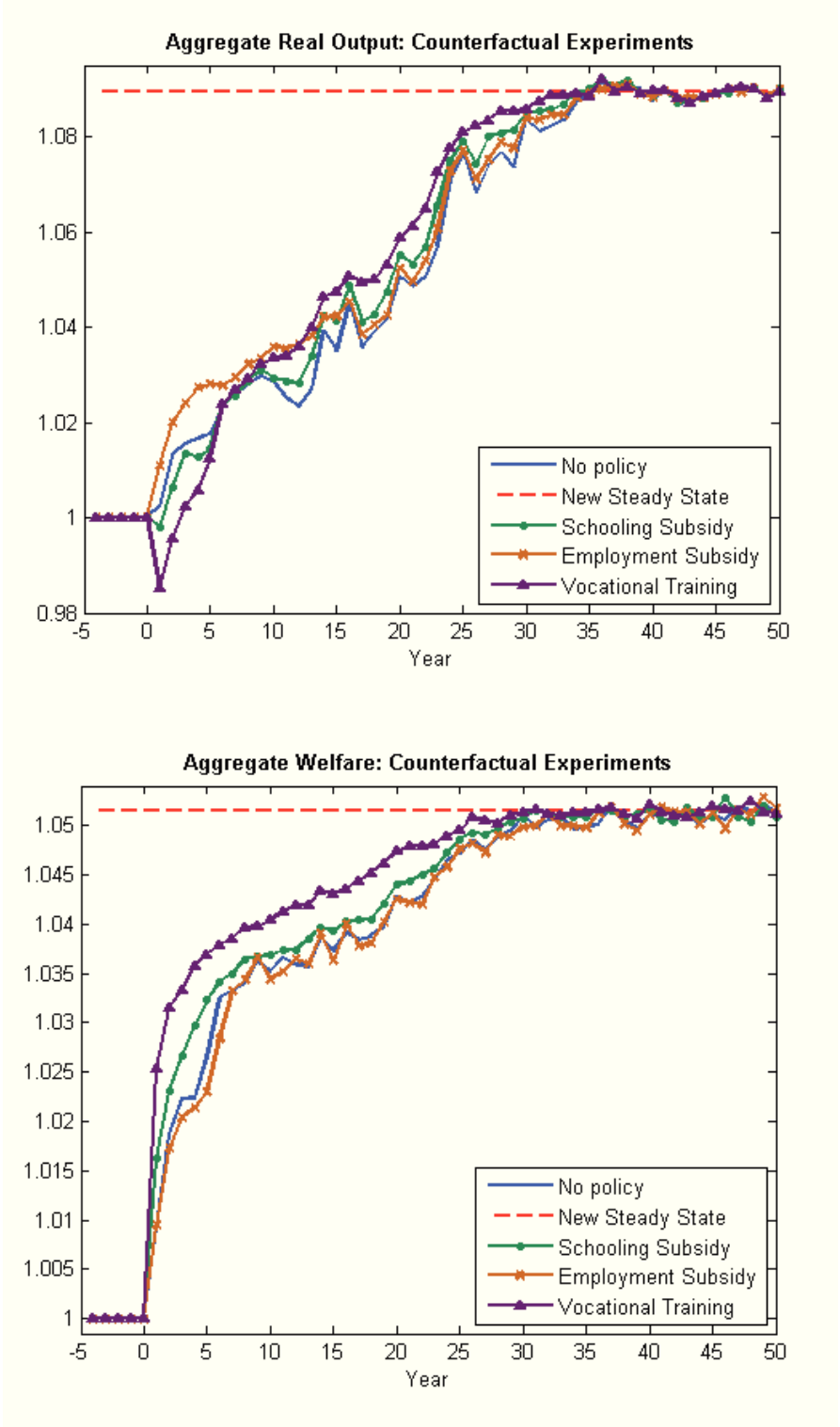


Figure 12: Skill Premium Transitions: With and Without Endogenous Human Capital

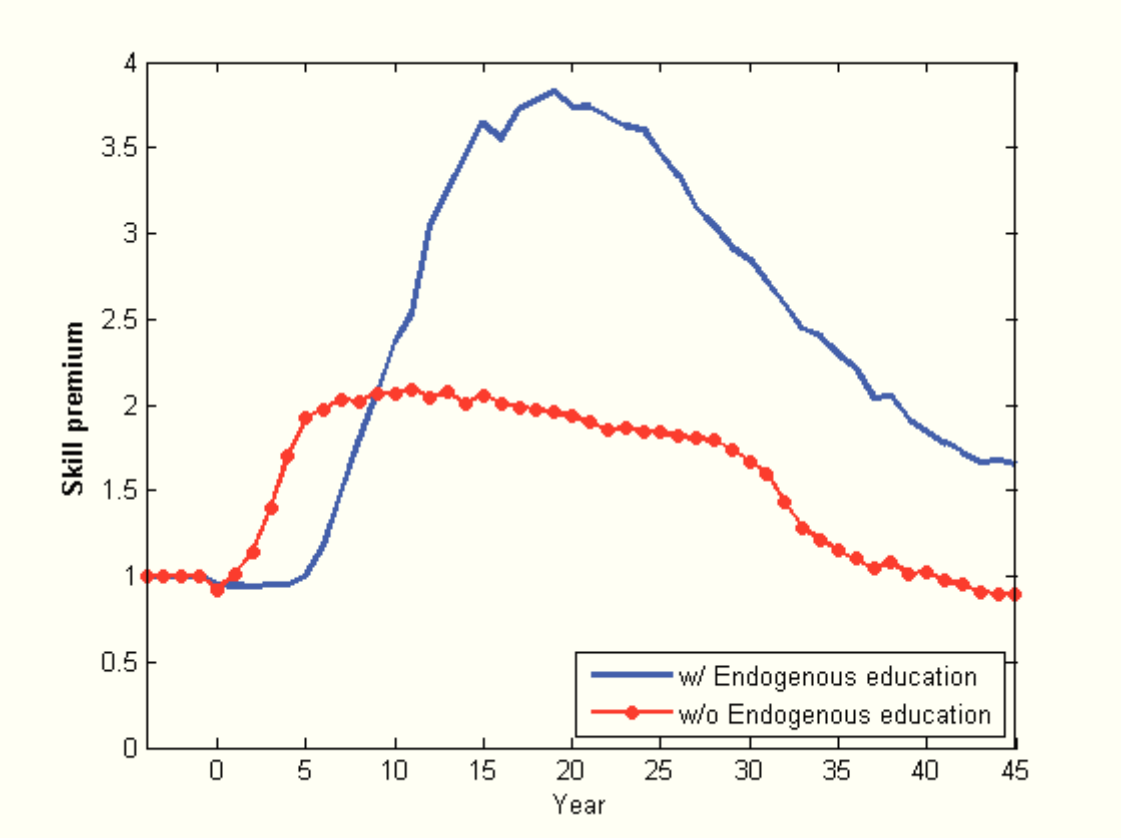


Figure D.1: Transitions: With Aggregate Capital and Manufacturing Productivity Growth:

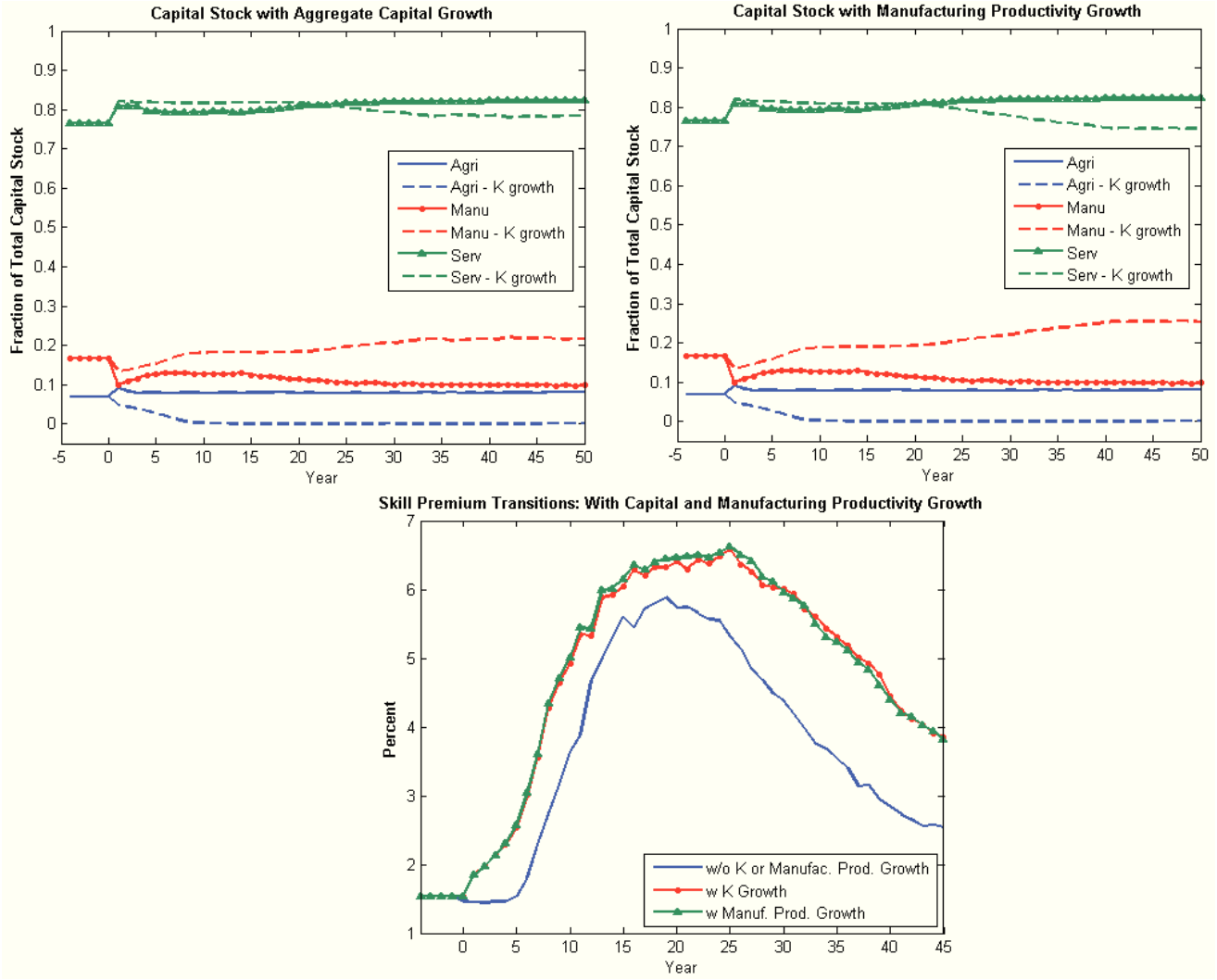
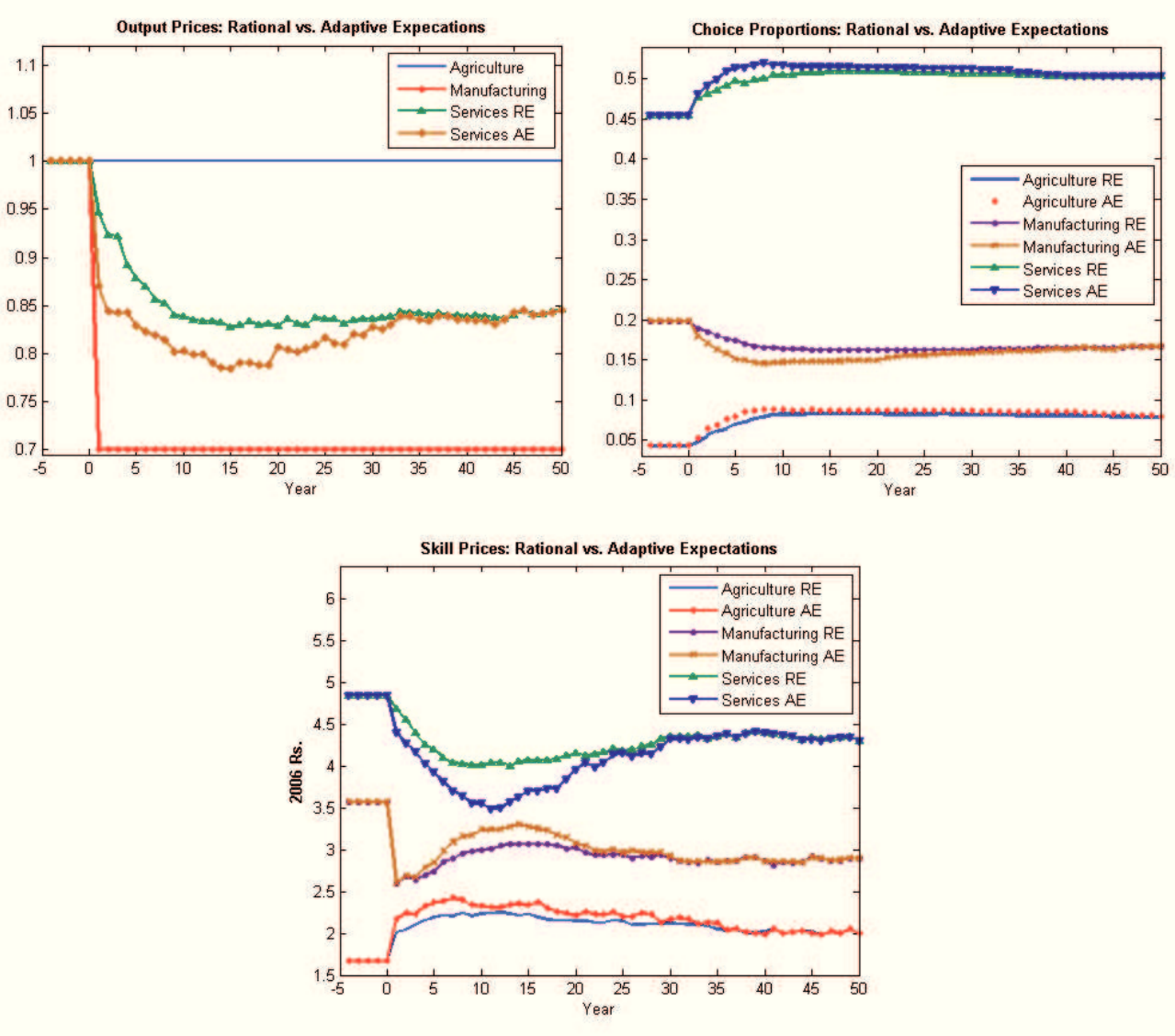


Figure E.1: Transitions: Rational vs. Adaptive Expectations:



Trade Liberalization and the Skill Premium: The Role of Factor Accumulation and Technology Spillovers

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Abstract

Empirical studies document rising wage inequality in a number of developing countries that liberalized trade, contradicting the predictions of the static Heckscher-Ohlin model. This trend has been attributed to trade-induced skill-biased technology from abroad. This paper develops a dynamic equilibrium model with endogenous physical and human capital accumulation, and demonstrates that trade liberalization can lead to rising skill premia *even in the absence of technology spillovers*. The time span of rising skill premia depends on the rate at which human capital adjusts to the new policy environment. This result highlights the shortcomings of reduced-form empirical work that correlates wage changes with changes in trade indicators across different points in time. In the presence of technology spillovers, the skill premium rises even more. However, the impact on factor *demand* depends on the type of technology; relative demand for low-skill labor decreases with skill-biased technical change (SBTC), but increases with total factor productivity growth. Using industry and labor force survey data from Sri Lanka — a small open developing country — the empirical analysis finds evidence of SBTC accompanying liberalization of the manufacturing sector. Skill premia have increased while employment and wage bill shares for low-skill labor have decreased; this is true regardless of how skill is defined. These results highlight the importance of labor market dynamics in determining the post-liberalization outcomes for wage inequality and human capital investment, and their interaction with technology.

*This research was conducted with restricted access data from the Department of Census and Statistics, Sri Lanka. All errors are my own.

1 Introduction

A surprising result from the empirical trade literature is that wage inequality increased in developing countries following trade liberalization.[1] This contradicts the prediction of the static Heckscher-Ohlin model; that wage inequality declines in low-skill abundant countries that liberalize trade. Rising wage inequality has been attributed to trade-induced skill-biased technology spillovers from abroad, and some empirical studies find evidence supporting this hypothesis.[2] This paper develops a dynamic, overlapping generations (OLG), general equilibrium model in which physical and human capital accumulation is determined by the optimizing investment decisions of households. The model demonstrates analytically that liberalization of the high-skill intensive sector can lead to rising skill premia along the transition path *even in the absence of technology spillovers*. The length of time in which the skill premium monotonically rises depends on the rate at which human capital adjusts to the new policy environment. In general, the impact of liberalization on the model's state variables differ significantly over the short vs. long run. These results have an important empirical implication; the perceived outcome of trade policy could depend on the time frame chosen for analysis. This highlights the shortcomings of empirical studies that correlate wage changes and changes in trade indicators across different points in time.

The model further demonstrates that trade-induced technology spillovers have ambiguous implications for differently skilled workers. While technology raises the skill premium, relative skill *demand* depends on the type of technology involved. Relative demand for low-skill labor decreases in the presence of skill-biased technical change (SBTC), but increases when technical change raises total factor productivity (TFP). Therefore, the impact of trade-induced technical change on the relative fortunes of low- versus high-skill labor is an empirical question that this paper attempts to answer. The empirical analysis is conducted with detailed industry and labor force survey data from Sri Lanka, a small open developing country that has experienced rising wage inequality since embarking on a program of trade reforms in the late 1970s. Technology is assumed to be embedded in imports of capital goods. The results show SBTC has been the dominant form of technical change in Sri Lanka. Increases in skill premia have coincided with declines in the employment and wage-bill shares of low-skilled labor. These results hold

[1] A large literature documents the relationship between wages and trade indicators in several countries. Some examples are Attanasio, Goldberg, and Pavcnik (2004) for Colombia, and Robbins (1996), Wood (1997) and Goldberg and Pavcnik (2007) for several Latin American and Asian countries.

[2] For example, Attanasio et al. (2004) conclude that skill-biased technical change (SBTC) may have been an indirect consequence of Colombia's trade liberalization, and that SBTC was more rapid in industries subjected to larger tariff reductions.

regardless of how 'skill' is defined.

This paper is related to previous work on the impact of trade liberalization on skill acquisition. Findlay and Kierzkowski (1983) develop a two-good, two-factor trade model in which education capital is an input to producing skilled labor. Using comparative statics, they show that the country with higher per capita education capital will export the skill-intensive good and increase its relative endowment of skilled labor following trade liberalization, thus amplifying its initial comparative advantage. This paper departs from their analysis in its use of a dynamic framework that allows for non-monotonic transitions of the state variables to their new steady state values. In Blanchard and Willmann (2013), ex-ante heterogeneous workers optimally choose among a continuum of skill levels, each mapped to a different production sector. In their comparative statics analysis, cross-country differences in education cost functions drive comparative advantage. However, eduction is not a sunk cost in their model, thus underestimating the welfare losses to workers who switch sectors.

In a related paper from the labor literature, Abraham (2008) develops a dynamic overlapping generations model with costly education investment and exogenous skill-biased technological progress. He uses numeric simulations to show that education investment and the wage skill premium both evolve non-monotonically, matching the non-cyclical evolution of college enrollment and the college wage premium in the US. This paper is similar to his in that sunk education costs and the finite individual time horizon interact to produce non-monotonic transitions between steady states. However, this paper differs from his in that it develops a tractable model that can be solved analytically while producing equally rich dynamics within an international trade setting.

The paper is organized as follows. Section 2 develops a dynamic overlapping generations model in which individual choices in consumption and investment in physical and human capital determine production, trade flows, wages, and thus, the economy's response to a trade policy change. Section 3 demonstrates analytically the impact of trade liberalization on the economy in the short, medium and long run. The differences in transition dynamics with and without trade-induced technology spillovers are highlighted. Section 4 conducts a numeric calibration of the model and visually demonstrates the transitional dynamics from Section 3. Section 5 conducts an empirical analysis to test whether rising wage inequality in Sri Lanka is due to trade-induced technology spillovers, and if so, the type of technology involved. Section 6 concludes.

2 Model

This section develops a dynamic overlapping generations version of the two-good, three-factor, specific factors model of Ricardo-Viner-Samuelson-Jones.[3] The combination of specific-factors with overlapping generations allows the model to capture the short, medium and long-run effects of trade liberalization. Individuals live for two periods and maximize lifetime utility by choosing their consumption, saving and skill levels while young. Individual decisions collectively determine the economy's production levels, physical and human capital stocks, trade flows, and wages.

2.1 Production

The economy produces two goods: X is both a consumption good and an investment good, and Y is a consumption good. The production functions are:

$$X = A_x H^{\alpha_x} K_x^{1-\alpha_x}$$

$$Y = A_y L^{\alpha_y} K_y^{1-\alpha_y}$$

where K_x and K_y are physical capital, H is high-skill labor, L is low-skill labor, and A_x and A_y are total factor productivity in each sector. High-skill labor is specific to the consumption-investment goods sector, while low-skill labor is specific to the consumption goods sector. Physical capital is perfectly mobile between sectors. The specific-factors assumption facilitates analytical results. However, individuals in each generation choose whether to become skilled or not, and thus, which sector to join. Labor supply is therefore mobile between sectors even though skills are not.

2.2 Factor prices

Factor markets are perfectly competitive, which means factors payments equal their marginal value products. The wages paid to a low-skill and high-skill workers are, respectively:

$$r^L = \frac{P_x \alpha_x X}{L} \tag{1}$$

$$r^H = \frac{P_y \alpha_y Y}{H} \tag{2}$$

[3] Viner (1931) first examined the specific factors model, and it was later formalized into a general equilibrium setting by Samuelson (1971) and Jones (1971).

where P_x and P_y are output prices for goods X and Y. Because of perfect inter-sectoral capital mobility, the rental rate is equal across sectors:

$$r^K = \frac{P_x(1-\alpha_x)X}{K_x} = \frac{P_y(1-\alpha_y)Y}{K_y} \tag{3}$$

Output prices are defined as $P_x = P_x^w(1+\tau_x)$ and $P_y = P_y^w(1+\tau_y)$, where P_x^w and P_y^w are the domestic prices for each good, and τ_x and τ_y are the ad-valorem import tariff rates imposed on each good. The domestic prices, P_x^w and P_y^w, are assumed to be the same as world prices and are taken as given (small open economy assumption).

2.3 Household decisions

Households consist of individuals who live for two periods. They provide labor services when young and consume out of their savings when old. Every young individual makes two choices to maximize his present discounted lifetime utility; whether to invest in education and how much of each good to consume.

If he chooses to invest in education, he works in sector X, and if not, in sector Y. Individuals are ex-ante heterogeneous in ability, γ, which determines their education costs. The distribution of ability, $F(\gamma)$, is exogenous and identical across generations, and each individual knows his draw of γ. For individual i who is young at time t, the decision to become skilled maximizes wages net of education costs:

$$w_{it} = \max\left\{r_t^H - P_{yt}\cdot e(\gamma_i), r_t^L\right\}$$

Education costs are in terms of the consumption good, Y. The cost function is:

$$e(\gamma) = \kappa_0 + \kappa_1\gamma$$

where $\kappa_0 > 0$ and $\kappa_1 < 0$ are parameters.

The young individual must also choose his consumption level to maximize his present discounted lifetime utility:

$$U = U_t^1 + \beta U_{t+1}^2 \tag{4}$$

The superscripts 1 and 2 stand for 'young' and 'old', respectively, and β is the time discount rate. Flow utility at any age is a constant elasticity of substitution (CES) function of goods X and Y. Flow utility for young and old individuals are, respectively:

$$U_t^1 = \left[\left(C_{xt}^1\right)^{\rho} + \phi \left(C_{yt}^1\right)^{\rho} \right]^{\frac{1}{\rho}} \tag{5}$$

$$U_t^2 = \left[\left(C_{xt}^2\right)^{\rho} + \phi \left(C_{yt}^2\right)^{\rho} \right]^{\frac{1}{\rho}} \tag{6}$$

The parameter ϕ is the weight given by consumers to good Y relative to good X, and ρ captures the degree of substitutablity of the two goods.[4] For simplicity, it is assumed that the two goods have equal weight ($\phi = 1$).

The aggregate net income of all young individuals living at time t is:

$$W_t^1 = r^L L + r^H H - P_{yt} E \tag{7}$$

where $r^L L$ is total labor income to young low-skill individuals, $r^H H$ is total labor income to young high-skill individuals, and $P_{yt}E$ is total education costs. The aggregate net income of old individuals living at time t is:

$$W_t^2 = P_{xt} K_t \left[1 + \frac{r_t^K}{P_{xt}} - \delta \right] \tag{8}$$

where K_t is the aggregate capital stock, $\frac{r_t^K}{P_{xt}}$ is the real rental rate, and δ is the depreciation rate for capital.

The maximization problem yields the following aggregate consumption demand functions for goods X and Y for young and old individuals:

$$C_{xt}^1 = \left(\frac{P_{xt}^{-\sigma}}{P_{xt}^{1-\sigma} + P_{yt}^{1-\sigma}} \right) \left(\frac{1}{1+\beta} \right) W_t^1 \tag{9}$$

$$C_{yt}^1 = \left(\frac{P_{yt}^{-\sigma}}{P_{xt}^{1-\sigma} + P_{yt}^{1-\sigma}} \right) \left(\frac{1}{1+\beta} \right) W_t^1 \tag{10}$$

$$C_{xt}^2 = \left(\frac{P_{xt}^{-\sigma}}{P_{xt}^{1-\sigma} + P_{yt}^{1-\sigma}} \right) W_t^2 \tag{11}$$

$$C_{yt}^2 = \left(\frac{P_{yt}^{-\sigma}}{P_{xt}^{1-\sigma} + P_{yt}^{1-\sigma}} \right) W_t^2 \tag{12}$$

where $\sigma = \frac{1}{1-\rho}$. Aggregate saving by young individuals is:

[4] The goods are perfectly substitutable if $\rho = 1$, not substitutable if $\rho = -\inf$, and have constant elasticity of substitution if $\rho = 0$.

$$S_t = \left(\frac{\beta}{1+\beta}\right) W_t^1 \tag{13}$$

2.4 Market clearing

At any time t, old individuals derive income by selling all of their capital stock holdings, net of depreciation, to young individuals. The savings of young individuals at time t are used to purchase the capital holdings of the old generation, $(1-\delta)K_t$, and pay for any new investment, X_t^I. With no international borrowing and saving, domestic saving equals domestic physical capital investment:

$$S_t = P_{xt} \cdot (1-\delta)K_t + P_{xt}X_t^I$$

The capital stock that enters period $t+1$ is therefore the stock of all capital investment purchases made by the young generation alive at time t. Because saving equals investment, this must equal real saving at time t:

$$K_{t+1} = (1-\delta)K_t + X_t^I = \frac{S_t}{P_{xt}} \tag{14}$$

Aggregate demand for good X is the sum of young and old consumption demand, C_{xt}^1 and C_{xt}^2, and investment demand X_t^I. Aggregate supply of good X is the sum of domestic production, X_t, and net imports, X_t^m. The market for good X clears by the equalization of aggregate demand and supply:

$$C_{xt}^1 + C_{xt}^2 + X_t^I = X_t + X_t^m \tag{15}$$

Aggregate demand for good Y is the sum of young and old consumption demand, C_{yt}^1 and C_{yt}^2, and total education costs, E_t. Market clearing for good Y is:

$$C_{yt}^1 + C_{yt}^2 + E_t = Y_t + Y_t^m \tag{16}$$

where Y_t^m is net imports of good Y. With no international borrowing and saving, the trade balance is zero each period:

$$P_{xt}X_t^m + P_{yt}Y_t^m = 0 \tag{17}$$

2.5 Skill distribution

Each individual's ability, γ, is drawn from a uniform distribution, $F(\gamma)$, with minimum and maximum values of $\overline{\gamma}$ and $\underline{\gamma}$, respectively. Denote as γ^* the threshold level of ability that makes an individual indifferent between becoming educated versus not. The stock of high-skill human capital in the economy at time t is:

$$H_t = \frac{\bar{\gamma} - \gamma^*}{\bar{\gamma} - \underline{\gamma}} \cdot \left[\mu_1 + \mu_2 H_{t-1}^{\mu_3}\right] \tag{18}$$

where μ_1, μ_2 and μ_3 are positive parameters. This equation shows that H_t is a decreasing function of γ^* (the threshold ability level) and an increasing function of H_{t-1}, the previous time period's stock of high-skill human capital. This specification allows the impact of previous generations' choices to persist over time. (If $\mu_2 = 0$, then H_t only depends on the current generation's education choices.)

If individuals lived — and worked — for many periods, then older generations will also supply labor services. Because of the finite-horizon lifetime, older generations may find it too costly to adjust their level of education in response to any change in market conditions. This is because the benefits of such an adjustment can only be reaped over their short remaining working life. Moreover, since education costs are sunk, education adjustment can only occur in one direction; high-skill individuals cannot go back to becoming low-skilled and recover their prior education costs. Thus, with 40- or 50-year working lives, the early choices of older generations persist over time, preventing aggregate skill stocks from adjusting instantaneously in response to an economic shock.[5] The economy will therefore respond slowly to a tariff reduction or other exogenous change in market conditions. Equation 18 allows for this persistence within an analytically solvable two-period setting. As will be demonstrated below, the adjustment of human capital has key implications for the evolution of the skill premium.

The quantity of low-skill human capital at any given time t is:

$$L_t = \frac{\gamma^* - \underline{\gamma}}{\bar{\gamma} - \underline{\gamma}} \tag{19}$$

[5]The structural empirical trade literature estimates that the economy takes between 25 and 80 years to fully adjust to a single trade policy change. This is because older generations find it too costly to adjust their stocks of human capital in response to the policy change. See Artuc (2009), Artuc et al. (2010), Cosar (2013), Dix-Carneiro (2013) and Seneviratne (2013).

3 Trade Policy and the Skill Premium

This section demonstrates analytically the impact of a trade policy change on the economy. The analysis focuses on the impact of a tariff reduction on the skill premium and relative factor employment during the economy's transition to its new steady state. Moreover, the implications for the short, medium, and long run — and their bearing on the results of empirical studies — are discussed. Time subscripts are omitted for clarity.

Since tariffs appear directly in output prices, the impact of a change in tariff policy can be evaluated by changing output prices. Using the zero-profit conditions for each sector, taking logs and totally differentiating, the relationship between changes in the skill premium and changes in output prices is derived as:

$$(\hat{r}^H - \hat{r}^L) = \frac{1}{c}\left\{(\hat{P}_x - \hat{P}_y) + (\alpha_x - \alpha_y)\left[\hat{H}\cdot\frac{H}{K}\left(\frac{K_x}{H} - \frac{K_y}{L}\right) - \hat{K}\right]\right\} \tag{20}$$

where $c = \alpha_x\frac{K_y}{K} + \alpha_y\frac{K_x}{K} > 0$ and the hat symbol () denotes the percentage change in the given variable (see Appendix A.1 for the derivation).

Since developing countries provide the motivation for this paper, assume that $\hat{P}_x - \hat{P}_y < 0$; the tariff imposed on the *high-skill* sector, X, experiences a relative decline. To evaluate the 'short-term' impact on the skill premium, it is assumed that production factors have not yet had time to adjust. This means $\hat{H} = \hat{L} = \hat{K} = 0$. The change in the skill premiun is:

$$(\hat{r}^H - \hat{r}^L) = \tfrac{1}{c}(\hat{P}_x - \hat{P}_y)$$

Thus, in the absence of any factor supply response, the skill premium falls when the developing country liberalizes trade. This conforms to the result for the classical 'immobile factors', or short-run, trade model in which production factors are fixed in terms of quantity and sector. In subsequent time periods, however, individuals will respond to the decline in the skill premium by reducing their investment in education. This means $\hat{H} < 0$. If X is the capital intensive sector, then $(1-\alpha_x) > (1-\alpha_y) \Rightarrow \alpha_x < \alpha_y$. It follows from the equilibrium conditions for cost minimization that $\frac{K_x}{H} > \frac{K_y}{L}$. Thus, equation 20 shows that the decline in H partially reverses the initial decline in the skill premium if X is the capital-intensive sector:

$$(\hat{r}^H - \hat{r}^L) = \tfrac{1}{c}\left\{(\hat{P}_x - \hat{P}_y) + (\alpha_x - \alpha_y)\left[\hat{H}\cdot\frac{H}{K}\left(\frac{K_x}{H} - \frac{K_y}{L}\right) - \hat{K}\right]\right\}$$

The same result is obtained if X is the labor intensive sector since $\alpha_x > \alpha_y$ leads to $\frac{K_x}{H} < \frac{K_y}{L}$ from the cost minimization conditions. This means that regardless of the relative

capital-labor intensities of the two sectors, when the high-skill sector experiences a tariff cut, the skill premium *rises* following its short-run decline.

This medium-run effect on the skill premium depends on the persistence of H across time. The larger the persistence of prior generations' human capital (μ_2), the smaller the decrease in H in response to the short-run fall in the skill premium. This is because the current young generation's education choices only partially affect the existing level of human capital. Because of this slow adjustment in human capital stocks, the monotonic rise in the skill premium occurs over a longer time span, thus taking longer to reach its new steady-state value.

Note that the new steady-state skill premium is lower than the old one. Thus, the model's *long-run* implications conform to the Heckscher-Ohlin — or long run — trade model in which all production factors reallocate instantly in response to the trade policy change. However, the Heckscher-Ohlin model assumes fixed quantities of production factors. The transitional dynamics in this model are the result of production factors responding endogenously to the trade policy change.

These transitional dynamics have important implications for empirical research on the labor-market impact of trade liberalization. With individual working lives spanning 40-50 years in most countries, the education decisions of multiple generations determine human capital stocks at any given time t. This means the aggregate human capital stock takes several years to adjust to the new policy environment, implying that a monotonic rise in the skill premium may occur over several years. The rising skill premia documented in developing countries could thus be attributed to the endogenous response of human capital to the liberalization of previously protected high-skill sectors. The main result here is that the skill premium's transition is *not* monotonic as predicted by classical trade models.

The evolution of the physical capital stock also has implications for the skill premium. The relative decline in the output price of the consumption-investment good, X, raises investment demand relative to consumption demand. Thus, the aggregate capital stock increases along the transition path to a new, higher steady state level; that is, $\hat{K} > 0$. If X is the capital intensive sector such that $\alpha_x < \alpha_y$, then the skill premium increases as the capital stock grows:

$$(\hat{r}^H - \hat{r}^L) = \tfrac{1}{c}\left\{(\hat{P}_x - \hat{P}_y) + (\alpha_x - \alpha_y)\left[\hat{H}\frac{H}{K}\left(\frac{K_x}{H} - \frac{K_y}{L}\right) - \hat{K}\right]\right\}$$

This means that the skill premium will initially decline, then rise monotonically to its new steady state value. However, if X is the labor intensive sector such that $\alpha_x > \alpha_y$, then the skill premium decreases as the capital stock grows. This is because the new additions to the capital stock are absorbed disproportionately by Y, the capital-intensive sector. Since Y is the

low-skill sector, low-skill wages will rise relative to high-skill wages. This means that the skill premium will decline initially, rise in the medium run, and then decline monotically to its new steady-state value. Since trade reforms in developing countries typically target capital-intensive manufacturing industries, the former trend is more likely to occur.

Because the tariff reduction targets the high-skill sector, the economy-wide demand for high-skill relative to low-skill labor decreases to a lower steady-state level. However, as with the skill premium, the transitional dynamics are not monotonic; $\frac{H}{L}$ falls in the short run following the trade policy change, but partially recovers along the transition path due to the rise in the skill premium.

The model's post-liberalization dynamics can be summarized as follows:

1. Trade liberalization that targets the high-skill sector will reduce the skill premium in the long run. However, the skill premium's evolution over the transition path will be non-monotonic.
2. The longer it takes for human capital to adjust to the new policy, the longer the relative time span during which the skill premium rises monotonically.
3. If the targeted sector is capital (labor) intensive, the skill premium increases (decreases) as the capital stock grows. Thus, the evolution of the skill premium depends not only on whether the targeted sector is high-skill versus low-skill intensive, but also on whether it is capital versus labor intensive.
4. The relative employment of low-kill versus high-skill labor increases in the long run, but has non-monotonic transtional dynamics.

3.1 The Role of Technology Spillovers

The main hypothesis in the literature for explaining rising skill premia is that trade liberalization has been accompanied by technology spillovers from abroad. Manufacturing industries being the main targets of liberalization, imports of manufactured goods from developed countries increased, bringing with them superior production technologies and knowledge that were previously unavailable to developing countries. If these new production processes complement high-skill labor and/or substitute low-skill labor, then the technology is said to be skill-biased, raising relative wages and employment for workers with better education and training. The net effect on inequality depends on the extent of the technology spillover (relative to the tariff reductions). Thus, trade liberalization could benefit the scarce factor in developing countries if accompanied by technology spillovers from abroad.

To evaluate this hypothesis, this section investigates the impact of technology on the skill premium and relative factor demand. Two distinct forms of technology are considered here; skill-biased technical change (SBTC) and total factor productivity (TFP) growth. Both types of technology are assumed to accompany liberalization of the consumption-investment good, X. As demonstrated below, SBTC and TFP growth have similar implications for the skill premium, but very different implications for the relative employment of high-skill versus low-skill workers.

Skill-Biased Technical Change

If a skill-biased technical change (SBTC) occurs in sector X, then at given relative factor prices, the demand for high-skill labor increases relative to capital. The simplest way to impose SBTC in the model is to assume $\hat{\alpha}_x > 0$. The relationship between changes in output prices and changes in the skill premium changes is now given by:

$$\begin{aligned}(\hat{r}^H - \hat{r}^L) &= \frac{1}{c}\left\{(\hat{P}_x - \hat{P}_y) + (\alpha_x - \alpha_y)\left[\hat{H}\frac{H}{K}\left(\frac{K_x}{H} - \frac{K_y}{L}\right) - \hat{K}\right]\right. \\ &\quad \left. + \hat{\alpha}_x\left[\alpha_x log\left(\frac{H}{K_x}\right) + \frac{(\alpha_y - \alpha_x)}{(1-\alpha_y)}\frac{K_x}{K}\right]\right\} \qquad (21)\end{aligned}$$

where $c = \alpha_x \frac{K_y}{K} + \alpha_y \frac{K_x}{K} > 0$.

Appendix A.2 shows that $log\left(\frac{H}{K_x}\right) > 0$. Therefore, $\hat{\alpha}_x > 0$ raises the skill premium. Whether the new steady-state skill premium is higher or lower than the old depends on the magnitude of SBTC relative to the tariff cut; if SBTC is very large, then the new steady-state skill premium will be higher than before, permanently increasing economy-wide wage inequality.

To evaluate the impact on factor demand, note that SBTC lowers production costs. Specifically, at given factor prices, SBTC allows producers to reduce the quantity of inputs while holding production levels fixed. To determine the relative change in labor and capital employed in sector X, note the following relationship between factor prices and factor employment in sector X:

$$\frac{r_H}{r_K} = \frac{\alpha_x}{(1-\alpha_x)}\frac{K_x}{H}$$

Taking logs and totally differentiating, and keeping factor prices fixed at their initial levels (i.e. $\hat{r}^H = \hat{r}^K = 0$):

$$\hat{K}_x = \hat{H} - \frac{\hat{\alpha}_x}{(1-\alpha_x)}$$

Since $\hat{\alpha}_x > 0$ by assumption, then $\hat{K}_x < \hat{H}$. Because producers reduce inputs at fixed factor prices, $\hat{K}_x$ and $\hat{H}$ are both negative. Thus, $\hat{K}_x < \hat{H}$ means that producers reduce K_x by *more* than they reduce H. SBTC therefore raises the ratio of H with respect to other production inputs within the liberalized sector. The empirical implication is that SBTC raises employment of high-skill labor relative to other inputs in the liberalized sectors. Whether the economy-wide demand for high-skill versus low-skill labor rises depends on the magnitude of SBTC relative to the tariff cut; if SBTC is large, the economy-wide $\frac{H}{L}$ ratio will increase, even though the tariff cut targeted the high-skill sector.

Total Factor Productivity Growth

TFP growth in sector X is modeled as an increase in A_x relative to A_y. The relationship between changes in output prices and the skill premium is now:

$$(\hat{r}^H - \hat{r}^L) = \frac{1}{c}\left\{(\hat{P}_x - \hat{P}_y) + (\alpha_x - \alpha_y)\left[\hat{H}\frac{H}{K}\left(\frac{K_x}{H} - \frac{K_y}{L}\right) - \hat{K}\right] + (\hat{A}_x - \hat{A}_y)\right\}$$

The equation shows that $(\hat{A}_x - \hat{A}_y) > 0$ implies a rise in the skill premium. Moreover, if TFP growth is large relative to the tariff cut, the new steady-state skill premium will be higher than the old.

To evaluate what this implies for relative factor employment in sector X, use factor price equalization for capital to obtain:

$$\frac{K_x}{K_y} = \frac{(1-\alpha_x)}{1-\alpha_y)}\frac{PxX}{PyY}$$

Taking logs, totally differentiating, and noting that $\hat{L} = -\left(\frac{H}{L}\right)\hat{H}$ and $\hat{K_y} = -\left(\frac{K_x}{K_y}\right)\hat{K_x}$, the following equation is obtained:

$$\hat{K}_x(\alpha_x + \alpha_y\frac{K_x}{K_y}) - \hat{H}(\alpha_x + \alpha_y\frac{H}{L}) = (\hat{P}_x - \hat{P}_y) + (\hat{A}_x - \hat{A}_y)$$

TFP growth in sector X raises factor returns in sector X relative to sector Y. Therefore, labor and capital start moving into sector X. This means a larger percentage of each young generation invests in education than before. If $\frac{K_x}{K_y} > \frac{H}{L} \Rightarrow \frac{K_x}{H} > \frac{K_y}{L}$, then X is the capital intensive sector. Thus, because the marginal return to capital is already low, the flow of labor exceeds the flow of capital into sector X; that is, $\hat{H} > \hat{K}_x > 0$. In contrast, if $\frac{K_x}{K_y} < \frac{H}{L} \Rightarrow \frac{K_x}{H} < \frac{K_y}{L}$, then X is the labor intensive sector. This means TFP growth will bring a greater flow of capital than labor into sector X; that is, $\hat{K}_x > \hat{H} > 0$.

The empirical implication of these results can be summarized as follows: TFP growth in a particular sector lowers the relative employment of the factor used most intensively in that sector. Thus, TFP growth in a high-skill intensive sector will lower the relative employment of high-skill labor. Note that this is in contrast to the empirical implication for SBTC which is that the relative employment of high-skill labor rises in the affected sector. Hence, while both types of technology spillovers have the same implications for the skill premium, they have different implications for differently skilled workers. Whether trade-induced technology spillovers come in the form of SBTC or TFP growth is therefore an empirical question that is tested in Section 5 of this paper using data from Sri Lanka.

4 Simulation

In this section, the model is simulated to demonstrate graphically the analytical results from Section 3. The model parameters used are listed in Table 1. Note that the consumption-investment good sector, X, is relatively more capital intensive than the consumption good sector, Y; i.e. $\alpha_x < \alpha_y$. Using initial guesses for the state variables, the model is simulated until the pre-liberalization steady state reached. Then, the tariff imposed on good X is reduced from 0.01 to 0 and the model is simulated until the economy reaches its new steady-state.

Figure 1 shows the economy's transition between the pre- and post-liberalization steady states when there is no persistence in human capital ($\mu_2 = 0$). All initial steady-state values have been normalized to 1. As predicted by the analytical results, the skill premium declines sharply at first (the short-run effect) and then rises monotonically to its new, lower steady-state level. Thus, the time frame in which the skill premium is observed to rise far exceeds that in which the skill premium is observed to fall. Similarly, the quantity of high-skill workers drops sharply at first, but then rises monotonically to a new, lower steady-state level. The quantity of low-skill labor shows the opposite trend, rising sharply then declining gradually to a higher steady-state level.

Both labor and capital reallocate to sector Y. Because the consumption-investment good becamse cheaper, both consumption and investment demand for good X increases. Net imports of X increase to satisfy part of this greater demand. Because of the influx of capital goods, the rental rate declines over time. Meanwhile, because good Y became relatively more expensive, demand for Y decreases, lowering net imports. The low-skill wage rises steadily to a higher steady-state level. However, the high-skill wage shows a non-monotonic transition. It first

declines sharply as a result of the tariff reduction in the high-skill sector. This decline is then partially reversed following the sharp initial drop in education investment.

Figure 2 shows the transition when human capital persists over time ($\mu_2 = 0$). The most important difference is that the transition period is now longer; the economy requires more time periods to reach its new steady state. This means the skill premium rises over a longer time span when human capital is persistent. (This also means the skill premium rises more gradually.) In an economy with 40- or 50-year working lives, human capital is very persistent; i.e. human capital stocks take several generations to adjust to a trade policy change. Thus, depending on the time horizon of the data used, an empirical analysis of a developing country's skill premium over time may lead to the erroneous conclusion that trade liberalization causes greater wage inequality.

Figures 3 and 4 show the transitions with skill-biased technical change (SBTC) and TFP growth, respectively, in sector X. In both cases, the skill premium rises monotonically throughout the transition; the short-term decline from the previous figures do not appear here.[6]

Figures 5 and 6 show the transitions for the ratio between high-skill labor and other production factors (i.e. capital) in sector X. As predicted in the analytical results, SBTC increases the ratio of skilled labor relative to the other production factor in the high-skill intensive sector, while TFP growth decreases this ratio. Thus, the impact of trade-induced technology spillovers depends on the type of technology involved. In reality, every sector uses a mix of high-skill and low-skill labor along with capital and other inputs. The empirical implication, therefore, is that the relative demand for a developing country's abundant factor — low-skill labor — will decline with trade-induced SBTC but will increase with trade-induced TFP growth. The opposite is true for the scarce factor — high-skill labor. These results suggest that the direction of change in the skill premium does not predict the direction of change in relative employment of differently skilled workers. These implications of trade-induced technology is tested empirically in the next section using data from Sri Lanka.

5 Empirical Analysis

5.1 Trade Liberalization in Sri Lanka

Sri Lanka embarked on a program of structural reform in the late 1970s following several decades of inward-looking policies. Tariff reductions were among several policies implemented

[6]These simulations do not have persistent human capital. If human capital were persistent, the qualitative results do not change; the only difference is that the transition to the new steady state takes longer.

among which were the privatization of several industries and the liberalizing of foreign investment. However, even through the early 1990s, manufacturing tariffs remained high. Once Sri Lanka joined the World Trade Organization (WTO) in 1994, significant tariff cuts took place subsequent two decades as a result of the reciprocal nature of WTO agreements. Figure 7 plots the simple average applied tariff rates for goods entering the country for different manufacutring industries for the 1990-2004 period. The tariff data is obtained from the database constructed in Nicita and Olarreaga (2006).[7] The plots show that tariffs declined for all 28 manufacturing industries by an average of 50% across the fourteen years.

To see what happened to relative wages and employment during this time period, data from the Sri Lanka Labour Force Survey (LFS) is used. The LFS covers approximately 5,000 nationally representative households every quarter and is conducted by the Department of Census and Statistics, a government agency in Sri Lanka. The data spans the 1992-2009 time period and contains individual-level information on wages, education, four-digit ISIC industry, and four-digit ISCO occupation along with many other variables.[8] Table 2 shows relative wages and employment shares in the manufacturing sector for 1992, 2000, and 2009 for workers classified by education level and occupation type (white- versus blue-collar).[9] As a comparison, the corresponding trends for the services (non-tradeables) sector is shown in the same table. The skill premium in the manufacturing sector has increased during this time period, regardless of whether skill is defined by education level or occupation type. In contrast, the services sector has experienced a decline in the skill premium. Thus, these skill premium changes in manufacturing are not indicative of a general, economy-wide trend.

The employment and wage bill shares of white-collar, educated workers — the most skilled labor — have both increased substantially during this time period. These increases have been more dramatic in manufacturing than in services. In constrast, blue-collar, less educated workers — the least skilled labor — experienced a large decline employment and wage bill shares in both sectors. These changes were much smaller for the two remaining groups — white-collar, less educated workers and blue-collar, educated workers. Note that the shares of both manufacturing and services in real GDP increased during this time period, from 14% to 18%, and

[7] Industries are classified at the 3-digit level according to Revision 2 of the International Standard Industrial Classification (ISIC). The data is available only for the 1990-2004 time period.

[8] ISCO stands for International Standard Classification of Occupations.

[9] White collar occupations are those numbering 1 through 5 under ISCO Revision 3, while blue collar occupations number 6 through 9. Workers classified as 'high-educ' are those who have completed and passed the *Ordinary Level* examination in high school. 'Low-educ' workers are all those who have an education level below the O'Level qualification. The O'Level is administered by the central government for studends aged 16. Passing grades are required for entering the Advanced (or collegiate) level and is also a requirement for admission to US colleges.

from 62.5% to 69.2%, respectively. Therefore, rather than contracting after the loss of tariff protection, the manufacturing sector increased in importance in Sri Lankan GDP.

Thus, a period of large-scale tariff cuts in the manufacturing sector coincided with a rising skill premium and rising employment and wage-bill shares for high-skill workers. This contradicts the classical trade models which predict that the relative wages and employment shares of *low-skill* labor will increase following trade liberalization in developing countries.

These trends in the manufacturing sector provide preliminary evidence of trade-induced SBTC. However, a more rigorous analysis is required to establish a relationship between trade and technology. This is discussed in the next subsection.

5.2 Empirical Specifications

As discussed in Section 3, the source of trade-induced technology spillovers is assumed to be imported capital goods. Therefore, the empirical analysis will use the *share of imported capital goods in total production inputs* as the variable that represents technology from abroad. The idea is that the larger the proportion of imported capital goods in total inputs, the larger the quantity of new, productivity-enhancing technology that benefits that particular sector.

To capture the impact of TFP growth, the following production function is assumed:

$$Y_j = A_j(IM_j) \cdot \left[H_j^{\alpha} L_j^{\beta} K_j^{\gamma} I_j^{\sigma} \right] \tag{22}$$

where Y_j is real value added in sector j, A_j is total factor productivity, H_j and L_j are high- and low-skill labor, respectively, K_j is capital, I_j is total intermediate inputs, and IM_j is the share of imported capital goods in total intermediate inputs. Taking logs and adding time subscripts yields the regression equation:

$$logY_{jt} = \alpha_0 + \alpha_1 IM_{jt} + \alpha_2 logH_{jt} + \alpha_3 logL_{jt} + \alpha_4 logK_{jt} + \alpha_5 logI_{jt} + \epsilon_{jt} \tag{23}$$

Equation 23 is estimated with industry and time fixed effects. A positive and statistically significant coefficient on IM_{jt} implies that capital imports carry productivity-enhancing technology; that is, the larger the share of capital imports in total intermediate goods, the larger is total factor productivity.

On the other hand, if capital imports bring about skill-biased technical change, then the skill premium and the employment and wage bill shares of high-skill workers in sector j should be

positively correlated with the share of capital imports in total intermediate goods in sector j. The regression specification is thus:

$$logZ_{jt} = \alpha_0 + \alpha_1 IM_{jt} + \alpha_2 logX_{jt} + \epsilon_{jt} \tag{24}$$

The term Z_{jt} is one of three different dependent variables; the skill premium, the ratio between high-skill and low-skill employment, and the low-skill wage bill share in industry j at time t. The vector X contains a number of industry-specific control variables that could also have an impact on Z; the shares of exports and imports in value added, the investment to value added ratio, and the capital to value added ratio. Equation 24 is estimated with industry and time fixed effects. A positive and statistically significant coefficient on IM_{jt} for all three dependent variables suggests the presence of trade-induced SBTC.

5.3 Data

The main data source for the analysis is the publicly available Annual Survey of Industries (ASI), a survey of all firms in Sri Lanka conducted by Department of Census and Statistics (DCS). The ASI gives detailed information on output, value added, employment and wages by skill level and occupation type, raw and intermediate input use, capital stock, and new investment for all manufacturing industries at the four-digit ISIC level.[10] This data is available on the DCS website for the years 2005-2009.

Data on imported intermediate inputs used in each manufacturing industry is not available for Sri Lanka. However, this can data can be constructed as in Feenstra and Hanson (1996) using input-output tables constructed for Sri Lanka by Amarasinghe and Bandara (2005) along with data on imports from UNComtrade. The share of capital imports in total intermediate goods is computed as:

$$IM_{jt} = S_{jt} \times I_{jt}$$

where S_{jt} is the share of capital inputs in total inputs in industry j at time t, and I_{jt} is the ratio of capital imports to total domestic demand for capital goods. The IO tables in Amarasinghe and Bandara (2005) are constructed for the year 2000 only. Therefore, it is assumed that $S_{jt} = S_{j,2000}$ for all industries j; that is, the share of capital inputs in total inputs in industry j is constant over time.

[10]The industries surveyed in the ASI are categorized according to the International Standard Industry Classification (ISIC) Revision 3. The industry codes covered in the ASI range from ISIC 1410 through 4100, which includes all manufacturing industries, utilities and some mining industries.

Capital goods are defined as the subset of manufactured goods that includes equipment, machinery, vehicles, and furniture. These are classified under ISIC two-digit codes 29 through 36. Table 3 lists the capital goods used in the analysis. Non-capital goods comprise chiefly of consumer products such as food, clothing and paper, as well as non-capital intermediate goods such as steel and fertilizer. Table 4 compares skill premia, relative employment and wage bill shares for capital and non-capital goods. As assumed in the model in Section 3, capital goods industries are more skill intensive and have larger skill premia. Thus, capital goods can be thought of as the high-skill sectors.

Three different categorizations of high-skill versus low-skill are tested for the regression analysis. The first two categorizations define skill by educational attainment and occupation type; these are the same categorizations used in Subsection 5.1. The quantity of labor in each skill category is constructed for every industry using individual data in the LFS. The third categorization is obtained directly from the the ASI. The ASI classifies workers in each industry as 'skilled operatives', 'unskilled operatives', 'administrative', 'technical', 'clerical', and 'other'. For the regressions, 'skilled operatives' are considered high-skill labor and 'unskilled operatives' are considered low-skill labor. The ASI gives the total number employed, the total wage bill, and the average wage per person for each type of worker. This information is used to construct the labor-market variables for equations 23 and 24.

5.4 Results

Table 5 shows the results for equation 23, which is tested for the three different categorizations of skill. The coefficient on the share of capital goods imports in total inputs (IM_{jt}) is positive and significant regardless of how skill is categorized. The results suggest that imports of capital goods have a positive impact on total factor productivity; that is, holding all production factors constant (labor, physical capital, and intermediate inputs), an increase in the share of imported capital goods in total inputs corresponds to higher output. These results provide evidence of trade-induced productivity enhancements through imported capital goods.

Table 6 gives the results for equation 24. When skill is measured as white- versus blue-collar, capital goods imports have a positive and significant impact on the skill premium. (The impact is positive but not significant when skill is measured by educational attainment.) Capital goods imports have a negative effect on the low-to-high skill employment ratio, and this effect is significant when skill is measured by educational attainment. Capital imports also have a negative impact on the wage bill share of low-skill workers, and this effect is significant when

skill is measured by educational attainment. Although the results are not significant for all categorizations of skill, the evidence points to the presence of trade-induced SBTC; relative wages, employment ratios, and wage bill shares of high-skill workers are all positively impacted by capital goods imports.

Tables 6 and 7 show the results for an additional test; the impact of capital imports on labor productivity, which is defined as industry value added divided by total industry employment. Table 6 gives the results for a panel regression while Table 7 shows the results for a first-difference regression. Both regressions include industry and year fixed effects. The model is tested for total industry employment calculated from both the LFS and ASI data. The results show that the impact of capital imports on labor productivity is positive and significant for all regressions.

Overall, these results suggest that imports of high-skill intensive capital goods entering Sri Lanka contain technologies that raise domestic productivity. The model developed in Section 3 predicted that trade liberalization accompanied by technology spillovers will raise the skill premium, and that the relative employment of high-skill labor with rise with SBTC but fall with TFP growth. The evidence from Sri Lanka points to SBTC being the dominant form of technology spillover. Thus, although *total* factor productivity and *total* labor productivity are positively impacted by an increase in trade flows, high-skill workers are relatively bettter off than low-skill workers in terms of both wages and employment.

6 Conclusion

This paper develops a tractable dynamic overlapping generations model of an economy to understand the impact of trade liberalization on the skill premium and human capital investment in a developing country. Analytical results show that liberalization of the high-skill sector can lead to rising skill premia even in the absence of any skill-biased technical change. Even though the new steady-state skill premium is below the old, as predicted by classical trade models, the transitional dynamics are non-monotonic. Moreover, the greater the persistence of prior generations' human capital over time, the longer the transition to the new steady state, and thus, the greater the time frame in which the skill premium monotonically rises. This suggests that in a typical economy with 40 or 50 generations in the workforce at any given time, the skill premium will rise over several years as human capital takes time to adjust to the new policy environment.

These results have importance implications for empirical work. Reduced-form studies that correlate trade policy changes with wage changes across different points in time fail to capture these crucial transitional dynamics and may erroneously conclude that trade liberalization causes rising wage inequality in low-skill abundant countries. The results in this paper point to the importance of considering labor market dynamics in evaluating the impact of trade policy changes on labor markets.

When trade liberalization accompanies technology spillovers, the skill premium rises throughout the entire transition (i.e. the transition is no longer monotonic). However, the impact on relative factor demand depends on the *type* of technology involved. If technology spillovers come in the form of total factor productivity growth (TFP), the employment share of high-skill labor declines. On the other hand, skill-biased technical change (SBTC) increases the employment share of high-skill workers. Therefore, the empirical implication is that the relative demand for a developing country's abundant factor — low-skill labor — will decreases if trade liberalization is accompanied with SBTC but will increase with TFP growth. This means the direction of change in the skill premium cannot predict the change in relative factor employment when technology spillovers accompany tariff reductions. Therefore, the impact of trade-induced technology on the labor market is an empirical question that is tested in this paper using data from Sri Lanka.

The empirical analysis assumes that imports of capital goods are the main source of trade-induced technological change. This is because capital goods — which includes equipment and machinery — involve relatively sophisticated production techniques in which developed countries have a comparative advantage. Capital goods are also more high-skill intensive than consumption goods; skill premia and employment and wage bill shares of high-skill workers are larger in capital goods than in consumption goods industries. For the regression analysis, the share of imported capital goods in total production inputs is the variable used to capture the impact of trade-induced technology spillovers across industries.

Results from different regression specifications all point to trade-induced technology spillovers in Sri Lanka. Moreover, capital imports have had a positive impact on the skill premium as well as on the employment and wage bill shares of high-skill workers. These results hold for three different categorizations of skill. Since high-skill workers have thus enjoyed a rise in both relative wages and relative demand, the evidence points to SBTC as the dominant form of technology spillover. Overall, the results in this paper point to the importance of considering labor market dynamics in evaluating the impact of trade liberalization on wage inequality and employment and their interaction with technology spillovers.

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A Derivations

A.1 Trade Policy and Skill Premium

Zero-profit conditions:

$$P_x = \frac{r^H H + r^K K_x}{X}$$

$$P_y = \frac{r^L L + r^K K_y}{Y}$$

Taking logs of the zero-profit equation for good X and totally differentiating yields:

$$dlogP_x = \frac{r_H dH + H dr^H + r^K dK_x + K_x dr^K}{r^H H + r^K K_x} - dlogX$$

For any variable z, define its percentage change as $\hat{z} = \frac{dz}{z}$. Then, the above expression becomes:

$$\hat{P_x} = \alpha_x(\hat{H} + \hat{r}^H) + (1 - \alpha_x)(\hat{K_x} + \hat{r}^K) - \hat{A_x} - \alpha_x\hat{H} - (1 - \alpha_x)\hat{K_x}$$

which simplifies to:

$$\hat{P_x} = \alpha_x\hat{r}^H + (1 - \alpha_x)\hat{r}^K K_x$$

Similarly, for good Y:

$$\hat{P_y} = \alpha_y\hat{r}^L + (1 - \alpha_y)\hat{r}^K K_y$$

The relationship between the change in relative output prices and the change in the skill premium is:

$$\hat{P_x} - \hat{P_y} = (\alpha_x\hat{r}^H - \alpha_y\hat{r}^L) - (\alpha_x - \alpha_y)\hat{r}^K$$

Assuming no underutilization of capital, we get the following expression:

$$K = K_x + K_y = \frac{P_x X - r^H H + P_y Y - r^L L}{r^K}$$

Taking logs and totally differentiating yields the following expression for $\hat{r}^K$:

$$\hat{r}^K = (\hat{H} + \hat{r}^H)\frac{K_x}{K} + (\hat{L} + \hat{r}^L)\frac{K_y}{K} - \hat{K}$$

Substituting this into the expression for the relative output price change and rearranging yields:

$$(\hat{r}^H - \hat{r}^L) = \frac{1}{c}\left\{(\hat{P_x} - \hat{P_y}) + (\alpha_x - \alpha_y)\left[\hat{H} \cdot \frac{H}{K}\left(\frac{K_x}{H} - \frac{K_y}{L}\right) - \hat{K}\right]\right\} \tag{25}$$

A.2 With SBTC

With SBTC, we now assume $\hat{\alpha}_x > 0$. Using the zero-profit conditions, the relationship between the change in relative output prices and the change in the skill premium becomes:

$$(\hat{P}_x - \hat{P}_y) = (\alpha_x \hat{r}^H - \alpha_y \hat{r}^L) - (\alpha_x - \alpha_y)\hat{r}^K - \hat{\alpha}_x \alpha_x log \frac{H}{K_x}$$

With the assumption of full capital utilization, the expression for $\hat{r}^K$ becomes:

$$\hat{r}^K = (\hat{H} + \hat{r}^H)\frac{K_x}{K} + (\hat{L} + \hat{r}^L)\frac{K_y}{K} - \hat{K} - \hat{\alpha}_x \frac{1}{(1-\alpha_x)}\frac{K_x}{K}$$

Substituting this into the expression for the relative output price change and rearranging yields:

$$(\hat{r}^H - \hat{r}^L) = \frac{1}{c}\left\{(\hat{P}_x - \hat{P}_y) + (\alpha_x - \alpha_y)\left[\hat{H}\frac{H}{K}\left(\frac{K_x}{H} - \frac{K_y}{L}\right) - \hat{K}\right] + \hat{\alpha}_x\left[\alpha_x log\left(\frac{H}{K_x}\right) + \frac{(\alpha_y - \alpha_x)}{(1-\alpha_y)}\frac{K_x}{K}\right]\right\} \tag{26}$$

To show how SBTC affects the skill premium, we need to show that $log(\frac{H}{K_x}) > 0$. Write the production function for sector X, take logs and totally differentiate, assuming $\hat{\alpha}_x > 0$:

$$\hat{X} = \hat{A}_x + \alpha_x \hat{H} + (1 - \alpha_x)\hat{K}_x + \hat{\alpha}_x \alpha_x log(\frac{H}{K_x})$$

With SBTC, producers can now reduce the quantity of inputs while keeping X fixed. Therefore, letting $\hat{X} = 0$ and noting that $(\hat{K}_x = \hat{H}) - \frac{\hat{\alpha}_x}{(1-\alpha_x)}$, we get:

$$\hat{\alpha}_x \alpha_x log(\frac{H}{K_x}) = \hat{\alpha}_x - \hat{H}$$

Because $\hat{\alpha}_x > 0$ and $\hat{H} < 0$ at fixed factor prices, then $\hat{\alpha}_x - \hat{H} > 0$, which means $log(\frac{H}{K_x}) > 0$.

B Figures

Figure 1: Trends in Manufacturing Tariffs

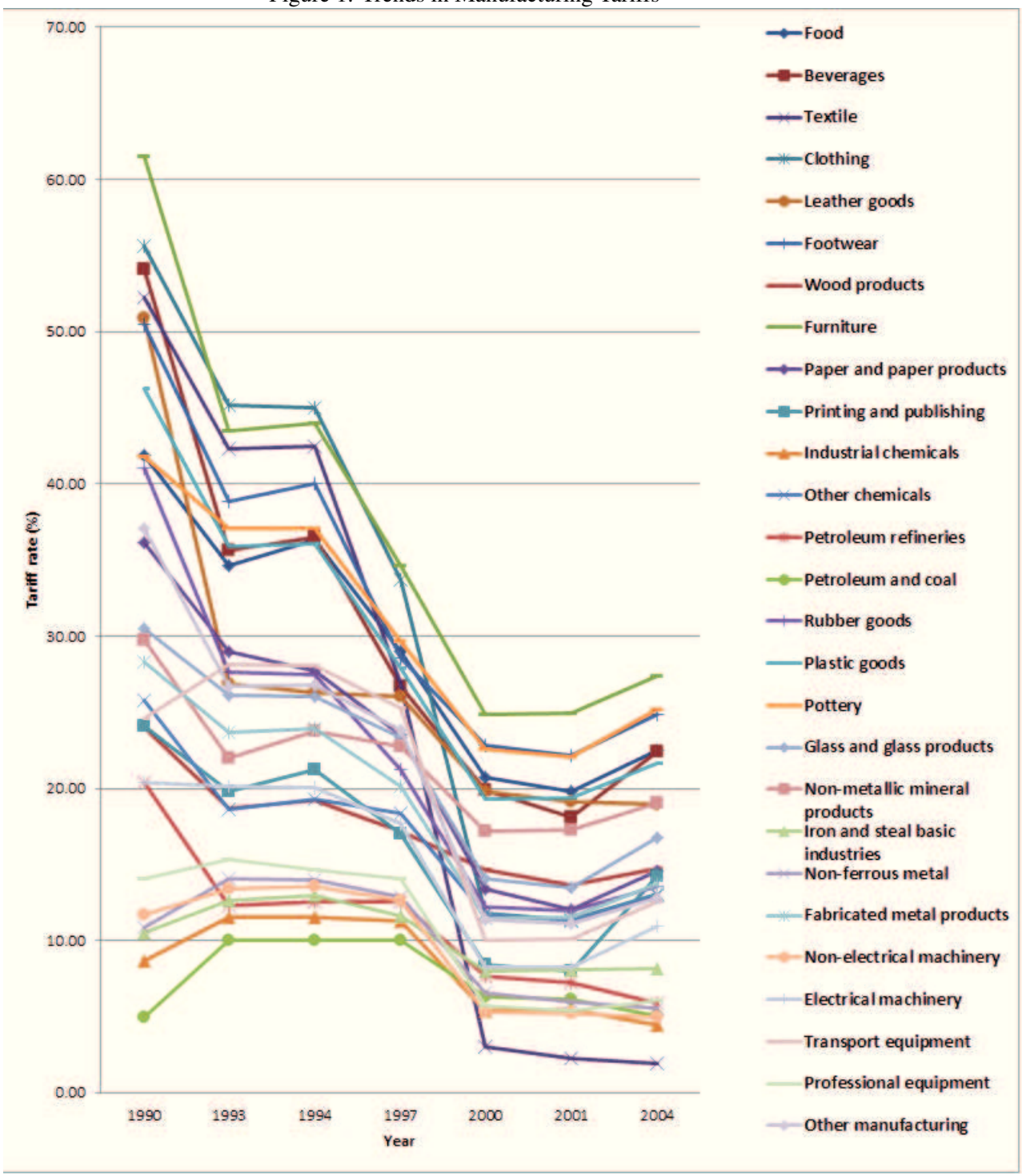


Figure 2: Transitions: Without Persistent H

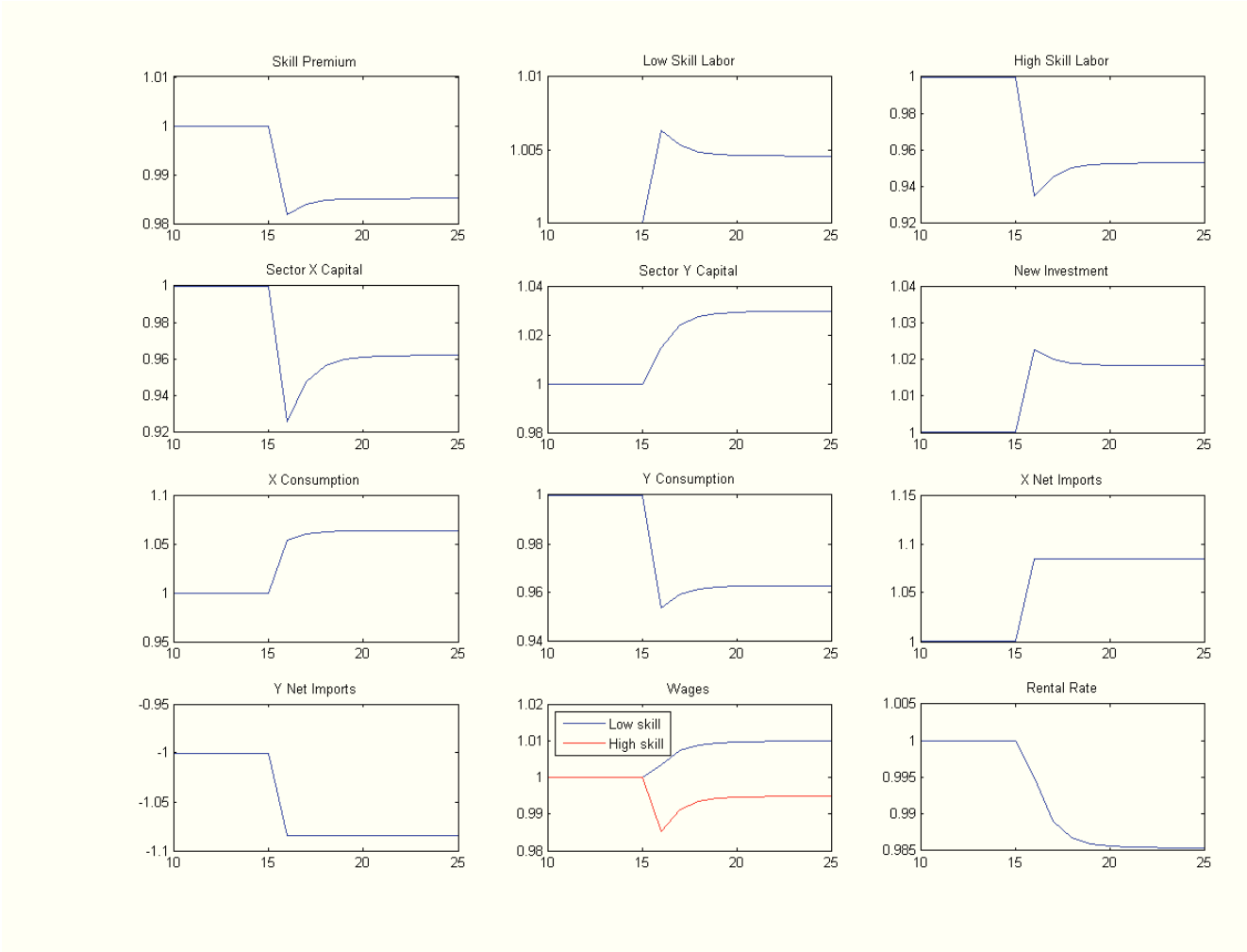


Figure 3: Transitions: With Persistent H

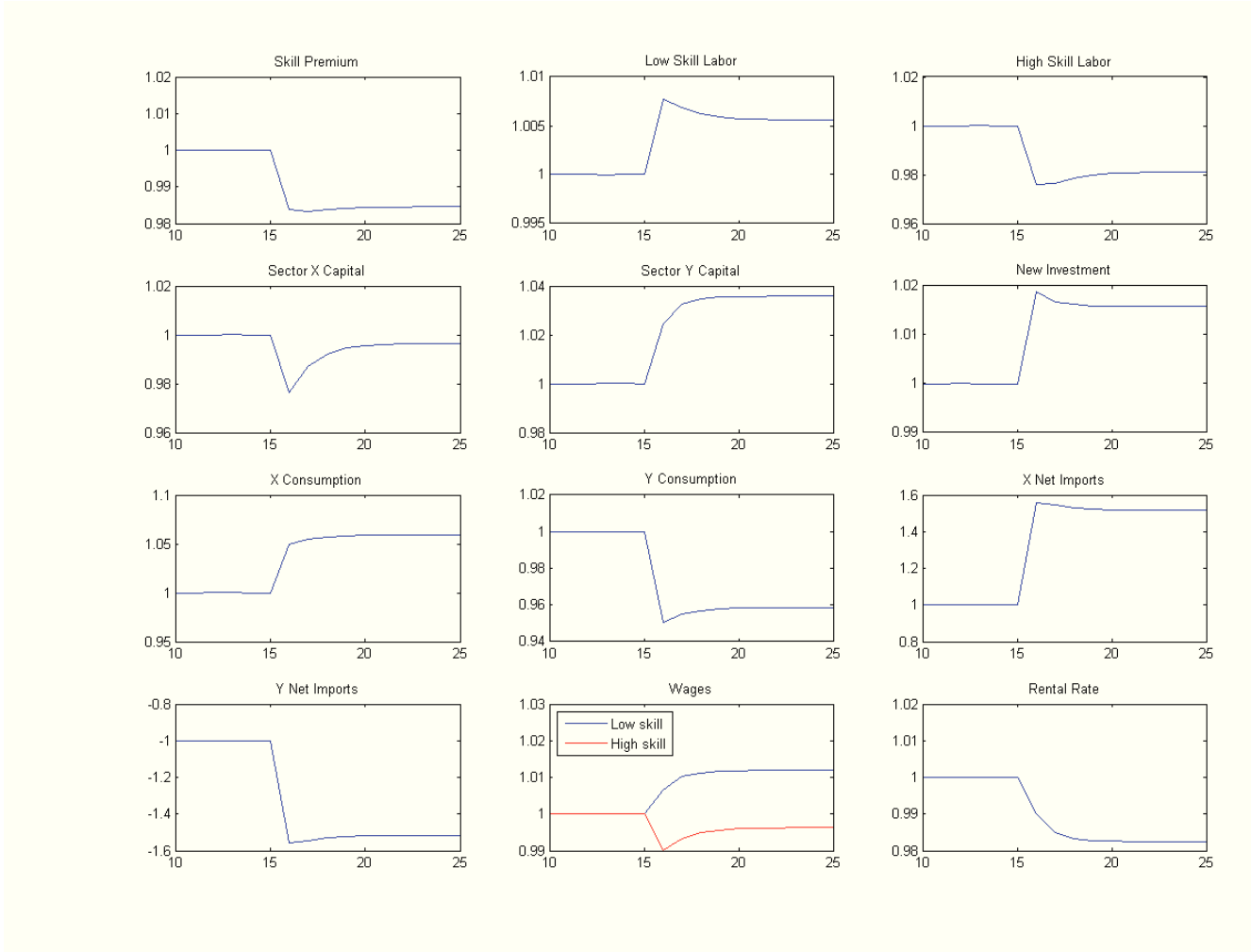


Figure 4: Transitions: With Skill-Biased Technical Change

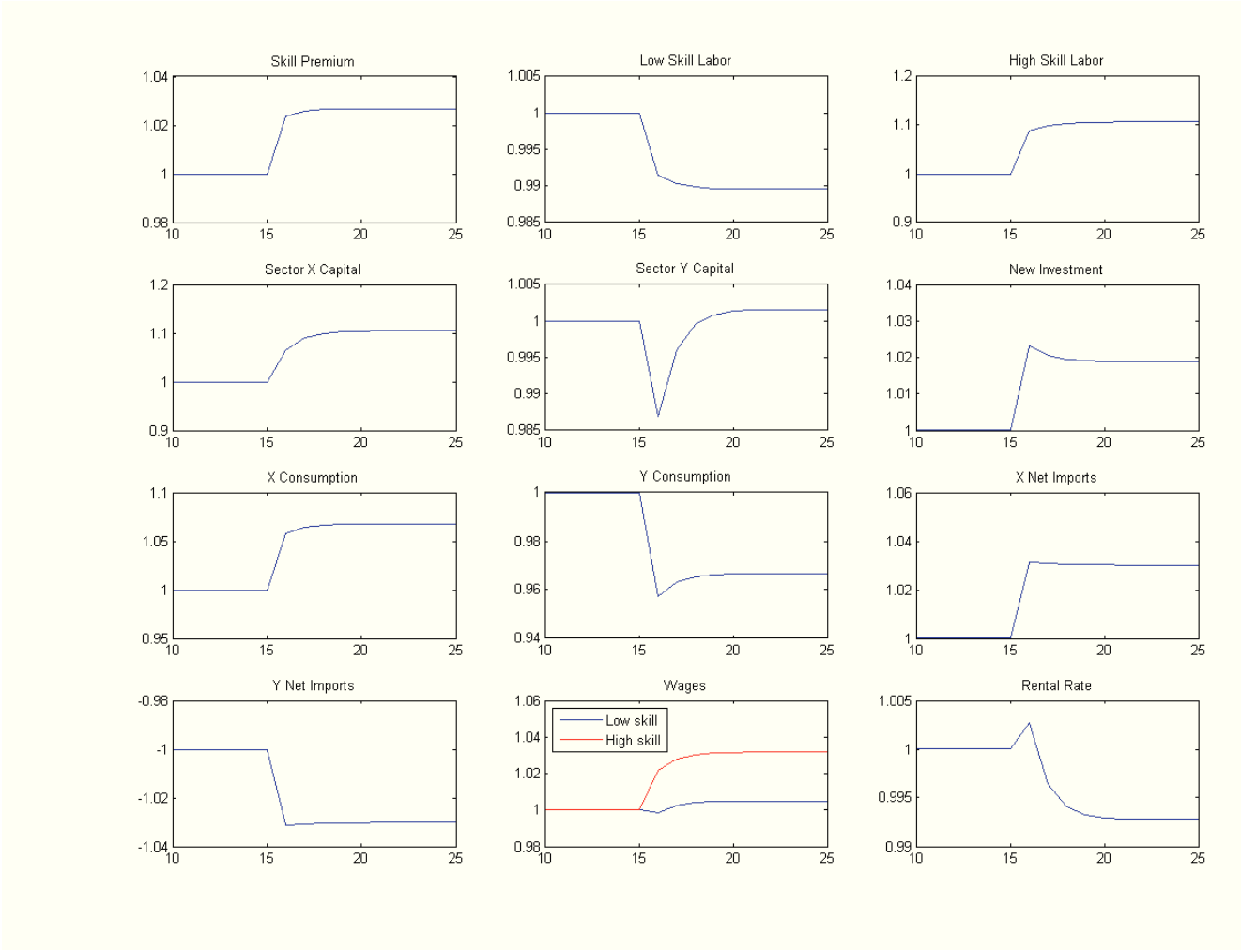


Figure 5: Transitions: With TFP Growth

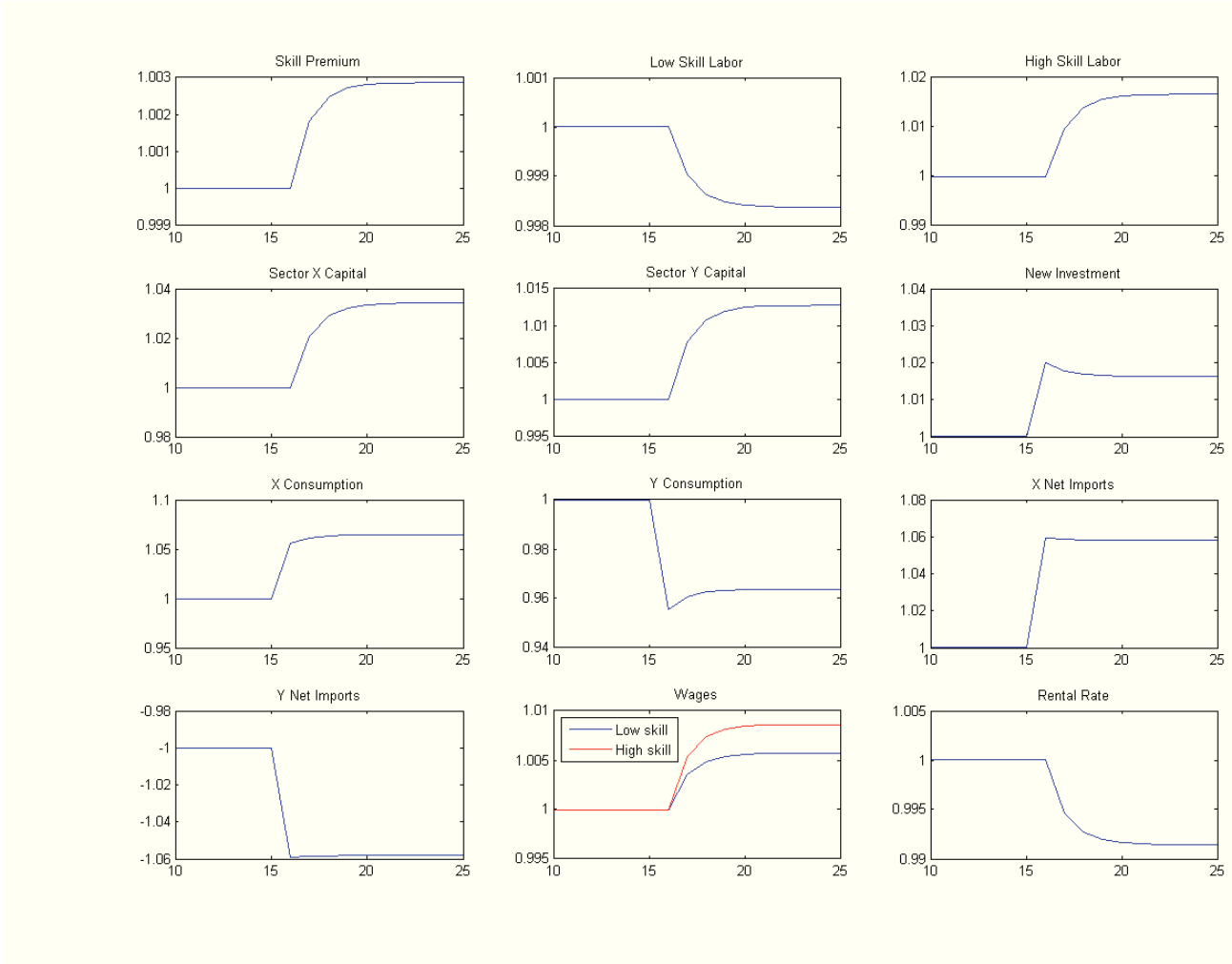


Figure 6: Skilled Labor-Capital Ratio with TFP Growth

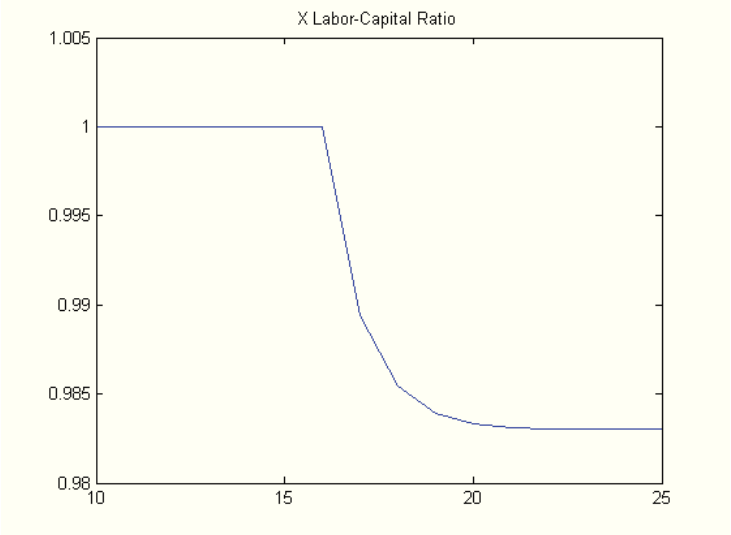
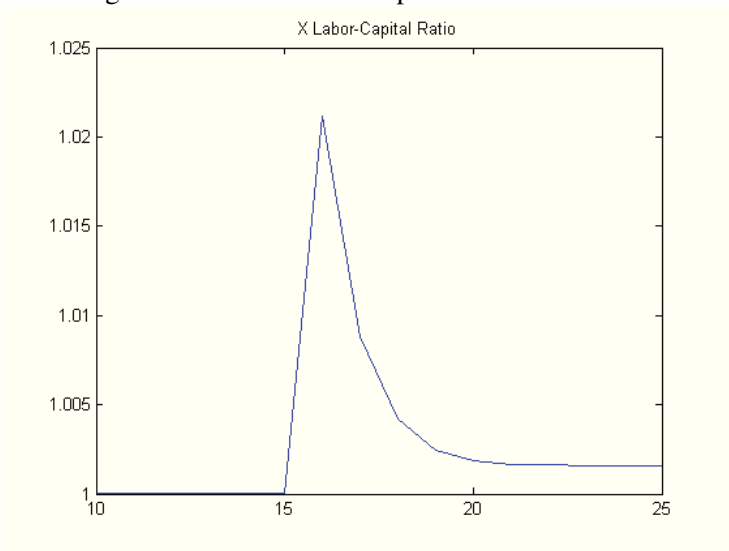


Figure 7: Skilled Labor-Capital Ratio with SBTC



C Tables

Table 1: Simulation parameters

Parameter		Value
Name	Symbol	Value
Consumpton goods substitutability	ρ	0.9
Minimum ability	$\underline{\gamma}$	0.01
Maximum ability	$\bar{\gamma}$	1
Education fixed cost	κ_0	1
Education variable cost	κ_1	1
Sector X labor income share	α_x	0.5
Sector Y labor income share	α_y	0.6
Sector X initial tariff	τ_x	0.01
Sector Y initial tariff	τ_y	0
Time discount factor	β	0.9
Physical capital depreciation rate	δ	0.5
Human capital evolution parameters	μ_1	2
	μ_2	0.2
	μ_3	0.2

Table 2: Capital goods industries

ISIC code	Description
29	Manufacture of machinery and equipment, n.e.c.
30	Manufacture of office, accounting and computing machinery
31	Manufacture of electrical machinery and apparatus n.e.c.y
32	Manufacture of radio, television and communication equipment and apparatus
33	Manufacture of medical, precision and optical instruments, watches and clocks
34	Manufacture of motor vehicles, trailers and semi-trailers
35	Manufacture of other transport equipment
36	Manufacture of furniture; manufacturing n.e.c.

Table 3: Wages and employment in capital vs. non-capital manufacturing industries

	Skill premium		Employment ratio		Wage bill share	
	White-blue	High-low educ	Blue-white	Low-high educ	Blue	Low educ
Capital	2.364	1.946	4.050	1.271	0.576	0.334
Non-capital	2.272	1.787	6.108	2.470	0.594	0.456

Table 4: Sector trends

	Manufacturing				Services			
	1992	2000	2009	% Δ	1992	2000	2009	% Δ
Ratio of mean wages								
White-blue collar	1.92	2.09	2.32	21%	1.71	1.69	1.52	-11%
High-low educ	1.52	1.59	1.86	22%	1.78	1.74	1.65	-7%
Employment share (%)								
White-collar	10.61	13.13	19.72	86%	51.93	55.70	55.99	7%
White-collar, high-educ	7.20	8.31	13.10	82%	31.42	34.86	37.08	18%
White-collar, low-educ	3.41	4.82	6.63	94%	20.51	20.84	18.91	-8%
Blue-collar, high-educ	18.59	20.42	19.63	5%	7.43	7.52	8.47	14%
Blue-collar, low-educ	70.51	66.39	60.65	-14%	40.20	36.71	35.52	-11%
Wage bill share (%)								
White-collar	20.67	24.94	45.37	119%	62.20	65.40	81.05	30%
White-collar, high-educ	16.37	20.59	40.33	146%	51.46	55.63	72.39	41%
White-collar, low-educ	4.30	4.35	5.04	17%	10.73	9.87	8.66	-19%
Blue-collar, high-educ	19.18	17.73	17.76	-7%	7.31	6.28	6.93	-5%
Blue-collar, low-educ	59.96	57.32	36.87	-38%	30.19	28.27	12.02	-60%

Table 5: Impact of capital goods imports on total factor productivity

Capital goods imports	3.66*	3.45*	3.90*
	(2.02)	(1.95)	(1.99)
More educated labor	-0.17**		0.1570
	(0.08)		(0.4432)
Less educated labor	0.16 ***		
	(0.06)		
White collar labor		-0.19***	
		(0.06)	
Blue collar labor		0.15***	
		(0.05)	
Skilled operatives			0.11*
			(0.06)
Unskilled operatives			-0.07
			(0.06)
Capital stock	0.07*	0.07*	0.09*
	(0.04)	(0.04)	(0.04)
Total inputs	0.84****	0.84****	0.80****
	(0.04)	(0.03)	(0.04)
R sq.	0.95	0.95	0.95
Adj. R sq.	0.64	0.64	0.66

The dependent variable is the log of real value added. The regression equation is tested for three different categorizations of skill; more educated vs. less educated, white collar v.s blue collar, and skill operatives vs. unskilled operatives. The symbolds *, **, ***, and **** mean that the coeffiient estimates are significant at the 10%, 5%, 1% and 0.1% levels.

Table 6: Impact of capital goods imports on skill premium, employment ratios and wage bill shares

	Skill premia		Employment ratios		Wage bill shares	
	White-blue collar	High-low educ	Blue-white collar	Low-high educ	Blue collar	Low educ
Capital goods imports	2.28**	0.85	-4.57	-2.87**	-0.03	-0.31**
	(1.07)	(0.61)	(5.73)	(1.17)	(0.15)	(0.14)
Exports	7.78e-05	-8.00e-5	0.01	-1.77e-3	4.94e-4	1.28e-4
	(0.01)	(4.88e-3)	(0.05)	(1.06e-2)	(1.28e-3)	(1.18e-3)
Imports	-1.50e-3	8.42e-4	-0.01	2.13e-3	-2.25e-4	-4.29e-4
	(3.04e-3)	(1.90e-3)	(0.02)	(4.14e-3)	(4.97e-4)	(4.60e-4)
Investment	0.40***	0.22***	0.54	0.39**	5.56e-3	0.01
	(0.12)	(0.08)	(0.79)	(0.16)	(0.02)	(0.02)
Capital stock	-3.52e-4**	-1.30e-4	3.16e-4	1.33e-4	1.48e-5	2.93e-5
	(1.70e-4)	(1.04e-4)	(1.08e-3)	(2.24e-4)	(2.71e-5)	(2.51e-5)
R sq.	0.17	0.12	0.03	0.15	0.03	0.10
Adj. R sq.	0.15	0.11	0.03	0.13	0.02	0.09

The regression tests three different dependent variables; the skill premium, the ratio between high-skill and low-skill labor, and the wage bill share of low-skill labor. For each of the three dependent variables, the regression equation is tested for three different categorizations of skill; more educated vs. less educated, white collar vs. blue collar, and skill operatives vs. unskilled operatives. The results for the latter skill categorization are not significant, so are not shown here. The symbolds *, **, ***, and **** mean that the coeffiient estimates are significant at the 10%, 5%, 1% and 0.1% levels.

Table 7: Impact of capital goods imports on labor productivity

	ASI	LFS
Capital goods imports	7.80**	8.88**
	(3.94)	(5.30)
Capital stock	-0.27***	-0.14
	(0.09)	(0.13)
Total inputs	0.35****	0.51****
	(0.08)	(0.12)
Import share	0.002	-0.01
	(0.002)	(0.01)
Export share	-0.006	-3.56e-4
	(0.005)	(0.01)
R sq.	0.26	0.46
Adj. R sq.	0.18	0.30

The dependent variable is labor productivity, which is defined as the ratio between value added and total employment for a given industry. The regression is for total employment computed from the ASI (Annual Survey of Industries) and the LFS (Labor Force Survey). The symbolds *, **, ***, and **** mean that the coeffiient estimates are significant at the 10%, 5%, 1% and 0.1% levels.

Table 8: Impact of capital goods imports on labor productivity: first difference

	LFS	ASI
Δ Capital goods imports	7.20**	5.67**
	(3.62)	(2.64)
Δ Capital stock	-0.24*	-0.30***
	(0.13)	(0.09)
Δ Total inputs	0.51****	0.33****
	(0.11)	(0.08)
Δ Import share	-0.01*	7.8e-4
	(0.006)	(0.002)
Δ Export share	0.002	-3.56e-4
	(-0.01)	(0.004)
R sq.	0.45	0.24
Adj. R sq.	0.41	0.23

The dependent variable is labor productivity, which is defined as the ratio between value added and total employment for a given industry. The regression is for total employment computed from the ASI (Annual Survey of Industries) and the LFS (Labor Force Survey). The symbolds *, **, ***, and **** mean that the coeffiient estimates are significant at the 10%, 5%, 1% and 0.1% levels.

Wage Inequality and Occupational Tasks: Evidence from Sri Lanka

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Abstract

Rising wage inequality has been observed in developing countries that reduced industry tariffs and liberalized their economies, contradicting traditional trade theory. Using labor force survey data from Sri Lanka — a small open developing economy — this paper documents rising wage *polarization* since the early 1990s; that is, wage inequality has increased in the upper half of the distribution but decreased in the lower half. Moreover, these changes occurred at the level of occupations rather than industries. Decomposing these wage changes reveals that the returns to occupational tasks associated with technology spillovers and outsourcing have played a key role in wage polarization. In particular, returns have increased to routine mechanized tasks linked to low-wage occupations, and to information and communication tasks linked to high-wage occupations. Both sets of tasks are found to be highly conducive to technology growth and outsourcing. These results highlight the importance of considering occupation-specific skills, in addition to schooling and work experience, when assessing the labor market impacts of greater international competition.

*This paper benefitted from the guidance of Richard Spady. This research was conducted with restricted access data from the Department of Census and Statistics, Sri Lanka. All errors are my own.

1 Introduction

The empirical trade literature has documented rising wage inequality and skill premia in developing countries that opened their economies to foreign competition. This result is at odds with traditional trade theory which predicts that the relative returns to low-skill labor should increase in low-skill abundant countries. The previous literature on Sri Lanka — a small open developing country — finds evidence of the same (Karunaratna, 2007; Marjit and Acharyya, 2003). However, using Sri Lanka Labour Force Survey data for the 1992-2009 period, this paper documents the more complex trend of wage *polarization*; that is, wage growth has been more rapid at the upper and lower ends of the distribution relative to the middle. Further analysis reveals that these changes have taken place within and between occupations rather than industries, even though trade liberalization policies target the latter.

The role of occupations in the evolution of the wage distribution has only recently been brought to attention. In the labor literature, Autor, Levy, and Murnane (2003) find that computers replacing human routine tasks, as opposed to non-routine tasks, explains 60% of the relative demand shift favoring college-educated workers in the US in the 1970-1998 period. Autor, Katz, and Kearney (2006) find that the 1990s wage polarization in the US can be rationalized by computerization of routine cognitive job tasks. Goos and Manning (2007) show that job polarization in the UK can explain between one-third and one-half of the rise in wage inequality during the 1975-1995 period. Yamaguchi (2013) finds that a decline in the returns to motor skills relative to cognitive skills explains 40% of the narrowing gender-wage gap in the US between 1979 and 1996. Firpo, Fortin, and Lemieux (2011) find evidence that technological change, de-unionization and outsourcing have each played a role in changes in the US wage distribution at different time periods. In the trade literature, Artuc and McLaren (2012) use US data to establish that both industry and occupation determine workers' welfare changes following a trade shock. The general consensus is that occupations are a potentially key channel through which technological change and international competition are driving the observed changes in the wage distributions of developed countries.

It is then entirely plausible that occupations play a similarly crucial role in developing economies. Skill-biased technical change (SBTC) as a by-product of trade liberalization is a common explanation in the trade literature for rising wage inequality. Although it is standard practice to associate SBTC with education levels, technology advancements raise the productivity of specific job tasks, not of educated workers across the board. For example, consider technicians and human resources managers who have the same education level. Technology

changes that facilitate hand-eye coordination will raise the productivity of technicians more than that of HR managers, impacting the wage distribution between these two occupations. Moreover, technicians with better hand-eye coordination will benefit more than those less endowed with this particular skill, widening the wage distribution within the occupation. While SBTC implies a monotonic relationship between technology and wages, linking technology with tasks suggests that this relationship is ambiguous; for example, low-wage jobs involving mechanized tasks are also conducive to technology-driven productivity growth.

A similar argument can be made for outsourcing, where jobs cross national borders. Sri Lanka is a long-time outsourcing destination for low-wage manufacturing jobs, such as those in the garment industry. More recently, outsourcing has come in the way of high-wage services jobs in information and communications technology (ICT) and financial, business, and legal services. The global shift away from manufacturing towards services along with organizational restructuring and technical change have in general raised the emphasis of cognitive tasks, such as people skills, relative to physical tasks, such as machine operation (Borghans, ter Weel, and Weinberg, 2006). Thus, changes at the occupation level are potentially important drivers of changes in wage inequality in developing economies.

The goal of this paper is to investigate the role of occupations in the evolution of Sri Lanka's wage distribution during the 1992-2009 period. To that end, a Roy model of occupational choice is presented where the returns to distinct job skills differ across occupations. The key empirical implication of the model is that the evolution of wages over time is determined by changes in both the *composition* of and *returns* to job skills. This implication is tested using the decomposition method described in Machado and Mata (2005) using Sri Lanka Labor Force Survey (LFS) data. Each occupation in the LFS is expressed as a set of constituent tasks intended to capture its relationship with technology, outsourcing, and cognitive and physical skills. The mapping between occupations and tasks is taken from the Occupational Information Network (O*NET). The results show that changes in the returns to occupational tasks closely match the pattern of wage polarization in Sri Lanka over this time period. This highlights the importance of considering occupational tasks in future investigations of wage inequality in post-liberalization economies.

The paper is organized as follows. Section 2 documents changes in the Sri Lankan wage distribution and their relationship to industry and occupation trends. Section 3 describes a model of occupational choice that links wages to job tasks and other labor-market characteristics. Section 4 discusses the methods for empirically testing the model's implications. Section 5 describes the use of O*NET data to map occupations to different sets of tasks. Section 6 gives

the results from the decomposition, and Section 7 concludes.

2 Changes in the Wage Distribution

This section documents the evolution of Sri Lanka's wage distribution over the 1992-2009 period. The data is obtained from the Sri Lanka Labour Force Survey (LFS), conducted by the Department of Census and Statistics. The LFS is a quarterly survey of approximately 5,000 nationally representative households and extracts information from every household member on wages, four-digit ISIC industry[1], four-digit ISCO occupation[2], hours worked, years of schooling completed, sex, race, work experience, and other characteristics. Nominal hourly wages are computed from monthly or daily wages and weekly or daily hours worked[3], and are converted into year 2006 values using the GDP deflator.

Denote as w_t^q the median log hourly wage in a given quantile q of the wage distribution in year t. The wage change from time 0 to time t in a given quantile is $\Delta w_t^q = w_t^q - w_0^q$. Figure 1 plots Δw_t^q against w_0^q using one hundred quantiles. The base and final years are, respectively, 1992 and 2009. Wage growth is strong at the upper and lower portions of the distribution relative to the middle, taking a convex or U shape. To determine whether these changes are statistically significant, the following regression is tested:

$$\Delta w_t^q = \alpha_{0t} + \alpha_{1t} w_0^q + \alpha_{2t} w_0^{q2} + \epsilon^q \tag{1}$$

The convex shape in Figure 1 implies that $\alpha_{1t} < 0$ and $\alpha_{2t} > 0$. The equation is tested separately for each $t = 1993, ..., 2009$ while holding the base year, $t = 0$, fixed at 1992. Figure 2 plots the estimated linear and square coefficients for each year. The coefficients take on the predicted signs and become larger in magnitude over time. This implies that wages have become *more* polarized over time relative to the base year. All but one of the coefficient estimates are highly significant and the R-squared values range from 0.53 to 0.85. Thus, Sri Lanka has experienced gradually rising wage inequality in the upper half of the distribution and falling inequality in the lower.

If international competition and technical change are driving these economy-wide changes, then they should arguably be driving changes in the industry wage structure or occupation wage structure (or both). For example, the structural trade literature has long established that a tariff

[1] ISIC International Standard Industrial Classification

[2] International Standard Classification of Occupations

[3] Salaried workers report monthly wages and weekly hours worked. Daily wage earners report daily wages and daily hours worked.

cut in one industry affects relative wages across all industries.[4] Similarly, Autor, Levy, and Murnane (2003) find that computerization lowers (raises) the relative return to routine (non-routine) cognitive occupations. Thus, the next step is to determine whether wage trends at the industry and occupation level mimic the economy-wide trends. This is tested with the following regression:

$$\Delta w_{jt} = \alpha_{0t} + \alpha_{1t} w_{j0} + \alpha_{2t} w_{j0}^2 + \epsilon_{jt} \tag{2}$$

where j stands for industry or occupation, and w_{jt} is the median wage in industry/occupation j at time t. The expectation is that $\alpha_{1t} < 0$ and $\alpha_{2t} > 0$. Industries and occupations are aggregated to the three-digit level to ensure a sufficient number of observations to compute the median wage. As before, the equation is tested separately for each t while holding the base year fixed at 1992.[5]

Figure 3 plots the coefficient estimates for industries, while Figure 4 does the same for occupations. For both industries and occupations, $\alpha_{1t} < 0$ and $\alpha_{2t} > 0$, implying a convex relationship between wage growth and base-year wages. However, the effects are stronger for occupations as evidenced by the larger coefficient magnitudes. Moreover, the coefficients have increased in magnitude over time, suggesting that wage polarization has been a gradual process over the eighteen-year data span. The coefficients are statistically significant, but more so for occupations than for industries.[6]

Thus, the evolution of the industry and occupation wage structures closely match that of the economy-wide distribution, although the results are stronger for occupations. However, these results say nothing about the specific industries and occupations that are contributing to these trends. If, for example, computerization enhances productivity in the finance industry, then the finance industry would contribute to rising wages at the upper end of the economy-wide wage distribution. Moreover, if computerization complements the most skilled workers, then wage inequality would increase *within* the finance industry. Therefore, the next section determines which specific industries and occupations have contributed to wage polarization.

[4] Refer to Artuc (2009), Artuc, Chaudhuri, and McLaren (2010), Cosar (2013), Dix-Carneiro (2013), and Seneviratne (2013).

[5] For industries, the equation is tested only for $t = 1992, ..., 2001$. This is because the LFS uses ISIC Revision 2 for 1992-2001 and Revision 3 for 2002-2009. The mapping between Revision 2 to 3 is not straightforward, so the latter years are omitted.

[6] The t-statistics range from 1.7 to 7.6 for industries, and from 3.1 to 10.4 for occupations.

2.1 Changes Within Industries and Occupations

To examine changes across and within industries and occupations, the wage distribution of each industry/occupation j is divided into ten quantiles (deciles). The median wage in each quantile of industry/occupation j is computed. The regression equation is:

$$\Delta w_{jt}^{q} = \gamma_{j0} + \gamma_{j1} w_{j0}^{q} + \eta_{j}^{q} \tag{3}$$

where Δw_{jt}^{q} is the change in the median wage in quantile q of industry or occupation j between the years 0 and t, and w_{j0}^{q} is the base-year median wage in quantile q. The coefficients vary with j.[7] The slope coefficient, γ_{j1}, captures changes across *and* within industries/occupations. For instance, if $\gamma_{j1} > 0$, then wage growth was stronger for higher quantiles, increasing wage inequality within j. If $\gamma_{j1} > \gamma_{j'1} > 0$, then wage growth was stronger and inequality grew faster in j than in j'. Industries and occupations are aggregated to the two-digit level to allow for sufficient observations per wage quantile. Figure 5 plots the fitted values of Δw_{jt}^{q} against w_{j0}^{q} for industries, and Figure 6 does the same for occupations. Each plot is labeled with the corresponding ISIC or ISCO title.

The industry plots (Figure 5) show no clear pattern to indicate that wage changes across or within industries are driving wage polarization. However, some trends are worth noting. Inequality has risen in services industries associated with high levels of education and/or specialized training, as evidenced by their upward-sloping plots ($\gamma_{j1} > 0$); for example, 'social and community services' (which includes medical services and scientific research), 'financial institutions', and 'real estate and business services'. In contrast, the plots are downward-sloping for services industries associated with low education levels and training ($\gamma_{j1} < 0$); for example, 'restaurants and hotels', 'retail trade', and 'personal and household services'. The distinction between these two sets of industries lies primarily in *job* quality and skills, which are more closely related to occupations than industries.

Indeed, the occupation plots (Figure 6) show a clear U-shaped pattern of wage growth. High-wage occupations have experienced rising inequality as evidenced by their positive slopes; for example, 'physical, mathematical and engineering professionals' and 'other professionals' (which includes lawyers, accountants, and psychologists). Low-wage occupations show falling inequality; for example, 'salespersons' and 'machine operators'. Middle-wage occupations have relatively flat slopes ($\gamma_{j1} \approx 0$), implying little to no change in inequality; for example,

[7] γ_{j0} is a *vector* of j-specific dummies while $\gamma_{j1} \cdot w_{j0}^{q}$ is a vector of j-specific dummies interacted with base-year wage in quantile q of j.

'drivers and mobile-plant operators' and 'metal and machinery workers' (which includes aircraft mechanics and tool-makers). [8]

2.2 Discussion

The above results suggest that changes at the occupation rather than industry level are driving economy-wide wage polarization. Moreover, changes across *and* within occupations appear to be simultaneously contributing to these trends. Some notable similarities exist amongst occupations sharing common wage growth patterns. In the upper portion of the distribution, occupations that have experienced rising inequality are those that require highly specialized professional qualifications involving technical and analytical skills (e.g. MD, MBA, JD). Thus, the best-paid science technicians, lawyers and accountants, for example, also enjoyed the highest wage growth. The technical nature of these jobs suggests that they are likely to benefit from technology spillovers from abroad. Moreover, many high-wage services occupations are now outsourced. For example, Sri Lanka is a growing outsourcing destination for ICT, business and legal services jobs.

In the lower part of the distribution, occupations experiencing falling inequality are routine manufacturing and services jobs. Thus, salespersons and machine operators earning low wages enjoyed the highest wage growth. Many routine jobs, such as those in the garment and textile industries, are outsourced to developing countries. In addition, jobs that involve the use of machinery are conducive to technology advancements.

Thus, one of the main goals of this paper is to formally identify the specific features of occupations that might help explain wage polarization. To that end, the next section develops a model of occupational choice where occupations are disaggregated into the tasks and skills required to perform them. The model is then tested using a decomposition exercise that isolates the relative contributions of these tasks/skills and other worker characteristics to wage polarization.

[8] Figures 1 and 2 in the Appendix A plot the fitted values of Δw_{jt}^{d} from the same as above regression, but with quantiles dummies included to capture any quantile-specific trends. The quantile effects are strong, and further emphasize the extent of wage polarization.

3 Occupational Choice Model

3.1 Model

This section describes a Roy model of occupational choice that links wages to occupational tasks. Assume that individuals are endowed with K types of skill. For example, if $K = 2$, these could be 'analytical' ($k = 1$) and 'routine' skills ($k = 2$). Each individual possesses different stocks of these skills accumulated through education, training, work experience, etc. The vector of skills for individual i at time t is $s_{it} = (s_{i1t}, ..., s_{iKt})$.

Individuals can choose to work in one of many occupations in the economy. Each occupation j is disaggregated into a bundle of tasks. Define as $m_j = (m_{j1}, ..., m_{jK})$ the vector of K task indices that capture the task content of occupation j. For example, if the skill types are 'analytical' and 'routine' ($K = 2$), then each occupation is defined by an analytical and routine task index. Each task index, m_{jk}, can be thought of as the relative importance of task k in occupation j.

An individual who chooses to work in occupation j at time t produces $q_{ijt} = \phi_{j0} \prod_{k=1}^{K} s_{ikt}^{\phi_{jk}}$ units of output. Denoting the output price of j as p_{jt}, the individual's wage is his marginal value product:

$$w_{ijt} = p_{jt}\phi_{0j} \prod_{k=1}^{K} s_{ikt}^{\phi_{jk}}$$

and the log wage is:

$$ln(w_{ijt}) = \alpha_{jt} + \sum_{k=1}^{K} \beta_{jkt} s_{ikt} + \epsilon_{ijt}$$

where β_{jkt} is the return to skill type k in occupation j, and ϵ_{ijt} is an idiosyncratic shock to wages. The intercept, α_{jt}, and slope terms, $(\beta_{j1t}, ..., \beta_{jKt})$, all vary with occupation and time. Thus, the return to an individual's stock of skills differs across occupations.

To allow for additional worker characteristics such as education and sex to determine wages, the log wage equation is rewritten as:

$$ln(w_{ijt}) = \alpha_{jt} + \sum_{k=1}^{K} \beta_{jkt} s_{ikt} + \gamma_{jt} Z_{it} + \epsilon_{ijt} \tag{4}$$

where Z_{it} is a vector of individual i's other labor force characteristics and γ_{jt} is a vector of time-varying returns to Z_{it}.

Since each occupation is defined as a bundle of tasks, β_{jkt} can be expressed as a function of task index m_{jk} in occupation j:

$$\beta_{jkt} = \tilde{\beta}_{jkt}(m_{jk}) \tag{5}$$

where $\tilde{\beta}_{jkt} > 0$. The interpretation is that the return to skill type k depends on the *relevance* of that skill to occupation j. For example, analytical skills have little relevance to a manual laborer. Therefore, the return to analytical skills is low for all individuals who choose to be manual laborers.

3.2 Empirical implications

The model yields a set of empirical implications that will be tested under the decomposition exercise in Section 5. Changes in the return to skill type k will affect the wage distribution across and within occupations. This, in turn, will affect the economy-wide wage distribution. For example, suppose a technology advancement raises the return to analytical skills in all occupations. Consider a low-wage occupation, 'machine operator' ($j = 1$), and a high-wage occupation, 'computer programmer' ($j = 2$). Assume that the analytical tasks are of greater relative importance for programmers than for machine operators; $m_{1k} < m_{2k}$. If so, a technology advancement will raise the return to analytical skills in both occupations, β_{1k} and β_{2k}. However, because $m_{1k} < m_{2k}$, wage growth will be higher for programmers than for machine operators, widening the wage gap between the two occupations. Moreover, for a given occupation, individuals possessing higher stocks of analytical skills will enjoy higher wage growth, widening wage inequality within occupations. As evidenced by Figure 6, both changes across and within occupations can drive the overall pattern of wage growth.

Changes in the *distribution* of skills have a similar effect. Suppose that education policy reform pushes individuals to invest more in analytical skills. The greater supply of analytical skills in the workforce will lower the relative returns to analytical skills. The wage gap between programmers and machine operators will fall. However, empirical evidence shows that the positive impact of education increases with wages.[9] This is because wage dispersion tends to widen at higher levels of skill. Thus, greater investment in analytical skills could raise wage inequality through this dispersion effect. The net impact of a change in workforce composition on the wage distribution is therefore an empirical question.

The purpose of the decomposition exercise is to measure the relative contributions of changes in skill returns and changes in workforce composition to wage polarization. Defining occupations as bundles of tasks allows for identifying common features amongst occupations that share

[9] See Lemieux (2006) for the US and Biagetti and Scicchitano (2011) for Europe.

similar wage growth patterns. Moreover, because the number of tasks in O*NET is far below the number of occupations, the task approach allows for more parsimonious empirical specifications than using hundreds of occupation-specific dummies. The next section describes the construction of occupational task indices using O*NET data.

4 Task Data

The task content of occupations is taken from the Occupational Information Network (O*NET) developed by the Employment and Training Administration of the US Department of Labor.[10] O*NET assigns to each occupation numeric measures of the knowledge, skills and abilities required to perform the job, as well as the activities and tasks that constitute performing it.

For example, O*NET provides a list of 'work activities' for each occupation j, and then assigns two numbers for each work activity; one for its 'importance' and another for its 'level'. For the work activity defined as 'performing for or working directly with the public', O*NET assigns an 'importance' score of 0.46 for actors and 0.38 for fire-fighters, and a 'level' score of 0.8 for actors and 0.64 for fire-fighters. Engaging with the public is thus more important and more intensively performed for actors than for fire-fighters.

The O*NET measures are used to construct several *task indices* intended to capture the occupational features that might be driving changes in the wage distribution. One set of task indices captures an occupation's exposure to outsourcing, called 'offshorability'. Following Jensen and Kletzer (2005), five offshorability indices are constructed: 'information', 'physical presence', 'interpersonal', 'decision/creativity', and 'routine'. Each index, TI, is constructed from a set of 'work activities' and 'work contexts' taken from O*NET:

$$TI_{jk} = \frac{\sum_{l=1}^{L_k} \left(\frac{2}{3} * IM_{jl} + \frac{1}{3} * LV_{jl} \right) + \sum_{m=1}^{M_k} C_{jm}}{L_k + M_k} \tag{6}$$

where TI_{jk} is the value of index k in occupation j. The terms L_k and M_k are the total numbers of work activities and work contexts, respectively, used to construct index k. The terms IM_{jl} and LV_{jl} are the importance and level, respectively, of work activity l in occupation j, and C_{jm} is the value of work context m in occupation j. Following Blinder (2009), weights of $\frac{2}{3}$ and $\frac{1}{3}$ are assigned for 'importance' and 'level', respectively. Table 1 lists the work activities and work contexts used to construct each of the five indices.

[10] O*NET is the replacement to the Dictionary of Occupational Titles (DOT).

The 'information' index captures the use of data, information and the internet in an occupation. Jobs in information and communications technology (ICT) are heavily outsourced with Sri Lanka being an increasingly important destination country. 'Physical presence' captures the necessity of a worker's on-site presence in the work environment to fulfill his job requirements. Because jobs requiring less physical presence are easier to outsource, the inverse of 'physical presence' is used to capture offshorability. 'Interpersonal' captures the extent of face-to-face interaction, and 'decision/creativity' the extent of independent decision-making and creativity. Because jobs entailing face-to-face interaction and high-level decision-making are difficult to outsource, the inverse values of these indices are used to capture offshorability. 'Routine' captures the extent of performing repetitive tasks. Many routine jobs, such as cellphone assembler, are outsourced to developing countries since they require little specialized training.

Another set of task indices is constructed to capture skill-biased technical change (SBTC). Previous empirical studies suggest that SBTC has raised the returns to cognitive skills relative to physical skills, especially with advancements in computer technology.[11] Therefore, two task indices — 'cognitive' and 'physical' — are constructed using O*NET's 'abilities' and 'skills' measures:

$$TI_{jk} = \frac{\sum_{l=1}^{L_k} A_{jl} + \sum_{m=1}^{M_k} S_{jm}}{L_k + M_k} \tag{7}$$

where A_{jl} is the numeric value of ability l in occupation j, and S_{jm} is the numeric value of skill m in occupation j. These are similar to the indices constructed in Yamaguchi (2013) using DOT data. Table 2 lists the abilities and skills included for each index.

Table 3 gives the mean values by major ISCO occupation group for each task index constructed. The occupations are ranked by median wage. [12] The highest information task content is found for 'technicians and associate professionals' and 'clerks'.[13] The most routine jobs are 'plant machine operators and assemblers' and 'skilled agricultural and fishery workers'. The latter group also has the highest score for on-site physical presence. Tasks involving inde-

[11] See Autor, Levy, and Murnane (2003) and Yamaguchi (2013).

[12] O*NET uses the Standard Occupational Classification 2010 (SOC-2010) system while the Sri Lankan Labour Force Survey (LFS) uses the International Standard Classification of Occupations 1988 (ISCO-1988). Therefore, a concordance mapping between SOC-2010 and ISCO-1988 is constructed using the mapping between SOC-2010 and ISCO-2008, provided by the Bureau of Labor Statistics (BLS), and the mapping between ISCO-2008 and ISCO-1988, provided by the International Labour Organization (ILO). At the most disaggregated level, the SOC-2010 has 840 occupations while the ISCO-1988 has 672. Therefore, for any one-to-many mappings from SOC-2010 to ISCO-88, the same O*NET task content value is assigned to all corresponding ISCO-1988 occupations.

[13] The major group 'clerks' includes a wide range of occupations, including data entry operators, secretaries, and receptionists.

pendent decision-making are most relevant for 'Legislators, senior officials and managers' and least relevant for 'elementary occupations'. The former group also has the lowest routine and physical presence task content. The interpersonal task content is highest for 'legislators' and 'clerks'.

Physical skills are most relevant for 'skilled agricultural/fishery workers' and least relevant for 'professionals'. In general, low-wage occupations involve low levels of cognitive skill; for example, 'service, shop and sales workers' and 'elementary occupations'. Cognitive skills are most relevant for 'clerks'. This occupation includes statisticians and accounting clerks for whom mathematical ability is important. Cognitive skills are also important for legislators, managers, and technicians. Because SBTC has been found to raise the relative return to cognitive skills, the ratio between cognitive and physical skills is used in the empirical section.

5 Decomposition

This section describes the procedure for decomposing Sri Lanka's wage polarization into distinct contributing factors. Specifically, changes in the wage distribution are decomposed into changes in the *composition of* and *returns to* different workforce characteristics (which include occupational tasks). This method allows for distinguishing whether, for example, changes in educational attainment or changes in the returns to education had a greater role to play in wage polarization. It is also possible to determine whether changes in education mattered more than changes in labor-market tenure. The decomposition method and its empirical implementation is described in detail below.

5.1 Decomposing changes in the wage distribution

Let $f(w_t)$ be the density of log hourly wage, w, in year t. Then let $\nu(f(w_t))$ be a summary statistic of interest of $f(w_t)$. For example, $\nu(\cdot)$ could be the mean, median, variance, skewness, u^{th} quantile, etc. of $f(w_t)$. The goal is to decompose the change in $\nu(f(w_t))$ from some base year $t = 0$ to some final year $t = 1$. Let $\Delta\nu$ be the *overall* change from $t = 0$ to $t = 1$ in the distributional statistic ν:

$$\Delta\nu = \nu(f(w_1)) - \nu(f(w_0))$$

where $f(w_0)$ and $f(w_1)$ are the wage densities at $t = 0$ and $t = 1$, respectively. This can decomposed into a 'composition effect' and a 'coefficient effect'. The composition effect captures

changes in the distribution of workforce characteristics, while the coefficient effect captures changes in the returns to workforce characteristics:

$$\begin{aligned}\Delta\nu &= \nu(f(w_1)) - \nu(f(w_0)) \\ &= \overbrace{\nu(f(w_1)) - \nu(f(w_1)|X(0))}^{\text{composition effect}} \\ &+ \overbrace{\nu(f(w_1)|X(0)) - \nu(f(w_0))}^{\text{coefficient effect}} \\ &+ \eta\end{aligned}$$

The term $\nu(f(w_1)|X(0))$ is the wage distribution that *would have* prevailed at $t = 1$ if *all* workforce characteristics had been distributed as at $t = 0$. This measures the contribution of *all* characteristics simultaneously to changes in the wage distribution.

The contribution of a single characteristic (e.g. education) can be measured in a similar manner. Denoting this characteristic as y, the decomposition can be expressed as:

$$\begin{aligned}\Delta\nu &= \nu(f(w_1)) - \nu(f(w_0)) \\ &= \overbrace{\nu(f(w_1)) - \nu(f(w_1)|y(0))}^{\text{composition effect}} \\ &+ \overbrace{\nu(f(w_1)|y(0)) - \nu(f(w_0))}^{\text{coefficient effect}} \\ &+ \eta\end{aligned}$$

The term $\nu(f(w_1)|y(0))$ is the wage distribution that would have prevailed at $t = 1$ if characteristic y has been distributed as at $t = 0$. Thus, for any statistic of interest, $\Delta\nu$, the composition effect and coefficient effect can be measured for each independent variable in the wage equation (Equation 4) .

5.2 Empirical procedure

The decomposition described above requires the construction of counterfactual wage distributions, $f(w_1)|y(0)$, which give the wages that would have prevailed at $t = 1$ if characteristic y has been distributed as at $t = 0$. The counterfactuals are constructed using the method of Machado and Mata (2005) which utilizes quantile regressions.

Let $Q_{u_n}(w|X)$ be quantile u_n of the distribution of wages, w, given a vector of characteristics, X. The relationship between w and X in quantile u_n is:

$$Q_{u_n}(w|X) = X'\beta(u_n)$$

where $\beta(u_n)$ is a vector of coefficients specific to quantile u_n. The construction of $f(w_1)|y(0)$ proceeds as follows:

1. Determine the number of quantiles, N, with which to divide the total wage distribution. Generate a random sample of size N from the uniform distribution $U(0,1)$: $u_1, u_2, ..., u_N$.

2. Estimate the log wage equation at $t = 1$ (the final year) for each quantile, u_n:

   $$Q_{u_n}(w|X(1)) = X'\beta(u_n)$$

   The term $Q_{u_n}(w|X(1))$ is quantile u_n of the wage distribution at $t = 1$ given the vector of characteristics, $X(1)$, prevailing at $t = 1$. Save the estimated coefficients $\hat{\beta}(u_n)$ for each quantile u_n.

3. Generate a random sample of size N, with replacement, from the individual observations in $X(1)$:

   $$\{x_n^*(1)\}_{n=1}^N$$

   The symbol * indicates that the sample was randomly generated.

4. Used the estimated coefficients from step 2 to compute:

   $$w_n^*(1) = x_n^*(1)'\hat{\beta}_{u_n}(1)$$

   for each quantile u_n, $n = 1, ..., N$.

5. Choose the characteristic of interest, y, and partition its space into P categories. (For example, if y is age, then construct $P = 5$ categories of $15-24, 25-34, ..., 55-64$.) Denote as f_p the relative frequency of category p at $t = 1$. Then select the subset of observations in category p from the constructed distribution $\{w_n^*(1)\}_{n=1}^N$. (For example, if $p = 1$, select the subset of individuals aged 15-24 from the constructed distribution at $t = 1$.) Denote this subset as $\{w_n^{*p}(1)\}_{n=1}^N$.

6. From $\{w_n^{*p}(1)\}_{n=1}^N$, generate a random sample, with replacement, of size equal to the number of observations in category p at $t = 0$. (For example, if there are 2,000 people aged 15-24 at $t = 0$, then generate a random sample of 2,000 from $\{w_n^{*p}(1)\}_{n=1}^N$ where $p = 1$.)

7. Repeat steps 5 and 6 for all P categories of characteristic y.

The above procedure generates the counterfactual distribution $f(w_1)|y(0)$ for characteristic y. All other characteristics are assumed to be distributed as at $t = 1$.

5.3 Estimating equation

Step 2 in the decomposition procedure requires estimating the wage equation for different quantiles. The model of occupational choice in Section 3 gives the following wage equation:

$$ln(w_{ijt}) = \alpha_{jt} + \sum_{k=1}^{K} \beta_{jkt} s_{ikt} + \gamma_{jt} Z_{it} + \epsilon_{ijt}$$

where s_{ikt} is individual i's endowment of skill in task k at time t. Unfortunately, the LFS does not contain information on individuals' endowments of task-specific skills. The LFS being a repeated cross section, this information cannot be constructed from occupational histories either. However, all that is required for the decomposition exercise is to distinguish between changes in the returns to tasks and changes in the composition of tasks in the workforce. Thus, as long as there is variation across the workforce in the task content of occupations, the estimating equation for wage quantile u can be written as:

$$ln(w_{i,u}) = \alpha_{0,u} + \sum_{k=1}^{K} \beta_{k,u} TI_{ik} + \gamma_u Z_i + \epsilon_{i,u} \tag{8}$$

where the skill endowments, s_{ikt}, are replaced with the task indices, TI_{ik}. The vector Z contains potential experience and its squared term, sex, and years of schooling.[14] The wage distribution is divided into 99 quantiles. Two specifications of Equation 8 are tested. The first uses the five offshorability task indices and the second uses the cognitive ratio (the ratio between the cognitive and physical task indices).

6 Results

This section describes the results of the decomposition exercise. Section 6.1 describes the estimated coefficients for the quantile regressions, and Section 6.2 describes the composition and coefficient effects.

[14] Potential experience is computed as age minus years of schooling.

6.1 Quantile regression coefficients

Offshorable tasks

Figure 7 compares the estimated quantile regression coefficients for 1992 (base year) and 2009 (final year). The coefficient estimates (solid lines) and their 95% confidence intervals (dotted lines) are plotted against quantile number. The plots show that males earn more than females across all jobs, but that this gender gap is smaller for high-wage occupations. Figure 8 shows the coefficients for all years (1992-2009) and the plots are drawn to become darker with time; i.e. the lightest (darkest) lines represent the earliest (latest) years. The gender gap is shown to have risen over the 18-year time period with the most acute change occurring for low-wage jobs. This implies that male wage inequality has decreased relative to female wage inequality.

The effect of education on wages has changed quite dramatically (Figure 7). In 1992, the positive impact of education on wage gets smaller at higher quantiles, suggesting that education decreases wage inequality. In 2009, however, the trend is almost reversed; education has a greater positive impact at higher quantiles. This reversal over time is even more evident in Figure 8. Thus, education has contributed to greater wage inequality over time.

The positive coefficient on potential experience and the negative coefficient on its squared term both increase in magnitude over time, and this effect is strongest in the middle of the wage distribution. Thus, even after controlling for education, experience-wage profiles have become more concave over time; this means that, compared to the early 1990s, wages rose more steeply for younger workers and declined more rapidly for older workers in the late 2000s.[15]

Turning to the offshorability task measures, Figure 7 shows that the positive wage return to information tasks declines with quantile. Moreover, returns have increased for the middle and upper portions of the wage distribution, and has fallen for the lower. Firpo et al. (2011) report an almost identical trend for the US. A plausible explanation is that new information and communication technology (ICT) has substituted low-skill workers in favor of high-skill workers since the latter are complements to ICT. Moreover, the literature attributes developments in ICT to the outsourcing of middle-skill jobs in developed countries. Since developing country skill distributions lie below those of developed countries, this outsourcing should benefit the middle- and high-skill workers of the recipient countries.

[15] Similar trends have been documented for developed countries. Steeper wage profiles are usually attributed to greater human capital, all else equal (Becker, 1994). For example, Kredler (2008) documents a rise in the 'experience premium' in Germany for the 1975-2001 period and, in a companion paper, attributes this to new technologies that lead to faster wage growth for young workers. Thus, the increasing concavity of the wage-experience profiles in Sri Lanka may be due to technological change, better on-the-job training, and other factors that raise human capital above and beyond schooling.

The wage returns to routine tasks are *negative*, implying that the greater the routine content of a job, the lower the wage. The returns show a marked decline over time, and this decline is strongest for the lower portion of the distribution. One possible explanation is routine jobs became have become mechanized as a result of technology changes, substituting humans in favor of machines. Since low-skill workers are more likely to hold routine jobs, they thus experienced the largest wage declines. Another explanation is that the expansion of the services sector in Sri Lanka has corresponded with growth in non-routine jobs. Services job growth may also be a consequence of outsourcing since Sri Lanka is a popular destination for finance, business processing and ICT jobs which are typically non-routine.

Note that the trends for both information and routine tasks can be attributed simply to technology changes, not necessarily outsourcing. Therefore, for the decomposition exercise, these two task indices are summed up to construct a separate 'technology' index to evaluate the potential role of technology advancements to changes in the wage distribution.

The returns to (the inverse of) decision-making and creative tasks have increased over time. This increase is stronger for the middle and upper portions of the distribution. This is consistent with the outsourcing prediction; jobs that require less independent decision-making and creativity are more likely to be shipped to low-skill abundant countries like Sri Lanka.The inverse of the physical presence index shows decreasing returns over time. This contradicts the outsourcing hypothesis; if outsourcing has grown over time in Sri Lanka, jobs requiring less face-to-face interaction and on-site physical presence should have experienced higher wage returns since they are easier to outsource. The interpersonal index does not show a clear pattern of change over time.

The coefficient estimates are statistically significant for each of the 99 quantiles. The overall results point to large changes over time in the returns to occupational tasks and demographic characteristics. Furthermore, these changes have varied considerably *across* wage quantiles, contributing to either increased or decreased wage inequality between different points of the distribution. The decomposition below will explicitly measure the contribution of each independent variable to changes in the economy-wide wage distribution.

Cognitive and physical skills

The bottom panels in Figures 7 and Figure 8 plot the estimated coefficients for the cognitive ratio (the ratio between cognitive and physical skills required in an occupation). The relative return to cognitive skills has increased markedly over time for the middle and upper portions

of the wage distribution and has declined for the lower tail. These trends may be indicative of skill-biased technical change (SBTC) that either complements cognitive skills or substitutes physical skills, or both.[16]

Jobs that typically pay low wages have low cognitive ratios. Table 3 shows that the bottom five occupation groups ranked by wage have average cognitive ratios in the range of 0.93-1.14, while the top four occupation groups have a range of 1.61-2.97. If SBTC substitutes physical skills and complements cognitive skills, then it should put downward pressure on wages in low-wage jobs and upward pressure for high-wage jobs. [17]

6.2 Decomposition

Aggregate effects

The first decomposition exercise considers *all* workforce characteristics simultaneously. The composition effect is therefore $\nu(f^*(w_1)) - \nu(f^*(w_1)|X(0))$, and the coefficient effect is $\nu(f^*(w_1)|X(0)) - \nu(f^*(w_0))$. The term $X(0)$ denotes the workforce characteristics in the base year (1992).

Table 4 reports the results for the offshorability regressions. The first column lists the names of the distributional statistics of interest, $\nu(\cdot)$; the median log hourly wage for several quantiles, and the mean and variance. The second and third columns show the estimated statistics for the base and final years, respectively, along with their bootstrap standard errors in parentheses. Column 4 shows the *change* in the estimated statistics between 1992 and 2009, $\nu(f^*(w_1)) - \nu(f^*(w_0))$, along with the bootstrap 95% confidence intervals for those changes. The numbers show that the largest changes have taken place at the lower and upper portions of the wage distribution, with the smallest changes in the middle. This confirms that Sri Lanka experienced wage polarization between 1992 and 2009.

The last two columns show the composition and coefficient effect along with their bootstrap 95% confidence intervals. The composition effect is weak, contributing relatively little to wage changes between 1992 and 2009. The change in log hourly wage ranges from 0.028 to 0.075, which translates to wage growth of 2.8-7.5%. Moreover, the confidence intervals are large and include zero for all of the statistics. In contrast, the coefficient effect is strong, contributing to log wage changes in the range of 0.22-0.36 or wage growth of 22-36%. Moreover, the

[16] Yamaguchi (2013) finds evidence of a relative decline in the return to physical skills in the US, and attributes this to the closing gender wage gap since men have greater relative endowments of physical skills.

[17] Note that while occupations at the very top of the wage distribution have a high cognitive component, many do not have a significant technical component (e.g. legislators, teachers). This may explain why the upper end of the distribution has experienced only a modest rise in the relative return to cognitive skills.

confidence intervals are narrow and do not include zero for any statistic except variance. The coefficient effect takes on a U-shape, matching the pattern of wage polarization in the economy. For example, wage growth is larger at quantiles 10 and 90 than at quantile 50. The composition effect does not show such a pattern.

The first panel of Figure 9 shows these same results visually. The coefficient effect plotted against quantile is U-shaped and is virtually superimposed on the plot showing total wage changes. In contrast, the plot for the composition effect is relatively flat across quantiles and lies substantially beneath the coefficient effect. This is a strong indication that wage polarization between 1992 and 2009 occurred primarily due to changes in the returns to workforce characteristics, rather than changes in the composition of those characteristics.

Table 5 reports the results for the cognitive ratio regressions. Both the composition and coefficient effects are of similar magnitude, suggesting that both effects contributed equally to changes in the wage distribution. The first panel of Figure 10 shows this result visually. The coefficient effect again takes on the familiar U shape. However, the confidence intervals are wide for all statistics (Table 5), and the coefficient effect in particular is much weaker here than for the offshorability specification.

These results provide preliminary evidence that changes related to outsourcing and technology spillovers played a key role in the evolution of Sri Lanka's wage distribution. In the next section, the individual contributions of workforce characteristics are assessed.

Individual characteristics: composition effect

For a given workforce characteristic, y, the composition effect is $\nu(f^*(w_1)) - \nu(f^*(w_1)|y(0))$ and the coefficient effect is $\nu(f^*(w_1)|y(0)) - \nu(f^*(w_0))$, where $y(0)$ denotes the distribution of characteristic y in the base year (1992). Table 6 reports the composition effects. The first entry in each cell gives the estimated composition effect, and the second and third entries are its bootstrap standard error and 95% confidence interval, respectively.

Education is the *only* variable with a strong composition effect. The effect is positive and significant at all quantiles and is larger for the upper quantiles, suggesting that rising educational attainment has increased wage inequality through the dispersion effect.[18] Indeed, the last cell in the 'Education' column shows that changes in educational attainment had a positive and significant effect on wage dispersion. Potential experience and sex had a negative composition effect on the wage distribution, although their impact is weak; the standard errors are large

[18] See Section 3.2 for a discussion.

and the confidence intervals include zero. This suggests an increase in the ratio of women to men in the workforce and a decline in labor-market tenure. The former is supported by the raw LFS data; the proportion of women in the workforce has increased from 30.3% in 1992 to 35.9% in 2009. The decline in labor-market tenure is a likely consequence of greater educational attainment which delays labor market entry. The second panel of Figure 9 shows these results visually. The composition effect for education most closely matches the pattern of wage polarization.

The composition effects are also weak for the offshorability task indices. Column 5 of Table 6, titled 'Offshorability', gives the aggregate effect of all five task indices. Column 6, titled 'Technology', gives the combined effect of the information and routine task indices.[19] Column 7, titled 'Human', gives the combined effects of (the inverse values of) the physical presence, interpersonal and decision task indices. Together, they capture the hands-off nature of an occupation. The results show that the composition effects for 'offshorability', 'technology' and 'human' are not statistically significant. However, 'offshorability' and 'technology' show positive changes for all quantiles, suggesting an increase in outsourced and technology-conducive jobs in the economy. The third panel of Figure 9 confirms these results; none of the plots match the pattern of wage polarization.

The composition effect for the cognitive ratio is shown in the last column of Table 6 and the second panel of Figure 10. The individual effects are weak, which is not surprising given the weak aggregate effects.

In conclusion, education is the only variable that has had a statistically significant composition effect on the wage distribution. However, while greater educational attainment has contributed to greater wage inequality by increasing wage dispersion at the upper quantiles, it cannot explain wage polarization. Thus, Sri Lanka's wage polarization cannot be attributed to changes in the composition of its workforce.

Individual characteristics: coefficient effect

Table 7 shows the results for the individual coefficient effects. Unlike the composition effects, the coefficient effects are large in magnitude and highly significant (except for variance). The returns to education, labor-market tenure and males (relative to females) have increased over time for all quantiles of the wage distribution. The fourth panel of Figure 9 shows that these changes take on a convex shape, matching the general pattern of wage polarization, although the

[19] As discussed in Section 6.1, time trends in the returns to ICT and routine tasks may be capturing technology spillovers.

education effect flattens out somewhat at the top half of the distribution. Comparing this to the second panel of Figure 9 shows that the returns to demographic characteristics have contributed much more to wage polarization than the composition of the these characteristics.

The results for offshorability are even stronger. Panel 5 of Figure 9 shows that the coefficient effect for *each* offshorable task index closely mimics both the pattern and magnitude of wage polarization. Table 7 shows that the effects for 'offshorability', 'technology' and 'human' are all large and significant, suggesting that structural changes related to outsourcing and technology are a driving force behind Sri Lanka's wage polarization. This, along with the almost negligible composition effect, points to *demand-driven* — rather than supply-driven — changes in the labor market. This aligns with the findings of the structural trade literature; that labor supply is slow to adjust to trade policy changes.[20]

The pattern of wage polarization and the offshorability coefficient effects also coincide with the wage changes documented between and within occupations (Figure 6). This prompts the following question: do the occupations most susceptible to outsourcing and technical change lie at the extremes of the wage distribution? Table 8 lists the fifteen occupations with the highest offshorability scores along with each occupation's rank by base-year median wage. The occupations are disaggregated to the three-digit level (giving a total of 107 occupations). Of the 15 most information-related occupations, all but one ranks in the top half of the wage distribution. These include some of the most lucrative professions (e.g. business professionals, lawyers, engineers, doctors). Figure 5 shows that these occupations experienced both high wage growth and greater wage inequality, meaning that the best-paid workers enjoyed the highest wage growth. Recall from the quantile regressions that wages are positively correlated with information content (Section 6.1). Thus, if outsourcing brought ICT jobs to Sri Lanka, wages should rise disproportionately at the top of the distribution.

In contrast, most occupations with a high routine content lie in the lower half of the wage distribution. Notably, they involve the operation of industrial machinery. Figure 5 shows that these occupations experienced high wage growth but lower wage inequality, meaning that the lowest-paid workers enjoyed the highest wage growth. Recall from the quantile regressions that wages are *negatively* correlated with routine content. Thus, if outsourcing brought routine jobs to Sri Lanka — such as those in the garment industry — wages should rise at the bottom of the

[20]While a one-time, one-sector trade policy change instantly alters (relative) wage returns across all sectors, labor supply requires an adjustment period of 30-80 years (Artuc, 2009; Artuc et al., 2010; Cosar, 2013; Dix-Carneiro, 2013; Seneviratne, 2013). This is because it is costly for the workforce to switch sectors and acquire new skills. It is therefore plausible that, over a relatively short 18-year time span, structural changes linked to international competition impact wage returns much more strongly than workforce composition.

distribution. Moreover, both ICT and routine occupations are conducive to technical change, further contributing to wage growth at the extremes.

Of the 15 occupations requiring the least amount of on-site physical presence, 13 are in the top half of the wage distribution and include well-paid professions that are commonly outsourced; e.g. business service agents.[21] Meanwhile, occupations requiring little face-to-face interaction and independent decision-making and creativity are mostly low-wage; some of these are heavily outsourced — e.g. textile and garment workers, computing professionals. Thus, depending on which offshorability index is used, the most offshorable occupations are clustered at the lower or upper portion of the wage distribution. This suggests that the five offshorability indices combined provide a quite comprehensive measure of occupations' exposure to international competition.

These results also have a key implication for future research. In trying to explain rising wage inequality in developing countries, the trade literature typically links skill-biased technical change to education levels. Yet, the decomposition results suggest that SBTC may be better linked to occupational task content, which is not necessarily correlated with years of schooling or educational milestones (e.g. high-school diploma, college degree, etc.)

7 Conclusion

In light of rising wage inequality observed in developing countries that liberalized their economies, this paper evaluates changes in the wage distribution of Sri Lanka. Using labor force survey data, rising wage polarization is documented for the 1992-2009 time period. This means that wage inequality *increased* in the upper half of the distribution but *decreased* in the lower half. Further investigation shows this trend matches wage growth patterns across and within *occupations* rather than *industries*, even though international competition is typically linked to industry-wide changes.

To formally link wages with occupations, a Roy model of occupational choice is presented where each occupation is broken down into its constituent tasks and skill requirements. An important feature of the model is that wage returns to distinct job tasks and skills vary across occupations and time. The model generates a key empirical implication; that changes in both the *returns* to tasks and the *composition* of tasks in the workforce can drive the complex patterns of wage growth observed in Sri Lanka. This implication is tested using a decomposition method

[21] Sri Lanka is an outsourcing destination for business services, in part because of the country's large supply of accountants.

adapted from Machado and Mata (2005). The results show that occupational tasks related to technological change and outsourcing have strong explanatory power for Sri Lanka's wage polarization.

Importantly, it is the change in wage returns rather than in workforce composition that appears to be driving these trends. This concurs with a now established finding in the structural trade literature; that workforce composition is slow to respond to trade policies that alter the wage returns to individual skill.

The main finding in this paper is that occupation-based tasks and skills play an important role in changes in wage inequality, even after accounting for education and work experience. This has an important implication for future research. The trade literature usually looks to traditional measures of skill, such as education, when explaining changes in wage inequality, especially when attributing skill-biased technical change (SBTC) to these changes. Yet, the results in this paper provide strong evidence that greater international competition and technology spillovers can impact the economy-wide wage structure through an additional dimension of skill — occupational tasks — leading to complex patterns of wage inequality changes.

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A Figures

Figure 1: Wage growth, 1992-2009

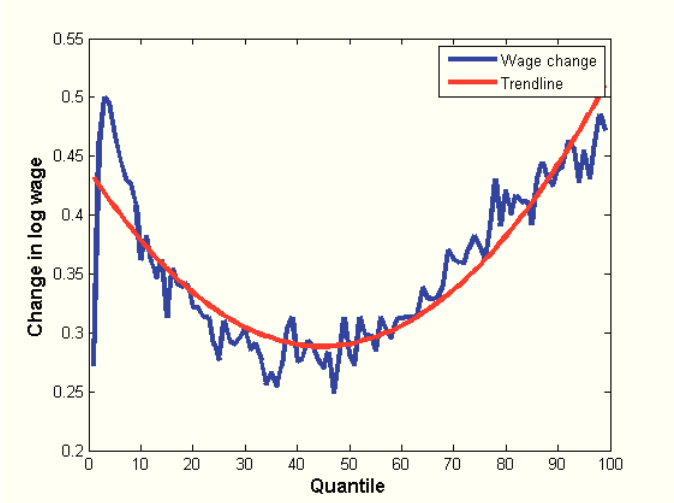
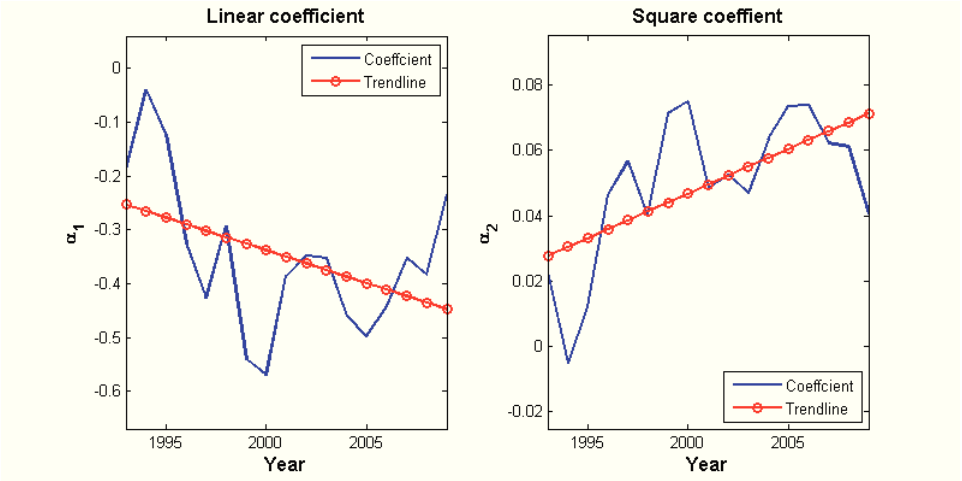
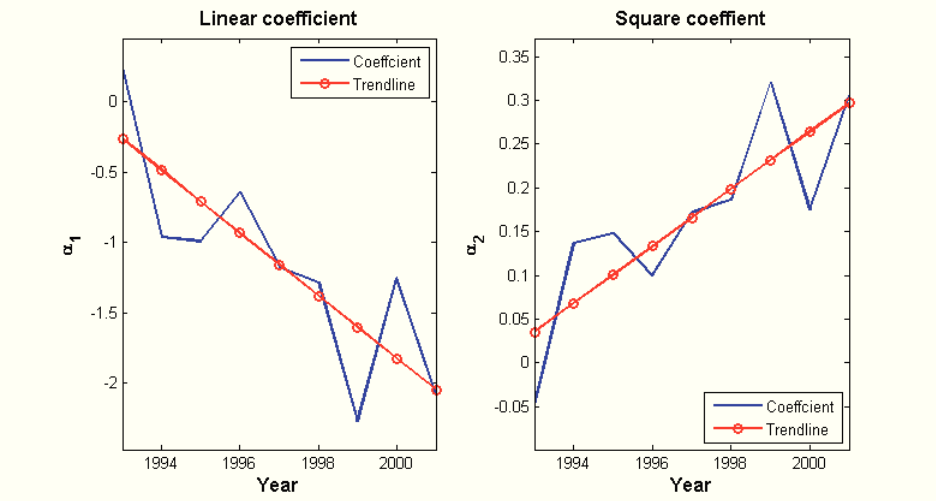


Figure 2: Estimated wage changes, 1992-2009



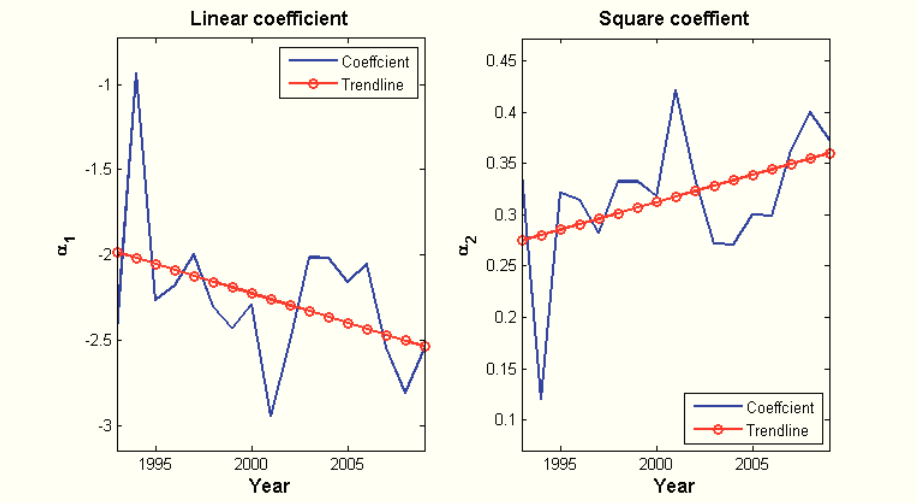
The results are for the regression equation $\Delta w_t^q = \alpha_{0t} + \alpha_{1t} w_0^q + \alpha_{2t} w_0^{q2} + \epsilon_t^q$ where w is log hourly wage and j stands for three-digit ISIC industry. The regression is weighted by the industry-specific employment numbers in the base year (1992). The figure plots the estimates of α_{1t} and α_{2t} for each year (t).

Figure 3: Estimated industry wage changes, 1992-2009



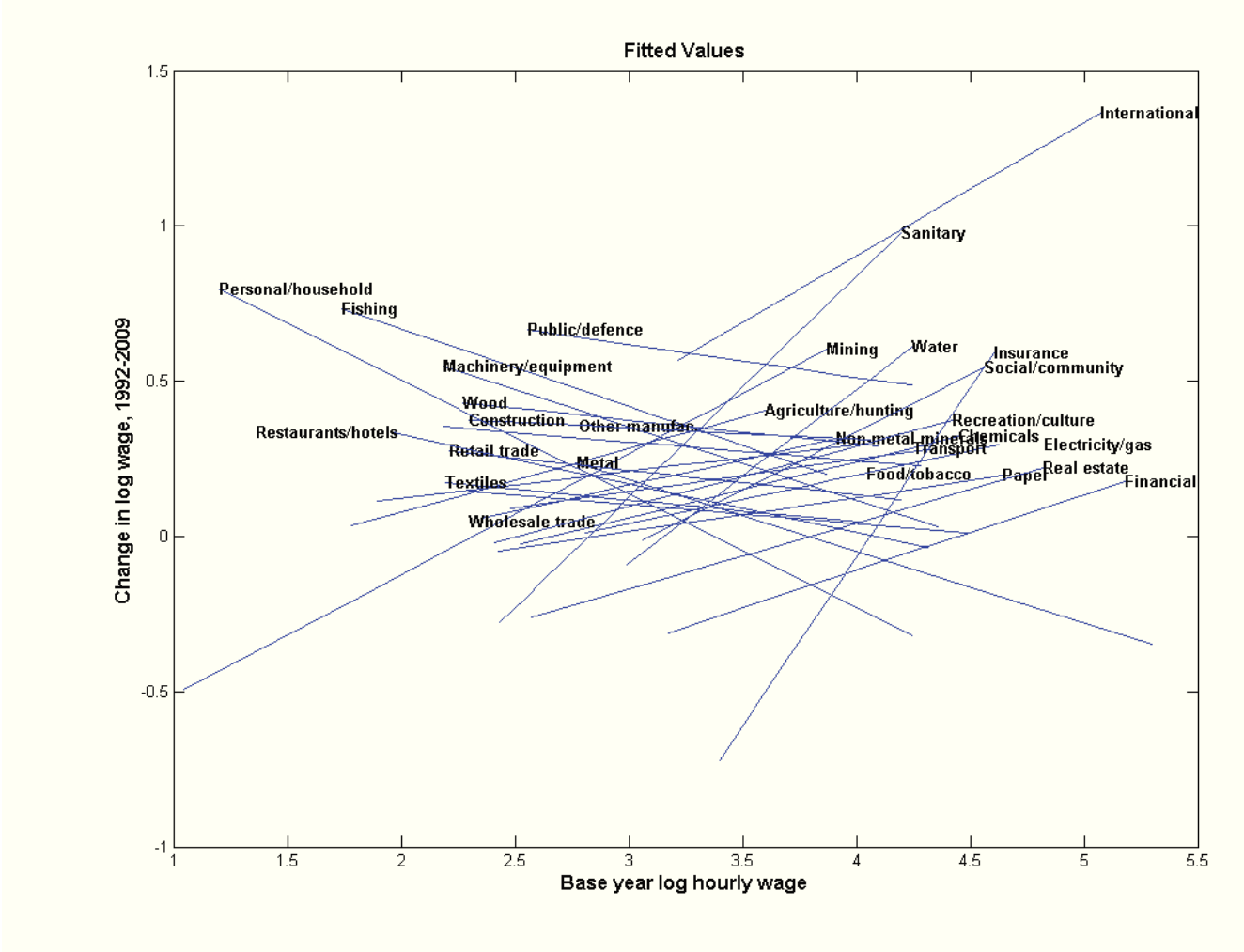
The results are for the regression equation $\Delta w_{jt} = \alpha_{0t} + \alpha_{1t} w_{j0} + \alpha_{2t} w_{j0}^2 + \epsilon_{jt}$ where w is log hourly wage and j stands for three-digit ISIC industry. The regression is weighted by the industry-specific employment numbers in the base year (1992). The figure plots the estimates of α_{1t} and α_{2t} for each year (t).

Figure 4: Estimated occupation wage changes, 1992-2009



The results are for the regression equation $\Delta w_{jt} = \alpha_{0t} + \alpha_{1t} w_{j0} + \alpha_{2t} w_{j0}^2 + \epsilon_{jt}$ where w is log hourly wage and j stands for three-digit ISCO occupation. The regression is weighted by the industry-specific employment numbers in the base year (1992). The figure plots the estimates of α_{1t} and α_{2t} for each year (t).

Figure 5: Wage growth by industry and quantile, 1992-2009



The results show the fitted values from regression equation $\Delta w_{jt}^q = \gamma_{j0} + \gamma_{j1} w_{j0}^q + \eta_j$ where $q = 1, ..., 10$ stands for quantile, γ_{j0} is a vector of industry dummies, and $\gamma_{j1} w_{j0}^q$ is the interaction between base-year wage and industry dummy. The fitted values are plotted against base-year wage for all ten quantiles of each two-digit ISIC industry.

Figure 6: Wage growth by occupation and quantile, 1992-2009

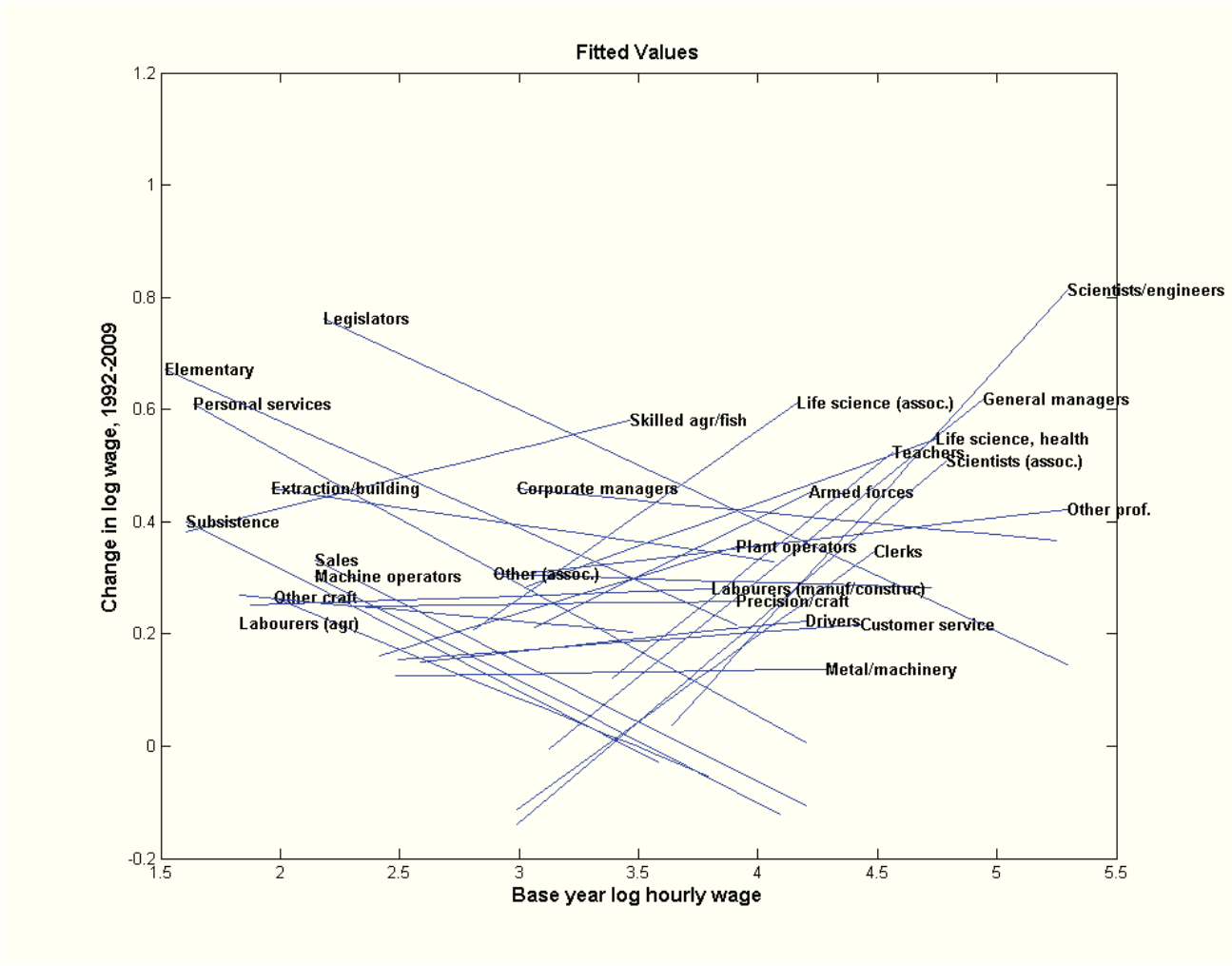


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Figure 7: Offshorability regression, 1992 and 2009

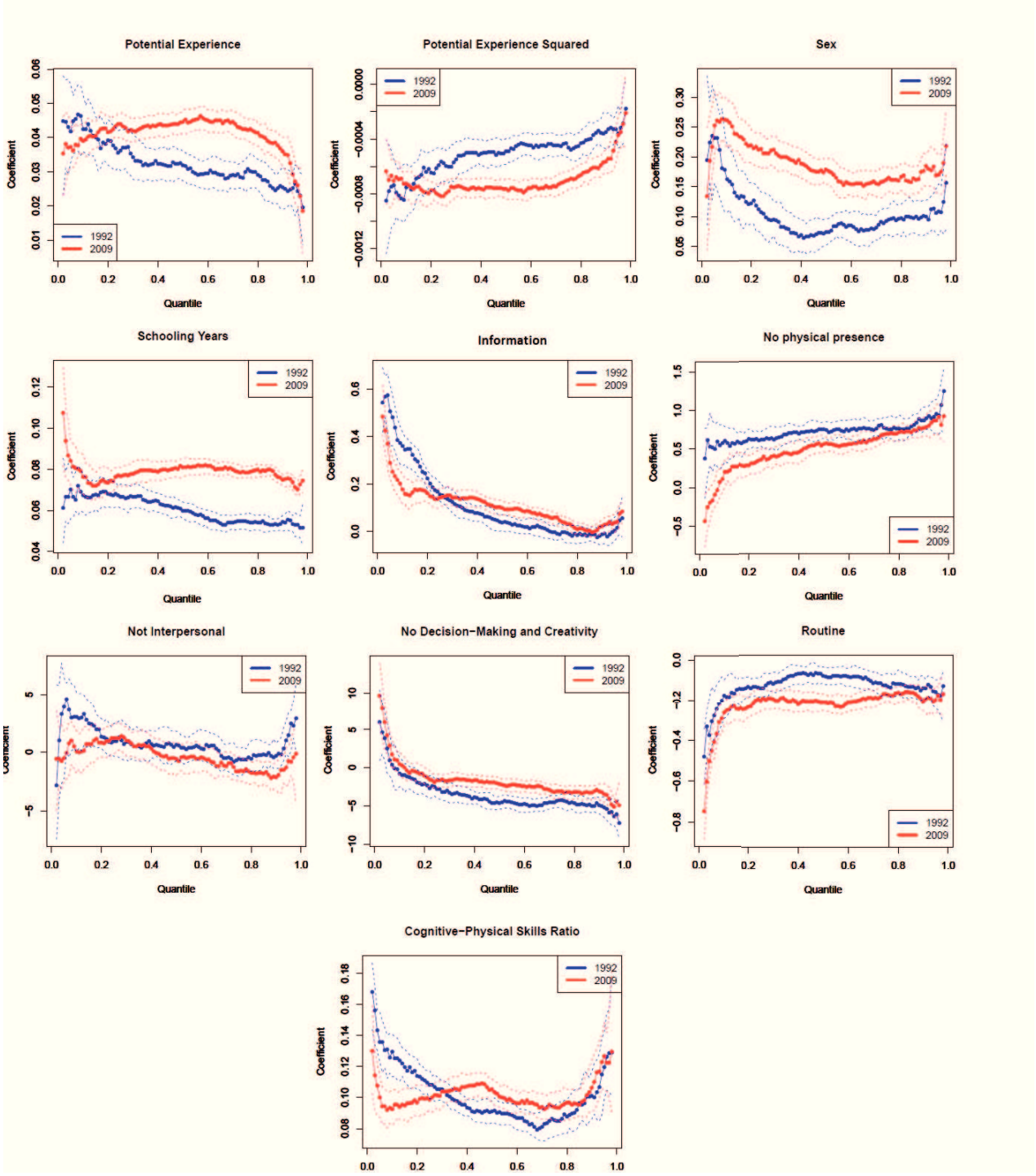
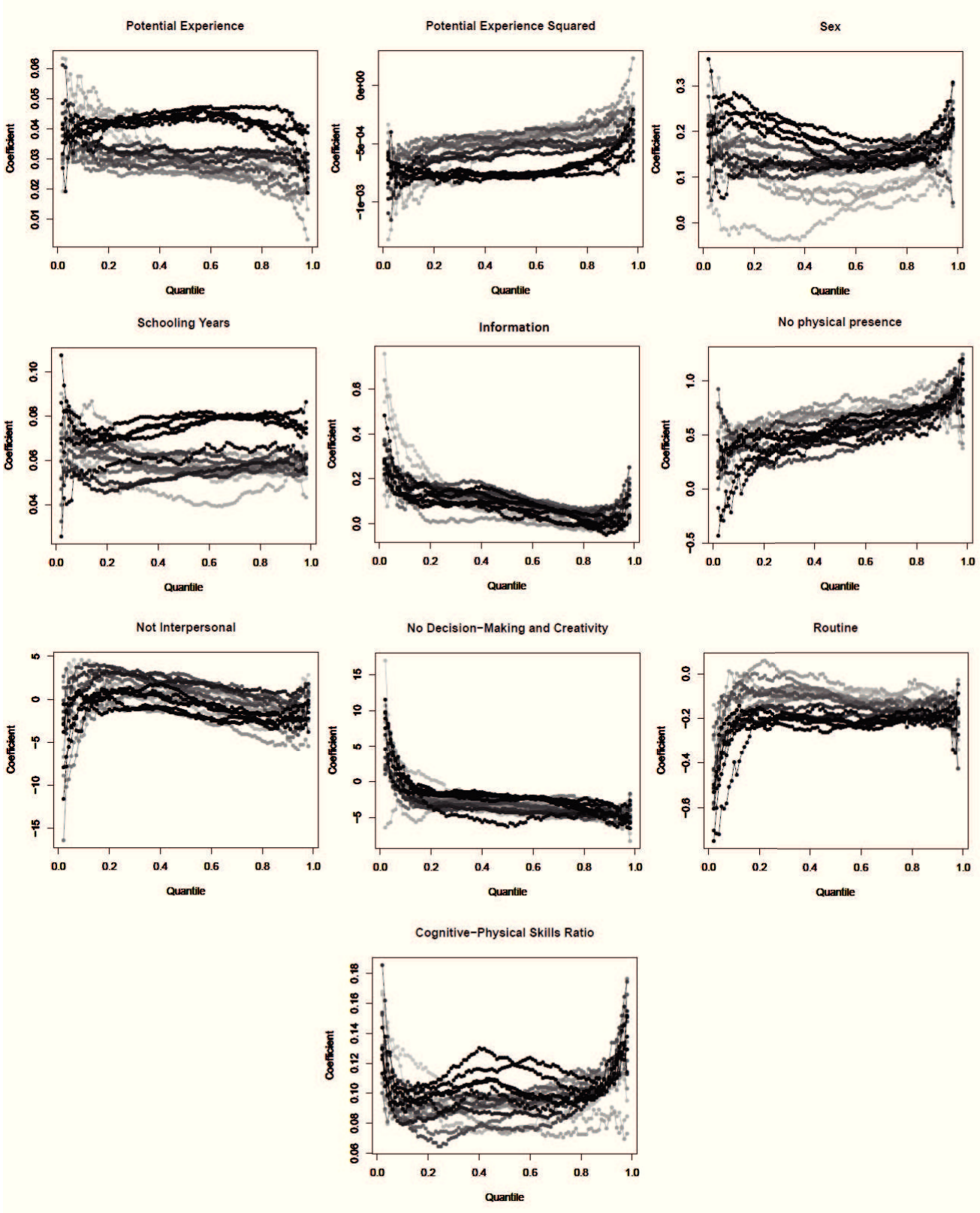


Figure 8: Offshorability regression, 1992-2009



Each plot represents a particular year. The plots get progressively darker from 1992 to 2009.

Figure 9: Total wage change

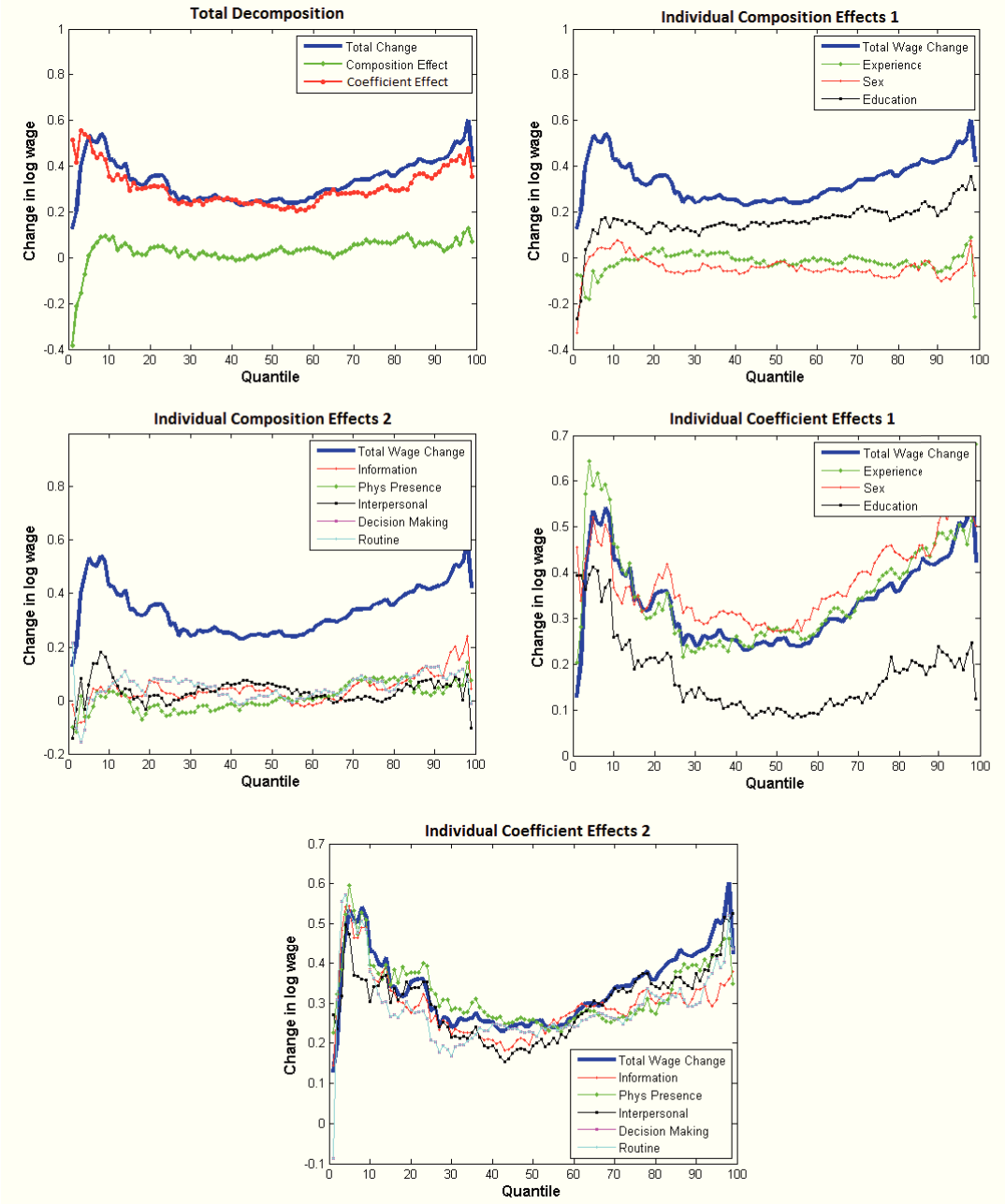
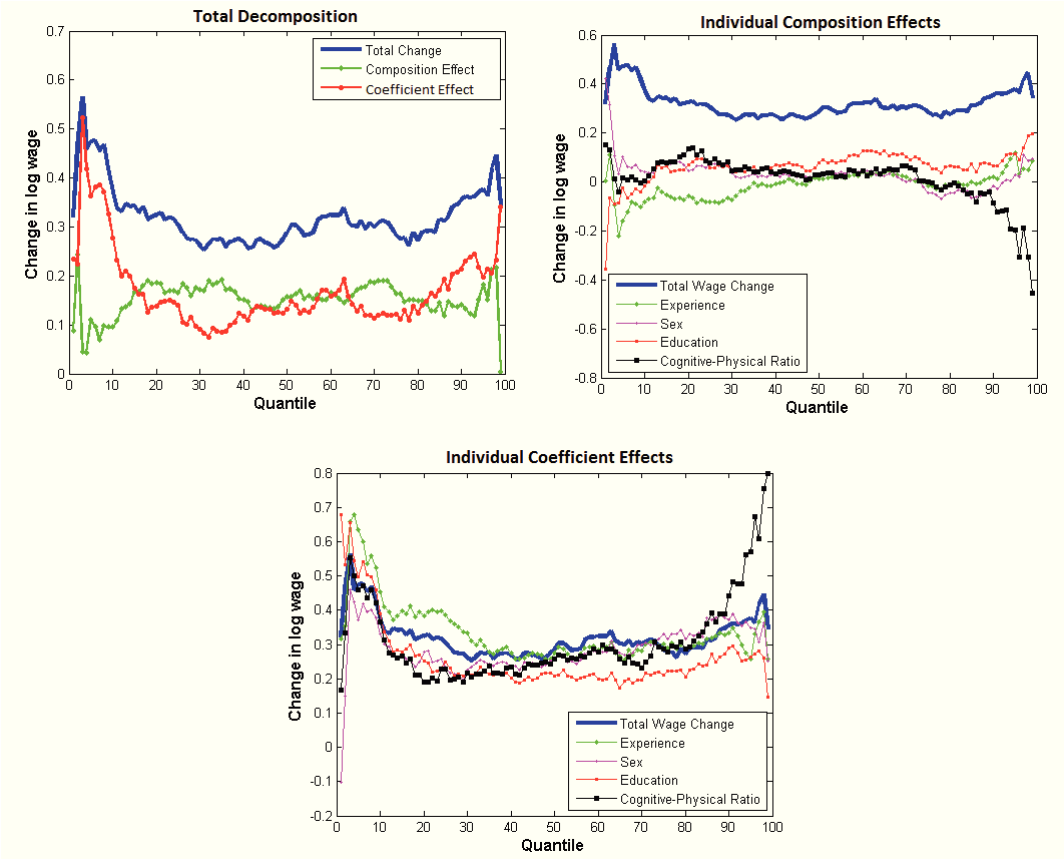


Figure 10: Total wage change



B Tables

Table 1: Offshorability indices

Task measure	O*NET Work activities	O*NET Work context
Information and internet	Getting information Processing information Analyzing data or information Interacting with computers Documenting/recording information	
Physical presence	Inspecting equipment, structures, or material Performing general physical activities Handling and moving objects Controlling machines and processes Operating vehicles, mechanized devices, or equipment Repairing and maintaining mechanical equipment Repairing and maintaining electronic equipment	
Interpersonal	Establishing and maintaining interpersonal relationships Assisting and caring for others Resolving conflict and negotiating with others Performing for or working directly with the public Coordinating the work and activities of others Guiding, directing, and motivating subordinates Coaching and developing others	Face to face discussions Coordinate or lead others
Decision-making and creativity	Making decisions and solving problems Thinking creatively Developing objectives and strategies	Responsibility for outcomes and results Impact of decisions on co-workers or company results Frequency of decision-making Freedom to make decisions
Routine physical		Spend time making repetitive motions Degree of automation Importance of repeating same tasks Structured versus unstructured work (reverse) Pace determined by speed of equipment

Table 2: Physical and cognitive skills

Task Measure	O*NET Abilities	O*NET Skills
Physical skills	Spatial orientation Manual dexterity Finger dexterity Control precision Multilimb coordination Response orientation Gross body coordination	
Cognitive skills	Oral comprehension Written comprehension Deductive reasoning Inductive reasoning Mathematical reasoning Number facility	Mathematics Critical thinking Social perceptiveness Complex problem solving

Table 3: Mean task content by major occupation group

Occupation group	Median Wage	Information	Routine	Physical Presence	Interpersonal	Decision	Physical Skills	Cognitive Skills
All		0.5596	0.2851	0.5713	0.7006	0.6841	0.4798	0.5157
Professionals	4.120	0.6579	0.2006	0.3686	0.7703	0.7437	0.2799	0.5593
Legislators, Senior Officials, Managers	3.953	0.6760	0.1886	0.4084	0.7899	0.8211	0.3497	0.5837
Clerks	3.752	0.7262	0.2812	0.3396	0.7955	0.7524	0.2097	0.6221
Technicians, Associate Professionals	3.734	0.7211	0.2157	0.4143	0.7159	0.7133	0.3542	0.5702
Plant Machine Operators, Assemblers	3.362	0.6645	0.3163	0.5735	0.7637	0.7319	0.4272	0.4875
Crafts and Related Trades	3.244	0.5052	0.2698	0.6010	0.6525	0.6752	0.5076	0.4891
Service, Shop and Market Sales	3.094	0.5633	0.2177	0.4407	0.7396	0.6886	0.4075	0.4571
Elementary	2.907	0.4940	0.3049	0.5345	0.6258	0.5591	0.4931	0.4823
Skilled Agricultural and Fishery	2.762	0.5549	0.3239	0.7191	0.7295	0.7431	0.5801	0.5460

Table 4: Aggregated decomposition: offshorability specification

Statistic	1992	2009	Change	Covariate effect	Wage struc. effect
10th quant.	2.192	2.620	0.429	0.075	0.353
	(0.102)	(0.042)	(0.260 ; 0.628)	(-0.064; 0.199)	(0.176; 0.588)
25th quant.	2.770	3.050	0.280	0.022	0.258
	(0.077)	(0.029)	(0.142; 0.417)	(-0.084; 0.104)	(0.107; 0.407)
50th quant.	3.292	3.546	0.254	0.029	0.225
	(0.038)	(0.032)	(0.167; 0.336)	(-0.052; 0.099)	(0.133; 0.315)
75th quant.	3.670	4.029	0.359	0.074	0.285
	(0.024)	(0.028)	(0.301; 0.425)	(-0.006; 0.147)	(0.205; 0.362)
90th quant.	4.007	4.430	0.423	0.059	0.364
	(0.0395)	(0.037)	(0.330; 0.524	(-0.059; 0.147)	(0.274; 0.500)
99th quant.	4.664	5.086	0.422	0.067	0.356
	(0.078)	(0.031)	(0.230; 0.626)	(-0.157; 0.174)	(0.209; 0.644)
Mean	3.181	3.512	0.331	0.028	0.303
	(0.031)	(0.024)	(0.268; 0.387	(-0.024; 0.096)	(0.226; 0.373)
Variance	0.549	0.590	0.042	0.057	-0.015
	(0.034)	(0.035)	(-0.037; 0.129)	(-0.029; 0.125)	(-0.101; 0.073)

Table 5: Aggregate decomposition: cognitive ratio specification

Statistic	1992	2009	Change	Covariate effect	Wage struc. effect
10th quant.	2.204	2.575	0.371	0.094	0.277
	(0.113)	(0.044)	(0.202; 0.587)	(-0.024; 0.211)	(0.084; 0.516)
25th quant.	2.734	3.039	0.304	0.165	0.139
	(0.057)	(0.030)	(0.194; 0.399)	(0.085; 0.246)	(0.011; 0.246)
50th quant.	3.240	3.528	0.288	0.156	0.131
	(0.031)	(0.036)	(0.195; 0.359)	(0.081; 0.241)	(0.043; 0.213)
75th quant.	3.691	3.975	0.284	0.163	0.121
	(0.036)	(0.017)	(0.207; 0.351)	(0.083; 0.223)	(0.039; 0.201)
90th quant.	4.049	4.405	0.356	0.141	0.215
	(0.039)	(0.032)	(0.265; 0.445)	(0.021; 0.228)	(0.099; 0.320)
99th quant.	4.748	5.092	0.344	0.003	0.341
	(0.091)	(0.078)	(-0.069; 0.530)	(-0.314; 0.338)	(-0.068; 0.620)
Mean	3.176	3.496	0.320	0.152	0.168
	(0.033)	(0.024)	(0.262; 0.381)	(0.085; 0.208)	(0.090; 0.245)
Variance	0.574	0.544	-0.030	-0.032	0.002
	(0.046)	(0.031)	(-0.121; 0.050)	(-0.142; 0.050)	(-0.105; 0.126)

Table 6: Individual composition effects

	Pot. exp.	Sex	Education	Offshorability	Technology	Personable	Cog-phys ratio
10th quant.	-0.0360	0.062	0.169	0.267	0.095	0.172	0.006
	(0.055)	(0.051)	(0.053)	(0.242)	(0.102)	(0.152)	(0.056)
	(-0.147; 0.061)	(-0.058; 0.142)	(0.069; 0.287)	(-0.254; 0.688)	(-0.109; 0.278)	(-0.157; 0.436)	(-0.102; 0.121)
25th quant.	0.012	-0.065	0.125	0.025	0.096	-0.071	0.077
	(0.041)	(0.042)	(0.039)	(0.157)	(0.080)	(0.097)	(0.045)
	(-0.060; 0.097)	(-0.157; 0.012)	(0.052; 0.202)	(-0.278; 0.322)	(-0.068; 0.249)	(-0.269; 0.110)	(0.000; 0.168)
50th quant.	-0.026	-0.018	0.152	0.128	0.059	0.069	0.030
	(0.043)	(0.043)	(0.038)	(0.171)	(0.081)	(0.102)	(0.038)
	(-0.119 ;0.054)	(-0.102; 0.063)	(0.086; 0.226)	(-0.234; 0.419)	(-0.111; 0.209)	(-0.147; 0.246)	(-0.047; 0.103)
75th quant.	-0.025	-0.079	0.205	0.284	0.139	0.145	-0.002
	(0.043)	(0.045)	(0.040)	(0.143)	(0.073)	(0.090)	(0.031)
	(-0.106; 0.060)	(-0.161; 0.014)	(0.125; 0.285)	(0.040; 0.600)	(0.010; 0.298)	(-0.017; 0.350)	(-0.064; 0.078)
90th quant.	-0.063	-0.086	0.184	0.397	0.213	0.184	-0.085
	(0.058)	(0.070)	(0.053)	(0.199)	(0.094)	(0.117)	(0.065)
	(-0.163; 0.057)	(-0.203; 0.047)	(0.079; 0.261)	(0.007; 0.757)	(0.003; 0.378)	(-0.080; 0.381)	(-0.203; 0.037)
99th quant.	-0.258	-0.080	0.299	0.010	0.031	-0.021	-0.456
	(0.130)	(0.088)	(0.083)	(0.337)	(0.270)	(0.185)	(0.099)
	(-0.481; -0.023)	(-0.256; 0.108)	(-0.072; 0.385)	(-0.899; 0.515)	(-0.781; 0.355)	(-0.363; 0.306)	(-0.649; -0.344)
Mean	-0.021	-0.044	0.158	0.149	0.079	0.069	0.011
	(0.034)	(0.034)	(0.031)	(0.135)	(0.063)	(0.084)	(0.031)
	(-0.095; 0.043)	(-0.115; 0.029)	(0.101; 0.217)	(-0.122; 0.408)	(-0.045; 0.197)	(-0.095; 0.230)	(-0.050; 0.072)
Variance	0.020	0.007	0.104	0.241	0.095	0.146	-0.100
	(0.047)	(0.048)	(0.042)	(0.181)	(0.082)	0.115	(0.050)
	(-0.071; 0.112)	(-0.085; 0.104)	(0.023; 0.193)	(-0.105; 0.602)	(-0.061; 0.261)	(-0.071; 0.399)	(-0.194; -0.002)

Table 7: Individual coefficient effects

	Pot. exp.	Sex	Education	Offshorability	Technology	Personable	Cog-phys ratio
10th quant.	0.465	0.367	0.259	1.876	0.761	1.114	0.365
	(0.110)	(0.104)	(0.109)	(0.503)	(0.210)	(0.315)	(0.111)
	(0.309; 0.697)	(0.217; 0.597)	(0.110; 0.499)	(1.226; 3.005)	(0.473; 1.219)	(0.685; 1.800)	(0.191; 0.592)
25th quant.	0.268	0.345	0.155	1.375	0.464	0.911	0.227
	(0.081)	(0.079)	(0.077)	(0.373)	(0.156)	(0.224)	(0.064)
	(0.121; 0.415)	(0.210; 0.490)	(0.009; 0.298)	(0.826; 2.123)	(0.183; 0.734)	(0.533; 1.336)	(0.105; 0.341)
50th quant.	0.280	0.272	0.102	1.141	0.448	0.693	0.258
	(0.050)	(0.048)	(0.044)	(0.198)	(0.087)	(0.116)	(0.038)
	(0.184; 0.379)	(0.183; 0.364)	(0.015; 0.188)	(0.795; 1.551)	(0.291; 0.625)	(0.486; 0.933)	(0.175; 0.329)
75th quant.	0.384	0.438	0.154	1.509	0.579	0.931	0.286
	(0.041)	(0.043)	(0.040)	(0.147)	(0.071)	(0.089)	(0.040)
	(0.310; 0.470)	0.351; 0.520)	(0.078; 0.245)	(1.222; 1.842)	(0.432; 0.715)	(0.740; 1.096)	(0.196; 0.357)
90th quant.	0.486	0.509	0.239	1.717	0.632	1.085	0.441
	(0.058)	(0.069)	(0.053)	(0.211)	(0.099)	(0.122)	(0.072)
	(0.374; 0.598)	(0.384; 0.650)	(0.144; 0.354)	(1.352; 2.189)	(0.464; 0.858)	(0.859; 1.380)	(0.310; 0.580)
99th quant.	0.680	0.503	0.124	2.101	0.813	1.288	0.800
	(0.155)	(0.122)	(0.119)	(0.512)	(0.306)	(0.331)	(0.110)
	(0.390; 1.022)	(0.279; 0.789)	(-0.037; 0.450)	(1.251; 3.253)	(0.129; 1.356)	(0.795; 2.118)	(0.250; 0.910)
Mean	0.352	0.375	0.173	1.508	0.583	0.925	0.309
	(0.040)	(0.039)	(0.035)	(0.158)	(0.070)	(0.101)	(0.037)
	(0.274; 0.433)	(0.300; 0.452)	(0.105; 0.241)	(1.181; 1.816)	(0.448; 0.717)	(0.712; 1.108)	(0.238; 0.383)
Variance	0.022	0.035	-0.062	-0.031	-0.011	-0.020	0.070
	(0.049)	(0.046)	(0.043)	(0.198)	(0.080)	(0.122)	(0.058)
	(-0.080; 0.111)	(-0.056; 0.122)	(-0.152; 0.019)	(-0.469; 0.327)	(-0.182; 0.142)	(-0.269; 0.204)	(-0.041; 0.177)

Table 8: Most offshorable occupations with wage distribution rank

Information		Routine	
Occupation	Rank	Occupation	Rank
Mathematicians, statisticians	44	Glass, ceramics plant operators	95
Physicists, chemists and related professionals	10	Wood-processing-, papermaking-plant operators	82
Life science professionals	1	Metal-processing-plant operators	21
Business professionals	9	Chemical-processing-plant operators	74
Life science technicians	39	Manufacturing laborers	79
Higher education teaching professionals	5	Agricultural and other mobile-plant operators	37
Nursing and midwifery professionals	33	Cashiers, tellers	58
Computing professionals	6	Optical, electronic equipment operators	54
Finance and sales associate professionals	25	Mining- and mineral-processing-plant operators	101
Legal professionals	2	Mining and construction laborers	85
Computer associate professionals	27	Metal-, mineral-products machine operators	59
Architects, engineers	7	Blacksmiths, tool-makers	65
Archivists, librarians	20	Printing workers	63
Police inspectors and detectives	67	Assemblers	41
Social science professionals	45	Printing, paper-products machine operators	51

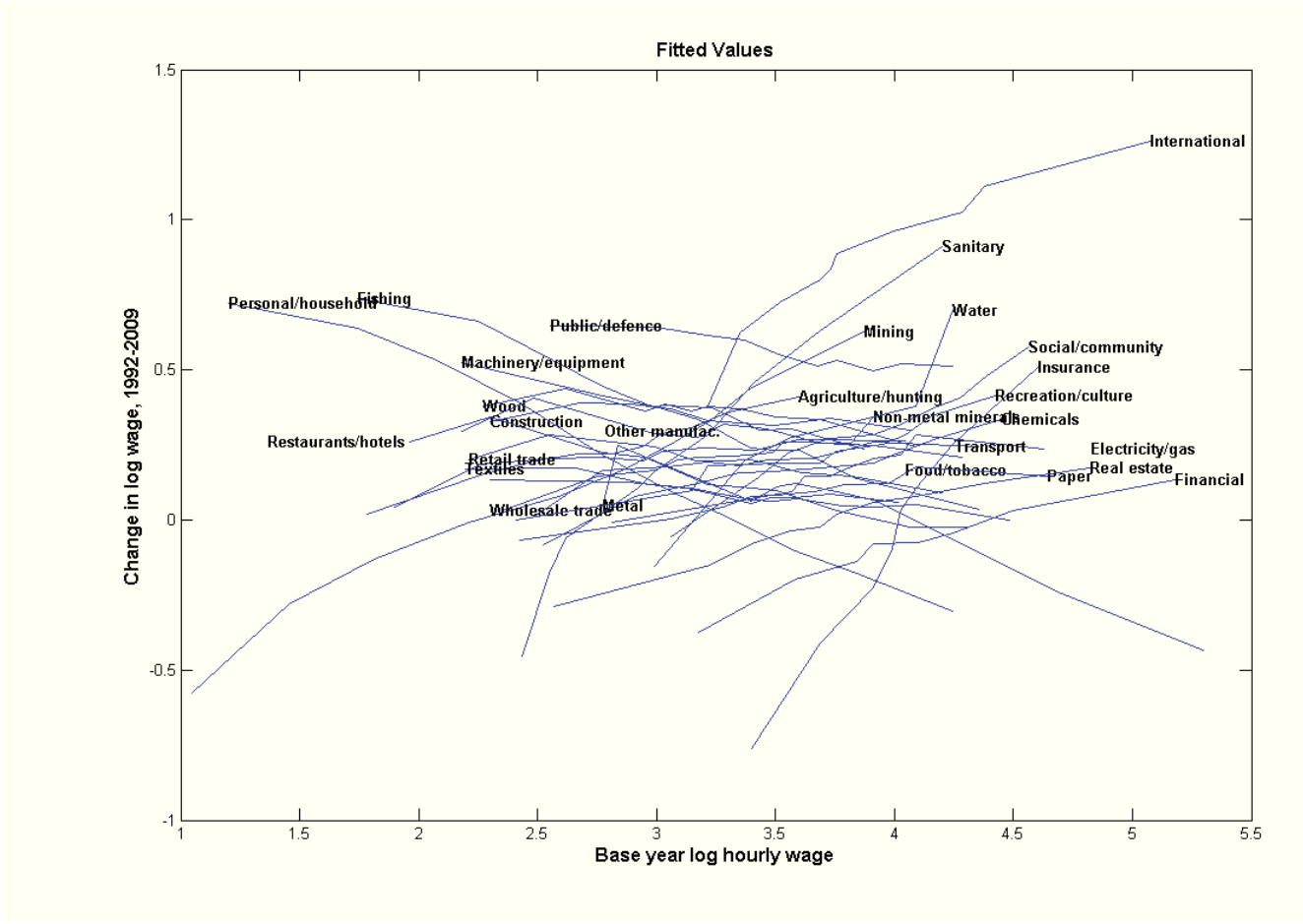
Table 8 (contd): Most offshorable occupations with wage distribution rank

Physical presence		Interpersonal		Decision/creativity	
Occupation	Rank	Occupation	Rank		
Mathematicians, statisticians	44	Fashion and other models	68	Fashion and other models	68
Legal professionals	2	Handicraft workers in wood, textile, leather	80	Subsistence agricultural and fishery workers	94
Higher education teaching professionals	5	Pelt, leather and shoemaking trades workers	83	Agricultural, fishery laborers	96
Stall and market salespersons	49	Potters, glass-makers	71	Building caretakers, window cleaners	35
Fashion and other models	68	Wood treaters, cabinet-makers	90	Pelt, leather and shoemaking trades workers	83
Business professionals	9	Metal-processing-plant operators	21	Agricultural and other mobile-plant operators	37
Directors and chief executives	3	Blacksmiths, tool-makers	65	Domestic helpers, cleaners and launderers	99
Senior government officials	4	Building caretakers, window cleaners	35	Street vendors and related workers	92
Traditional chiefs and heads of villages	40	Subsistence agricultural and fishery workers	94	Manufacturing laborers	79
Street vendors and related workers	92	Domestic helpers, cleaners and launderers	99	Stall and market salespersons	49
Other teaching associate professionals	26	Textile, garment workers	73	Ships' deck crews	8
Business services agents and trade brokers	43	Stall and market salespersons	49	Blacksmiths, tool-makers	65
Computing professionals	6	Agricultural, fishery laborers	96	Food processing workers	97
Other teaching professionals	13	Street vendors and related workers	92	Metal-processing-plant operators	21
Social science professionals	45	Computing professionals	6	Wood, paper plant operators	82

C Quantile effects

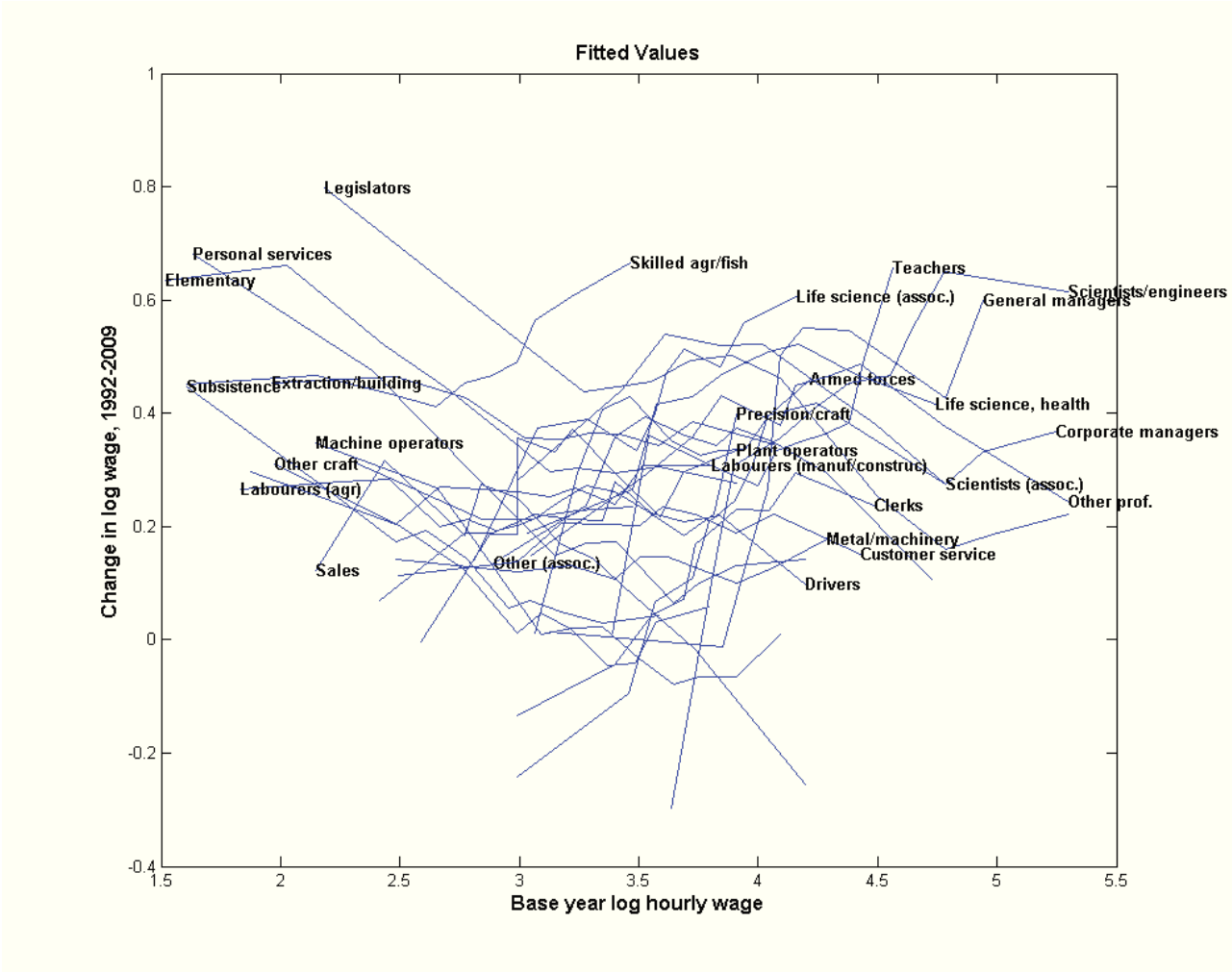
Figures C.1 and C.2 below show the fitted values of Δw_{jt}^{d} from Equation 3 with quantile dummies included to capture any quantile-specific trends. Again, the occupation plots show a distinct U shape. Low-wage (high-wage) occupations have convex (concave) plots, emphasizing the strong relative wage growth experienced by the lowest-paid (highest-paid) workers. The quantile dummies thus further emphasize the extent of wage polarization.

Figure C.1: Wage growth with quantile effects: industries:



The results show the fitted values from regression equation $\Delta w_{jt}^{q} = \gamma_{j0} + \gamma_{q2} + \gamma_{j1} w_{j0}^{q} + \eta_j$ where $q = 1, ..., 10$ stands for quantile, γ_{j0} is a vector of industry dummies, $\gamma_{j1} w_{j0}^{q}$ is the interaction between base-year wage and industry dummy, and γ_{q2} is a vector of quantile dummies. The fitted values are plotted against base-year wage for all ten quantiles of each two-digit ISIC industry.

Figure C.2: Wage growth with quantile effects: occupations:



The results show the fitted values from regression equation $\Delta w_{jt}^q = \gamma_{j0} + \gamma_{q2} + \gamma_{j1} w_{j0}^q + \eta_j$ where $q = 1, ..., 10$ stands for quantile, γ_{j0} is a vector of occupation dummies, $\gamma_{j1} w_{j0}^q$ is the interaction between base-year wage and occupation dummy, and γ_{q2} is a vector of quantile dummies. The fitted values are plotted against base-year wage for all ten quantiles of each two-digit ISCO occupation.

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EMPLOYMENT

Instructor, Department of Economics, Carleton College, September 2013 -

EDUCATION

Ph.D. in Economics, Johns Hopkins University, September 2013.

M.A. in Economics, Johns Hopkins University, May 2010.

B.A. in Economics, *magna cum laude*, Mount Holyoke College, May 2007.

RESEARCH AND TEACHING INTERESTS

Research: International Trade, Labor Economics, Applied Microeconomics.

Teaching: International Trade, International Finance, Microeconomics, Macroeconomics.

RESEARCH PAPERS

"Human Capital Investment and Labor Supply: Adjustments to Trade Policy," (*Job Market Paper*).

'Wage Inequality and Occupational Tasks: Evidence from Sri Lanka," (*in progress*).

'Trade Liberalization and the Skill Premium: The Role of Human Capital Investment and Technology," (*in progress*).

RESEARCH EXPERIENCE

Research Assistant to Prof. Larry Ball, Johns Hopkins University, Fall 2010, Spring 2011, Fall 2012.

Research Assistant to Dr. Saman Kelegama, Institute of Policy Studies, Colombo, Sri Lanka, Summer 2006.

Intern, International Centre for Ethnic Studies, Colombo, Sri Lanka, Summer 2005.

TEACHING EXPERIENCE

Instructor

Memorandums of Misunderstanding, Johns Hopkins University, Spring 2013.

International Trade, Johns Hopkins University, Summer 2009, Spring 2010, Spring 2011.

Macroeconomic Principles, Loyola University Maryland, Fall 2012.

Teaching Assistant

Elements of Macroeconomics, Prof. Lou Maccini, Fall 2009, Fall 2010, Fall 2011.

Macroeconomic Theory, Prof. Larry Ball and Dr. John Driscoll, Fall 2008, Spring 2010, Spring 2011.

Labor Economics, Dr. Matthew Wiswall, Spring 2012.

Corporate Finance, Prof. Greg Duffee, Spring 2009.

Investments and Portfolio Management, Dr. Matthew Pritsker, Spring 2008.

PROFESSIONAL EXPERIENCE

Co-editor, Options, The Women and Media Collective, Colombo, Sri Lanka, 2001-2003.

FELLOWSHIPS AND AWARDS

Professor Joel Dean Undergraduate Teaching Award, Johns Hopkins University, Department of Economics, Spring 2013.

Dean's Teaching Fellowship, Johns Hopkins University, Krieger School of Arts and Sciences, Spring 2013.

Graduate Fellowship, Johns Hopkins University, Department of Economics, 2007–2011.

Virginia Galbraith Prize, (best economics student), Mount Holyoke College, Fall 2006.

Sarah Williston Prize, (ranked second in class of 2007), Mount Holyoke College, Spring 2006.

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