Essays on the Labor Force and Aggregate Fluctuations

A Dissertation Presented

by

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ABSTRACT

The demographic composition of the U.S. labor force has changed dramatically over the past several decades. My Dissertation examines the age distribution, the supply of skills, and the participation of women in the workforce. The first chapter postulates a connection between the age distribution and the business cycle. I develop an overlapping generations model featuring search frictions and productivity shocks to present the theory. Chapter 2 studies the supply of high-skill workers and also relies on a labor matching model. In the model, firms react to changes in the distribution of skills by creating jobs designed specifically for high-skill workers. The new matches are more profitable and less likely to break apart. In quantitative simulations, the model economies in the first two chapters replicate a substantial portion of the recent moderation in cyclical output volatility. The findings suggest an important role for demographics in determining the magnitude of aggregate fluctuations. The third chapter is joint work with Daniele Coen-Pirani and Alexis León. We estimate the effect of household appliance ownership on the labor force participation rate of married women using micro-level data. The diffusion of household appliances can account for about one-third of the increase in married women's labor force participation rates observed during the 1960's according to our results.

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To Corey,

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CHAPTER I

DEMOGRAPHIC CHANGE AND THE GREAT MODERATION IN AN OVERLAPPING GENERATIONS MODEL WITH MATCHING FRICTIONS

Chapter Abstract

The fraction of the labor force under the age of 35, or youth share, has been positively correlated with the cyclical volatility of U.S. gross domestic product over the past several decades. For example, the youth share and business cycle fluctuations were both high during the 1970's. Then, as the population aged, output volatility rapidly declined. This chapter develops a tractable overlapping generations model featuring search frictions and aggregate productivity shocks. In the model, the age distribution affects cyclical volatility through two channels. First, employment for younger workers fluctuates more, creating a simple composition effect. Second, inexperienced workers are less productive, so firms decide how many jobs to create based on the age distribution. Young job searchers do not necessarily induce firms to post new vacancies. Both this endogenous response by firms and the composition effect increase aggregate volatility when the youth share is high. Quantitatively, the model can replicate a large portion of the recent moderation in the business cycle, suggesting an important role for demographics in determining the magnitude of cyclical employment and output volatility.

1.1   Introduction

In this chapter, I develop an overlapping generations (OLG) model in which varia-
tion of the age distribution can generate a substantial portion of the observed changes
in cyclical volatility. Figure 1 plots a measure of U.S. gross domestic product (GDP)
volatility against time.[1] The graph also shows the fraction of the U.S. labor force
under the age of 35, or youth share. The youth share was only about 48 percent in
1967, while GDP volatility was low. Then, the young baby-boom generation began
to enter the labor market. By 1982 the youth share had risen to over 58 percent, and
GDP volatility had dramatically increased. However, as the population aged, GDP
volatility rapidly declined. This large reduction in cyclical volatility has been labeled
the Great Moderation.

The model features a search friction. Workers and firms meet randomly and
matching takes time. A worker-firm match can be good or bad. Good matches
last longer on average. New young workers enter the labor force each period, and
the oldest workers retire. Match output depends on the worker's age and a persistent
aggregate productivity shock. The age distribution affects aggregate output volatility
through two channels - a composition effect and the endogenous response by firms.

The composition effect occurs because employment for young workers fluctuates
more than for older people over the cycle. Older workers are likely to be employed in
good matches; they have had ample search time. Young workers frequently move in
and out of employment because they tend to be in bad matches. Therefore, variation
in the job-finding rate generates more employment volatility for younger workers.[2]
When the youth share is large, all else constant, aggregate employment volatility is
high. High employment volatility translates into high output volatility.

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[1]The term volatility refers to the magnitude of the variations from trend at business cycle fre-
quencies. I measure GDP volatility at quarter t as the standard deviation of a 41-quarter window
centered around quarter t of the detrended, logged series of total output. See Section 2 for details.

[2]Empirically, employment volatility among teenagers and young adults is more than twice that of
prime age workers. Clark and Summers (1981) was the first paper to report employment volatility by
age group. See also, Rios-Rull (1996), Gomme, Rogerson, Rupert, and Wright (2004), and Jaimovich
and Siu (2007). Jaimovich and Siu (2007) point out that employment fluctuations for the oldest
workers (55+) do not occur at business cycle frequencies. Since I focus on the cycle and old workers
constitute a small portion of the labor force, I consider workers aged 16–54, only.

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The search friction also contributes to the second channel connecting the age distribution to aggregate output volatility. In the model, firms decide how many jobs to create based on the job searchers' ages because young workers produce less output. To illustrate, consider a negative productivity shock. Expected revenues decrease, so companies post fewer vacancies and the job-finding rate goes down. Employment falls, especially among poorly-matched young workers. The number of people looking for jobs increases. If the labor force is relatively young, then the average productivity level among job searchers decreases. Firms respond to a reduction in expected match output by posting even fewer vacancies, exacerbating the decline in employment. Thus, the endogenous response by firms propagates the original shock when the population is young.

I examine the model's quantitative implications by choosing parameter values to target relevant worker flow statistics. I change the size of the youngest worker cohort period-by-period to simulate the U.S. youth share over time. When the population is relatively old in the model economy, aggregate output volatility is low; when the youth share is high, output volatility is high. This relationship captures the main result; the model can replicate much of the observed cyclical volatility pattern. The model also replicates the differences in unemployment rates, job-separation rates, and employment volatility by age group.

The findings in Jaimovich and Siu (2007) help to motivate my research question. Using panel-data methods, Jaimovich and Siu (2007) exploit variation in the timing and the magnitude of population changes across G7 countries to show that the age distribution has a (statistically and economically) significant effect on cyclical volatility. In other words, they provide evidence that the youth share is positively correlated with aggregate output volatility in several countries.[3] Jaimovich and Siu (2007) also present a business cycle model linking aggregate volatility to the youth share. Their results and my model both imply that the age distribution has a large effect on cyclical volatility, but we differ on the reasons. The model in Jaimovich and Siu (2007) features capital-age complementarity and a static age distribution with

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[3]The U.S. and Japan make for a compelling comparision. The youth share and aggregate volatility in Japan both decreased in the 1960's; meanwhile in the U.S., the youth share and volatility were increasing.

only two age groups. Jaimovich and Siu (2007) do not consider matching frictions. I build a richer model of the labor market. I include search frictions and explicitly model the aging process, which allows for analysis of employment by age. Differences in employment across age groups arise naturally in my framework as a consequence of the matching process and the life-cycle. In Jaimovich and Siu (2007), the degree of capital-age complementarity and changes to the shock process come from outside the model. Also, my model delivers a full time series with changing demographics.

I borrow heavily from recent papers studying business cycles using search models, such as Shimer (2005) and Hall (2005). Standard matching models do not have a mechanism to examine changes in the age distribution. Hence, I extend the search framework to an OLG setting in order to address the question at hand. Two earlier papers, Rios-Rull (1996) and Gomme, Rogerson, Rupert, and Wright (2004), have imbedded real business cycles in OLG models. Neither paper uses labor matching; although, Gomme, Rogerson, Rupert, and Wright (2004) suggest, but do not pursue, search frictions as a way to examine employment fluctuations.

Nagypál (2004) argues that the worker-firm separation rate does not contribute much to cyclical volatility.[4] Instead, variation in the job-finding rate (e.g. job-to-job transitions) causes the employment fluctuations. I use this finding from Nagypál (2004) to justify using fixed and exogenous match destruction rates. Finally, many papers address the recent large decline in aggregate volatility. Existing theories fall into three categories: good luck, good policy, or a structural change in the economy (Stock and Watson 2002). Jaimovich and Siu (2007) add demographics as a fourth possibility. My model supports the demographics hypothesis by showing how exogenous variation in the youth share could have caused a substantial portion of the reduction in cyclical volatility associated with the Great Moderation.

In Section 2, I present data on the youth share and aggregate cyclical volatility. Section 3 develops the model of the labor market. I explain my parameter choices in Section 4. In Section 5, I examine the results quantitatively. Section 6 contains additional discussion of the model's mechanism, and Section 7 concludes.

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[4]The term separation refers to the breakup of a worker-firm pair. In my model, separations include retirements, deaths, and exogenous match destruction, and match destruction can result in the worker making a job-to-job transition or becoming an unemployed searcher.

1.2   Youth Share and Cyclical Volatility Data

In this section, I present data on the youth share and cyclical volatility. The employment data comes from the Current Population Survey (CPS), and the GDP data comes from the Bureau of Economic Analysis (BEA). I use seasonally adjusted quarterly observations from 1962 through the second quarter of 2007 restricted to individuals aged 16 to 54. The youth share equals the fraction of the labor force under the age of 35. I measure cyclical volatility at quarter t as the standard deviation of a 41-quarter window centered around quarter t of the de-trended, logged series. I remove the trend by applying the Hodrick-Prescott (HP) filter with smoothing parameter 1600 to the entire logged series. Then, I calculate the rolling standard deviation. This method is somewhat standard; see Jaimovich and Siu (2007) for example.

Figure 1 plots the youth share and GDP volatility from 1967 to 2002. The two time series clearly move together. The work force was relatively old during the 1960's. The baby-boom generation entered the labor market during the 1970's, and the youth share increased to almost 60 percent by 1980. Then, as the population aged, the youth share decreased. GDP volatility displays a similar pattern. GDP volatility was relatively low during the 1960's. In the 1970's and early 1980's output fluctuations were high. However, as the youth share decreased, GDP volatility rapidly declined.[5]

The standard deviation of the cyclical component of GDP from 1962–2007 is 1.49 percent; see Table 1. Table 1 also reports the standard deviation of the cyclical component of aggregate employment and employment by age group. Aggregate employment volatility has been lower than GDP volatility at 1.02 versus 1.49 percent. These numbers are based on employment's extensive margin. I have performed similar calculations based on annual total hours for 16–54 year-olds using CPS data from the March supplement. Since the observations are at an annual frequency, I set the HP filter to 10 and use a sliding 9-year window. The resulting pattern of cyclical volatility of total hours is shown in Figure 2. Jaimovich and Siu (2007) also examine

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[5]Figure 2 and Figure 3 depict other measures of aggregate volatility, and again the pattern resembles that of the youth share.

the volatility of total hours; their findings are similar to what I report here. Furthermore, Jaimovich and Siu (2007) document a large difference in volatility of total hours by age. Young workers experience more employment volatility over the cycle. I find the same relationship when looking at the extensive margin. The standard deviation of the series of deviations from trend employment equals 1.35 percent for young workers (aged 16–34) and 0.72 percent for older workers (aged 35–54) in the CPS data.

The difference between young and old workers suggests a simple compositional explanation for the recent moderation in cyclical fluctuations. The youth share began to shrink around 1983. Consequently, older workers, who typically experience less employment volatility, made up a larger share of the labor force, and aggregate employment volatility declined. However, this simple compositional effect cannot entirely account for the changes in employment volatility. Figure 3a plots employment volatility over time with the data split into the two age groups. Figure 3b contains aggregate employment for comparison. The within age group employment volatility for both young and old workers follows the same pattern as aggregate employment volatility and the youth share. The composition effect alone cannot account for changes in employment volatility within age groups. I argue that general equilibrium effects (e.g. the endogenous response by firms to the age distribution) drive the employment volatility changes within age groups.[6]

Overall, Table 1 and Figures 1–3 suggest that cyclical volatility is related to the age distribution. When the youth share was high, aggregate volatility was large. The remainder of Chapter 1 seeks to explain how the age distribution affects both GDP and employment volatility.

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[6]Figure 3c plots employment volatility for whites and non-whites. The same pattern emerges. Employment volatility for both whites and non-whites was high in the 1970's, when the youth share was at its zenith. However, employment volatility among non-whites has a strong decreasing trend. This trend might be due to the evolving composition or socioeconomic status of non-whites over time. In Figure 3d, I split the data by gender. Again, the same general pattern can be seen. Chapter 2 offers an analysis of how education and skills relate to aggregate output volatility.

1.3   Labor Market Model

This section develops a matching model with overlapping generations of workers. Events within a period unfold as follows. First, matched workers and firms produce together in one-to-one pairings. Output is a function of the worker's age and the current aggregate productivity shock. Second, some worker-firm pairs separate due to retirement, death, or match destruction. Third, firms post vacancies and randomly meet job searchers. New matches produce in the next period and can be either good or bad in quality. A match is good with probability ϕ. Good matches last longer on average.

Agents do not observe match quality. Instead, workers and firms form beliefs over the probability their match will be destroyed contingent on how long they have been together. Agents update their beliefs using Bayes' Rule. The expected survival rate for a match of tenure T is:

$$\theta^T = \frac{\phi\left(\theta^g\right)^{T+1} + (1-\phi)\left(\theta^b\right)^{T+1}}{\phi\left(\theta^g\right)^{T} + (1-\phi)\left(\theta^b\right)^{T}} \, ,$$

where T indexes θ, θ^g is the survival rate for a good match, θ^b is the survival rate for a bad match, and $\theta^g > \theta^b$. Agents' beliefs are correct on average, but they never know the quality of their match for sure. A new match has tenure zero, denoted T_0. The longer a pair stays together the more likely they have a good match. Neither ϕ nor θ^T change over the cycle.

1.3.1   Firms

Firms create vacancies at flow cost c and produce upon matching with a worker. Firms cannot age discriminate in terms of hiring or firing. In equilibrium, firms post vacancies until the expected profit from doing so equals zero. Equation (1) captures this free entry condition:

$$c = q\delta\lambda \sum_{a=1}^{\bar{a}-1} \frac{s_a}{\sum_{a=1}^{\bar{a}-1} s_a} \sum_{z'} \pi_{zz'} J\left(a+1, T_0, z'\right). \tag{1}$$

In equation (1), q is the matching rate or probability a vacancy meets a worker. The matching rate decreases with the number of vacancies posted. The parameter δ denotes the discount factor. A worker lives to produce in the next period with probability λ; all workers retire at age $a = \bar{a}$; and a total of s_a workers with age a search for a job in the current period. Next period's values are primed. Given a current aggregate productivity shock of z, the shock in the following period equals z' with probability $\pi_{zz'}$. Firms place value $J(a+1, T_0, z)$ on a new match with a worker of age a. Table 2 contains a list of the notation.

Equation (2) recursively defines the value of a matched firm:

$$J(a, T, z) = \beta z \xi_a + \theta^T \lambda \delta \sum_{z'} \pi_{zz'} J(a+1, T+1, z'). \tag{2}$$

Each match produces $z\xi_a$ per period. Firms keep share β of the output; the rest goes to the worker. $J(\bar{a}, T, z) = \beta z \xi_{\bar{a}}$ due to the worker's impending retirement. A tenure T match is destroyed with probability $(1 - \theta^T)$. The labor input ξ_a depends on the worker's age, reflecting experience. For now, I assume productivity increases with age at a decreasing rate.[7] Workers with the same productivity receive equal wages.

Splitting period-by-period output insures productive matches never voluntarily break apart. This stark wage rule has been used with search frictions before; see Acemoglu (1999) for example. The more common approach to wage determination in search models is cooperative Nash bargaining over total match surplus. Bargaining over surplus requires agents to speculate on future job-finding rates. Dividing output into fixed shares does not require agents to form forward looking expectations. This difference is significant, as it greatly simplifies the model. I discuss wages further in Section 6.

The value (2) placed on a job, once filled, does not depend on the age distribution among job searchers. However, the number of jobs created does depend on the distribution. The key decision made by firms is how many vacancies, v, to post given the aggregate productivity shock, z, and the age distribution of searching workers, $\{s_a\}_{a=1}^{\bar{a}-1}$. In equilibrium, firms create jobs until the free entry condition (1) is satisfied.

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[7] I find empirical support for this assumption in Section 4, where I select $\{\xi_a\}_{a=2}^{\bar{a}}$ so the model delivers wages by age group consistent with CPS wage income data. For higher values of a, ξ_a does start to decrease.

1.3.2 Workers

The information structure over θ^T simplifies the worker side of the model.[8] If a worker knew for certain that he or she had a bad match, then the worker might be tempted to quit in order to search for a good match. In the full knowledge scenario, young workers would be more likely to leave a bad match than older workers. Older workers care less about a job's potential duration because they are closer to retirement. Thus, young workers would move in and out of employment at an even greater frequency relative to older workers, strengthening my mechanism. However, solving the model would be difficult, so I assume agents update their beliefs over time. Several papers use similar assumptions about match quality; see Tasci (2006) and Pries and Rogerson (2005).

Given θ^T, the worker's decisions are straightforward. Unemployed workers always search for a job and accept any match. An employed worker never quits because matches only become more valuable as tenure increases. These choices do not depend on the aggregate state or the worker's age. Consequently, the worker side of the model does not enter into aggregate volatility considerations. The worker's value functions are presented next to complete the model.

An age a worker places value $W\left(a, T, \{s_a\}_{a=1}^{\bar{a}-1}, z\right)$ on a match with tenure T:

$$W\left(a, T, \{s_a\}_{a=1}^{\bar{a}-1}, z\right) = (1-\beta)\, z\xi_a \tag{3}$$
$$+\delta\lambda \sum_{z'} \pi_{zz'} \left(\begin{array}{c} \theta^T W\left(a+1, T+1, \{s_a'\}_{a=1}^{\bar{a}-1}, z'\right) \\ +p\left(1-\theta^T\right) W\left(a+1, T_0, \{s_a'\}_{a=1}^{\bar{a}-1}, z'\right) \\ +(1-p)\left(1-\theta^T\right) U\left(a+1, \{s_a'\}_{a=1}^{\bar{a}-1}, z'\right) \end{array} \right).$$

Workers receive share $(1-\beta)$ of the output per period. Future wages are discounted by δ and λ. The match survives into the next period with probability θ^T. If the match breaks apart, the worker can immediately search for a new job. With probability p the worker finds a new employer and does a job-to-job transition. The new match has tenure zero. The job-finding rate increases with the number of vacancies

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[8]Match quality does not directly impact any of a firm's decisions because the value of a firm's outside option always equals zero in equilibrium.

posted. Thus, p depends on $\{s_a\}_{a=1}^{\bar{a}-1}$ through the free entry condition (1). With probability $(1-p)$ the worker does not immediately meet a firm, so the worker becomes unemployed. Equation (4) summarizes the value of being an unemployed worker:

$$U\left(a,\{s_a\}_{a=1}^{\bar{a}-1},z\right) = \delta\lambda\sum_{z'}\pi_{zz'}\left(\begin{array}{c} pW\left(a+1,T_0,\{s_a'\}_{a=1}^{\bar{a}-1},z'\right) \\ +(1-p)\,U\left(a+1,\{s_a'\}_{a=1}^{\bar{a}-1},z'\right) \end{array}\right). \qquad (4)$$

Unemployed workers find a job with tenure zero at rate p, but they receive zero income while searching.[9] Workers retire at age $a = \bar{a}$, so $U\left(\bar{a},\{s_a\}_{a=1}^{\bar{a}-1},z\right) = 0$.

1.3.3   Stocks of Workers by Age

Let e_a^g stand for the stock of workers with age a in good matches. Similarly e_a^b denotes the number of workers aged a not searching for jobs and in bad matches. The following set of equations (5) update the worker stocks $\left\{s_a, e_a^g, e_a^b\right\}_{a=2}^{\bar{a}-1}$:

$$s_a' = (1-p)\,\lambda\left(s_{a-1} + (1-\theta^g)\,e_{a-1}^g + \left(1-\theta^b\right)e_{a-1}^b\right), \qquad (5)$$

$$e_a^{g\prime} = \theta^g\lambda e_{a-1}^g + p\phi\lambda\left(s_{a-1} + (1-\theta^g)\,e_{a-1}^g + \left(1-\theta^b\right)e_{a-1}^b\right),$$

$$e_a^{b\prime} = \theta^b\lambda e_{a-1}^b + p\,(1-\phi)\,\lambda\left(s_{a-1} + (1-\theta^g)\,e_{a-1}^g + \left(1-\theta^b\right)e_{a-1}^b\right).$$

All workers start life as searchers. Thus, s_1 defines the size of a generation. To simplify notation, let:

$$S = \sum_{a=1}^{\bar{a}-1} s_a.$$

The stocks of workers are updated after separations take place and just prior to the matching process. For example, a worker making a job-to-job transition is counted in S for one period and not in e_a^g or e_a^b for that period. When calculating employment statistics, the worker still is counted as employed.

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[9]Setting unemployment flow income to zero is an innocuous normalization as long as employment pays more than unemployment in all states of the world.

1.3.4 Matching Function and Equilibrium

I follow the literature and use a Cobb-Douglas matching function in vacancies and searchers with scale parameter A and elasticity σ, where m is the number of matches created:

$$m = AS^\sigma v^{1-\sigma}. \tag{6}$$

This function implies the following match probabilities:

$$p = A\left(\frac{v}{S}\right)^{1-\sigma}, \tag{7}$$

$$q = A\left(\frac{S}{v}\right)^{\sigma}. \tag{8}$$

Given a vector of state variables $\left\{\{s_a\}_{a=1}^{\bar{a}-1}, z\right\}$, I define an equilibrium as a list:
$\left\{J\left(a, T, z\right)\right\}_{a=2}^{\bar{a}}$ and $\left\{W\left(a, T, \{s_a\}_{a=1}^{\bar{a}-1}, z\right)\right\}_{a=2}^{\bar{a}}$ for $T = 0... (\bar{a} - 2)$, and
$\left\{U\left(a, \{s_a\}_{a=1}^{\bar{a}-1}, z\right)\right\}_{a=1}^{\bar{a}}$, $p\left(\{s_a\}_{a=1}^{\bar{a}-1}, z\right)$, and $q\left(\{s_a\}_{a=1}^{\bar{a}-1}, z\right)$
such that:

1. The free entry condition (1) holds

2. Firms' value functions satisfy equation (2)

3. Workers' value functions satisfy equations (3) and (4)

4. The match probabilities are given by (7) and (8).

1.3.5 Impact of a Productivity Shock

The impact of an aggregate shock depends on the age distribution among workers. The age distribution affects cyclical volatility in two connected ways. First, there is a composition effect. Second, there is an endogenous response by firms. The evolution of the worker stocks confounds an exact analytical representation. However, the next three paragraphs characterize the model economy's reaction to a change in productivity, z.

Aggregate employment of young workers fluctuates more than for older workers. Consider how the stocks of workers evolve with age, from the set of equations (5). Changes in employment levels occur through p, the job-finding rate. If many searchers have age a, then variation in p has a large impact on next period's stocks of workers aged $a + 1$. Although note, the job-finding rate does not directly affect employed workers keeping their job, $\theta^b \lambda e_a^b$ and $\theta^g \lambda e_a^g$. The percent of workers employed increases with age because older workers have had longer to find a job and in particular a good job. In some sense e_a^g is an absorbing state, and employment volatility decreases with age. Thus, when there are many older workers in the economy, the impact of a shock is low, all else constant. This relationship generates the composition effect.

To simplify notation, define $J^e(a, z)$ as:

$$J^e(a, z) \;=\; \frac{1}{\beta} \sum_{z'} \pi_{zz'} J(a + 1, T_0, z'),$$

and $\widehat{c}$ as:

$$\widehat{c} \;=\; \frac{c}{A\beta}.$$

Then, the free entry condition (1) can be rewritten using the matching rate (8) to solve for the equilibrium number of vacancies:

$$v = \left[\frac{\delta\lambda}{\widehat{c}S^{1-\sigma}} \sum_{a=1}^{\bar{a}-1} s_a J^e(a, z) \right]^{\frac{1}{\sigma}}.$$ (9)

Consider the total impact of a sustained drop in aggregate productivity, z. The expected value of any match, $J^e(a, z)$, falls. Firms immediately cut back the number of vacancies posted according to equation (9). The job-finding rate, p, goes down according to equation (7). Existing matches continue to separate at the pre-shock rate. However, upon separating from an employer, workers are less likely to find a new job. Employment among young workers declines rapidly because they tend to be in bad, short-lived, matches. If there are many young workers in the economy, then the number of job-searchers increases quickly (the composition effect). The average new searcher has low productivity because ξ_a is small for young workers. Firms react by posting even fewer vacancies (the endogenous response by firms). The job-finding rate, p, decreases further. Employment spirals downward as the composition effect and the endogenous response fuel each other. Conversely, if there are many older workers in the labor force, then the new job searchers tend to be highly productive. Firms react by posting new vacancies, mitigating the original productivity shock.

Thus, the impact of a productivity shock on aggregate employment depends critically on the age distribution in the labor force. This feature of the model encapsulates the main result. A high youth share coincides with high aggregate volatility because of the composition effect and the endogenous response by firms. Next, I choose parameter values and simulate the economy to further examine this finding.

1.4 Parameter Values

To select parameter values, I use a steady state of the model with the productivity parameter z normalized to one and a constant population. Table 3 summarizes the parameter choices. Each period represents one month. I base the survival rate on the average mortality rate reported in the U.S. Vital Statistics; $\lambda = 0.9998$.[10] The parameter δ equals 0.9959, part way between the values used in Shimer (2005) and Hall (2005). This choice for δ gives an annual discount rate of 4.8 percent. I restrict agents to 39 years of working life; thus, $\bar{a} = 468$. The resulting youth share equals 49.98 percent, close to the U.S. mean from 1962 to 2007.

I set $\hat{c} = 9.455$ to target a job finding rate of 0.42, about the percentage calculated in Nagypál (2004). In the model, if a match is destroyed, then the worker immediately searches for a new job. A worker losing his or her job in the current period finds a new employer at the same rate as other searchers because matching is random. Thus, nearly 42 percent of separations lead to job-to-job transitions, which is also close to the percentage reported in Nagypál (2004).

I select the labor input by age, $\{\xi_a\}_{a=2}^{\bar{a}}$, based on individual-level data from the March CPS for the years 1962–2006. I use the fitted values from a regression of weekly wages on a constant, age, age squared, and indicators for gender, education, and race, and year fixed effects. More specifically, I obtain ordinary least squares estimates of d, f, g, and vector h from:

$$w \;=\; d + f \times age + g \times age^2 + h \times X + \epsilon,$$

where w equals logged annual real wage income divided by the number of weeks worked (mid-point of interval) reported in the CPS, and X contains variables on sex,

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[10] The U.S. Vital Statistics are available from several sources. For example, the Centers for Disease Control and Prevention web site contains information on mortality by age. There are differences in death rates across age groups. People aged 20–24 survive to the next month with probability 0.9999 on average; whereas, 50–54 year-olds face a survival rate of 0.9996. I do not account for this difference across age groups, which seems small compared to productivity differences.

race, education, and a full set of year fixed effects. I normalize $\xi_{a=2}$ to one. The estimated coefficients for age and age squared are statistically significant at the one percent level using robust standard errors. I calculate ξ_a from the estimates (denoted with a hat) as follows:

$$\xi_a = \xi_{a-1} \frac{\exp\left(\widehat{f} \times a\right) \exp\left(\widehat{g} \times a^2\right)}{\exp\left(\widehat{f} \times (a-1)\right) \exp\left(\widehat{g} \times (a-1)^2\right)}; \quad \text{for } a = 3...\bar{a}$$

$$\widehat{f} = 0.0695462; \quad \widehat{g} = -0.0007429; \quad \xi_{a=2} = 1.$$

This simple procedure delivers a set of parameter values consistent with the data.[11] Figure 4 depicts $\{\xi_a\}_{a=2}^{\bar{a}}$. There exists a large amount of variation; prime age workers have twice the productivity of teens. The value decreases a little for the oldest workers. The set of values for the labor input by age is similar to that calculated and used in both Gomme, Rogerson, Rupert, and Wright (2004) and Rios-Rull (1996). Returns to experience have been studied previously in the literature. For example, Altonji and Williams (1998) cite estimates for the return to 10 years of experience on log wages ranging from 0.06 to 0.14. The increase in log wages for 10 years of experience using my calibration is about 0.12, except for the oldest workers.

The matching function elasticity parameter σ equals 0.72 as in Shimer (2005). I assume good matches are not destroyed. I choose the probability of a match being good and the survival rate of bad matches to simultaneously target an unemployment rate of 6.10 percent (the average rate from 1948 to 2007) and a monthly separation rate of 7.00 percent (Nagypál 2004). These targets require $\phi = 3.35$ percent and $\theta^b = 71.01$ percent.

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[11]Returns to experience and returns to tenure have been studied previously in the literature; see Altonji and Williams (2005) and the references within. A central question is whether the experience premium has changed at different rates across age groups (or for workers with different tenures) over time. Some authors, e.g. Katz and Autor (1999), argue that it has. My specification for the wage regression does not allow for interactions between year and age. In the next chapter, I study a model that does feature changes in wage inequality between groups of workers.

1.5 Quantitative Results

This section discusses the model's quantitative implications. In simulations, the model economy can replicate the general relationship between the age distribution and macroeconomic cyclical volatility. The model can also replicate the observed differences in unemployment rates, job-separation rates, and employment volatility by age group.

1.5.1 Steady State

Table 4 reports unemployment rates by age group for the CPS data and for the steady state of the model. Teenagers and young adults have higher unemployment rates than older workers. The model captures the basic trend. For example, over 17 percent of teenagers are unemployed in the model, but only about 2 percent of the oldest group are out of work.

Table 5 contains total monthly separations by age group. The U.S. data reported in Table 5 originates from Nagypál (2004). Separations by age in the steady state of the model economy display the same pattern as in the data. Young workers are more likely to separate from their employer. Only 2.6 percent of the 45–54 year old age group separates from their employer per period in the model, while 16.6 percent of teenagers separate from their job every month.

The differences in separation rates and unemployment rates across age groups arise in the model economy because older workers have had more time to find good quality matches, as captured by the equations (5) governing the stocks of workers. In contrast, young people begin life in unemployment and frequently move in and out of employment.

1.5.2 Business Cycles with Variable Youth Share

The parameter z takes two values $z^h = 1.0305$ and $z^l = 0.9695$ and evolves according to the following Markov transition matrix:

$$\Pi = \begin{bmatrix} \pi_{hh} = 0.9873 & \pi_{lh} = 0.0127 \\ \pi_{hl} = 0.0127 & \pi_{ll} = 0.9873 \end{bmatrix}.$$

This Markov process is selected to match both the standard deviation (1.56 percent) and the autocorrelation (0.86) of the cyclical component of the model output to the U.S. GDP data from 1962–2001.[12] I run the model with a constant population for several hundred periods to expunge the influence of the initial conditions (the steady state). Then, I simulate the economy by altering the size of the youngest generation. Each month, a new shock is drawn, and I change s_1 to approximate the pattern of the U.S. youth share. I simulate 160 quarters of data, roughly corresponding to the years 1962–2001. For the first 76 quarters, I vary the size of the youngest cohort from 1.6 to 1.9. These large generations correspond to the baby-boom. In all other periods, $s_1 = 1$. I repeat the entire process 500 times and report on the average across the simulations.

I calculate cyclical output volatility for the model generated time series with the same procedure I used for the U.S. GDP data. Output volatility at quarter t is the standard deviation of a 41-quarter window centered around quarter t of the de-trended, logged series of total output. I remove the trend using the HP filter with smoothing parameter 1600.

Figure 5 plots the youth share and aggregate output volatility for the simulation. Just as in the U.S. data (also shown for comparison), output volatility rises with the youth share, then falls rapidly as the youth share declines. Without the exogenous variation in the youth share the magnitude of the cyclical volatility would not change. The large swings in GDP volatility, therefore, suggest that the age distribution plays an important role in determining the size of cyclical fluctuations. Figure 5 represents

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[12] Tasci (2006) uses a similar productivity process to calibrate a matching model with a monthly frequency.

this chapter's main result. The model can replicate the general pattern of output volatility observed over the past several decades.

Table 6 reports employment volatility by age group for both the U.S. and the simulated data. Overall, the model matches the volatility pattern by age. Young people experience greater employment fluctuations over the cycle. Thus, aggregate volatility is higher when there are more young people in the labor force - the composition effect. Figure 6 depicts employment volatility with the model data separated into two age groups. As in the U.S. data (see Figure 3a), within age group employment volatility follows the pattern of the youth share. Employment volatility for each age group in the model tracks aggregate employment volatility (also pictured in Figure 6) over time. A high youth share corresponds to periods of high employment volatility for both young and old workers because of the endogenous response by firms.

To get a sense of scale, I compare the demographic-induced reduction in cyclical volatility in the model economy to the Great Moderation. The moderation in the U.S. began around 1984. Since then, GDP volatility decreased by about 52 percent (see Table 1). In the simulation, output volatility falls by about 14 percent over the same time period. Thus, by this calculation, changes in the age distribution can account for about 27 percent of the decline in output volatility associated with the Great Moderation.

Qualitatively, my results agree with the results reported in Jaimovich and Siu (2007). Both studies find a large role for changes in the age distribution in the recent moderation. Jaimovich and Siu (2007) suggest that demographics can explain $10 - 21$ percent of the fall in GDP volatility. My results indicate a larger role for the age distribution. This difference arises because Jaimovich and Siu (2007) only consider compositional effects and have no mechanism for firms to react to changes in the age distribution over the cycle.

To summarize, my model can reproduce the observed changes in employment volatility and the general pattern of output volatility. This finding is the main result. The swings in cyclical volatility caused by the demographic changes appear to be quite large when measured against the recent decline in aggregate fluctuations. The model also generates differences in unemployment rates, job-separation rates, and employment volatility by age.

1.6   Discussion

In this section, I elaborate on a few aspects of the model. First, I discuss wage bargaining and on-the-job search. Then, I document how the economy reacts to a one time permanent change in the aggregate productivity parameter.

1.6.1   Wages

An equilibrium in the model economy essentially consists of firms posting vacancies until the free entry condition (1) is satisfied. The simplicity of this solution is due in part to the wage setting rule. Wages equal a fixed share of output as in Acemoglu (1999), Shimer (2001), and Nagypál (2006). Cooperative Nash bargaining over total surplus is the main alternative method used to determine wages in matching models. However, bargaining over surplus could create a counter factual wage distribution in an OLG environment. Young workers may require higher wages than older workers because young workers live longer, creating a large outside option. Thus, the least productive workers might receive the most compensation. Wages would be a function of age rather than just productivity. In other words, young workers would be paid more than older workers net of productivity differences.[13]

The ability of a standard matching model with Nash bargaining to capture the observed business-cycle-frequency fluctuations in unemployment and vacancies is a matter of debate; see Shimer (2005) for example. Recent work generally down plays the value of unemployment (Hall and Milgrom 2008) and bargaining power (Cahuc, Postel-Vinay, and Robin 2006) for wage determination. My wage rule avoids some of the problems associated with Nash bargaining, but the wages in my model are too volatile relative to the data.

As already mentioned, the wage mechanism and the information structure over match quality simplify the model. Agents do not have to form expectations over future match-finding rates. In other words, even though the economy-wide employment

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[13]One reason to rule out this type of wage setting is that paying older workers less solely because of their age is illegal under the Federal Age Discrimination in Employment Act of 1967.

stocks are endogenously determined, there is no need to calculate a fixed point rational expectations equilibrium. Future values of the endogenously determined state variables do not enter into agents' decisions.

A more complicated wage mechanism is unlikely to change my results. Consider wages based on the worker's outside option like in Nash bargaining. The output produced by an older worker is high in the present. Thus, a change in current productivity has a relatively large effect on older workers and their outside option. Firms must adjust wages accordingly. The value, to a firm, of a young worker comes from future output. The current state has a smaller impact on the worker's outside option. Wages for young workers would change less than the wages of older workers over the cycle. This makes firms more sensitive to aggregate productivity shocks when there are many young workers (this is similar to the argument put forward in Hall (2005) regarding wages). Therefore, employment volatility might be even more closely tied to the age distribution if wages were based on the worker's outside option.

1.6.2   On-the-Job Search

The environment put forth in this chapter does not explicitly model an employed worker's decision to search for a new job while remaining with his or her current employer.[14]   Given the wage and information structure, workers never benefit, in expectation, from leaving their job. Equation (3) shows why. The expected value of $W\left(a, T, \{s_a\}_{a=1}^{\bar{a}-1}, z\right)$ is greater than the expected value of $W\left(a, T_0, \{s_a\}_{a=1}^{\bar{a}-1}, z\right)$ for all values of $T > 0$ because the value of a match increases with tenure. No worker would voluntarily leave a job to take a new position. Furthermore, if there is any cost associated with searching, then no workers will search while employed.

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[14]However, workers do make job-to-job transitions in the model economy. These transitions could be interpreted as capturing the worker flows associated with on-the-job search. In the simulation, the model delivers a large number of job-to-job transistions per month, in line with the data. Thus, the model is not incompatible with on-the-job search, even though it does not explicitly consider the worker's decision to search while employed.

1.6.3   Labor Market Mechanism

In the full dynamic model, the shocks are transitory; however, there exists a high level of persistence. The following experiment approximates the impact of a change in productivity, at least in the first few periods after the shock. The intention is to provide further insight into the labor market based mechanism.

Beginning from the steady state, I increase z by one percent. Figure 7 shows how employment responds after the permanent change. Panel (a) plots the percent difference from the steady state employment level in the months following the shock. The shock occurs in period three. Agents do not know the productivity shock will occur beforehand, but once it happens they know the change is permanent. Employment immediately increases because firms post more vacancies according to equation (9). Then, employment continues to increase as the stocks of workers adjust and firms respond to the new pool of available workers. Panel (b) examines the response by age group. Employment among young workers increases about twice as much as for older workers, in units of percent change. This difference by age group agrees with the data; see footnote 2 and Table 6.

Panels (c) and (d) contain the same information as (a) and (b). In addition, panels (c) and (d) depict the response of an economy with a survival rate of $\lambda = 0.9978$ (versus 0.9998 in (a) and (b)). This economy has a youth share of 61.37 percent (versus 49.89 percent). The other parameters are left unchanged. Employment jumps up considerably more for the economy with the higher youth share; the change in employment is about 30 percent greater. The within age group responses are also bigger in the economy with the larger youth share. In other words, this simple experiment indicates that younger populations have higher employment volatility because of both the composition effect and the endogenous response by firms.

1.7 Conclusion

Aggregate GDP volatility has been positively correlated with the youth share over the past fifty years. This chapter developed a tractable framework to demonstrate how exogenous variation in the age distribution relates to the changes in business cyclical volatility. The OLG model features search frictions, idiosyncratic match quality, and aggregate productivity shocks. There are two ways the age distribution affects aggregate output volatility in the model economy. First, employment for the young fluctuates more than for older workers. It follows that a composition effect exists. Second, firms decide how many jobs to create based on the age and experience profile of the available labor force. Young inexperienced job searchers do not induce firms to post new vacancies. This endogenous response by firms also increases cyclical volatility when the youth share is high. The model can reproduce the general shape of the aggregate volatility pattern observed over the past few decades, generating one-third of the decline in aggregate output volatility associated with the Great Moderation.

CHAPTER II

THE SUPPLY OF SKILLS IN THE LABOR FORCE AND AGGREGATE OUTPUT VOLATILITY

Chapter Abstract

The cyclical volatility of U.S. gross domestic product suddenly declined during the early 1980's and has remained low since. I develop a labor search model with worker heterogeneity and match-specific costs to show how an increase in the supply of high-skill workers can contribute to a decrease in aggregate output volatility. In the model, firms react to changes in the distribution of skills by creating jobs designed specifically for high-skill workers. The new worker-firm matches are more profitable and less likely to break apart due to productivity shocks. Aggregate output volatility falls because the labor market stabilizes on the extensive margin. In a simple quantitative exercise, the labor market based mechanism can generate a substantial portion of the observed reduction in output volatility.

2.1 Introduction

U.S. gross domestic product (GDP) volatility sharply declined during the 1980's and has remained low since (see Figure 8).[1] A gradual increase in the supply of high-skill workers may have contributed to this sudden stabilization. The supply of college graduates, a proxy for the skill supply, increased by an average of over two percent per year (see Figure 9). I argue that firms reacted to changes in the distribution of skills by creating new types of jobs and modifying their hiring strategies. As high-skill workers became plentiful, companies created jobs specifically for high-skill workers. These new positions generated more profits. The worker-firm decision to remain matched to one another reacted less to changes in productivity over the business cycle. Therefore, amplification of the shock along labor's extensive margin decreased, reducing aggregate output volatility.

I develop the intuition through a labor-search model, which extends the environment introduced in Acemoglu (1999). In my model, the matching process has a search friction, and each firm receives a match-specific set-up cost upon meeting a potential employee. Firms select capital based on the skill distribution. When skills are scarce, firms choose a middling amount of capital and hire any worker. Firms do not target high-skill workers because they are difficult to find. Neither high- nor low-skill workers produce with the optimal amount of capital. Thus, matches tend to be close to a shutdown level of productivity, which leads to aggregate output volatility. When high-skill workers are abundant, firms create different jobs for workers of different types. Matches are less likely to break apart in response to productivity shocks because firm capacity and worker skill-level fit better together. Thus, aggregate output volatility decreases. The model generates a substantial portion of the observed drop in GDP volatility. The model also generates an increase in wage inequality between high- and low-skill workers.

My interpretation of the real world events corresponding to the model goes as follows. The U.S. gained high-skill workers throughout the 1970's. In the early 1980's, firms reacted to the increasing supply of skills by creating new types of jobs

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[1]As in Chapter 1, the term volatility refers to the magnitude of the variations from trend at business cycle frequencies. See Chapter 1, Table 1, and Figures 1-3 for more on the decline of cyclical volatility.

and altering their hiring strategies. This structural change in the economy could have been related to the on-going shift from manufacturing to services. Aggregate volatility decreased because firms and workers became better matched. In other words, worker-firm matches are now less likely to be disrupted by changes in productivity over the business cycle.

Next, I discuss some of the extant papers on GDP stabilization and relate my approach to recent advances in the labor search literature. Then, I build the model economy in stages. The third section introduces a static model to help explain how the distribution of skills relates to aggregate output volatility. The basic model comes from Acemoglu (1999). In Section 4, I extend the model to include many periods, idiosyncratic shocks, and an aggregate productivity variable. Section 5 contains a comparison of steady states. I emphasize the decrease in aggregate output volatility when the supply of high-skill workers is sufficiently large. In Section 6, I discuss the model's implications for the economy. After a few concluding remarks, I provide an Appendix with algebraic derivations.

2.2 Related Literature

Kim and Nelson (1999) and McConnell and Perez-Quiros (2000) were among the first published papers to document the sudden and prolonged drop in GDP volatility. Several explanations have been suggested; they can be categorized as changes in either policy, luck, or the structure of the economy (Stock and Watson 2002).[2] Arguments favoring the good policy hypothesis include improved monetary policy (Clarida, Gali, and Gertler 2000), and reformed constraints on collateralized household debt (Campbell and Hercowitz 2006). Alternatively, Ahmed, Levin, and Wilson (2002) and Stock and Watson (2002) conclude that a fortuitous decline in the variance of structural shocks accounts for about half of the reduction in GDP volatility. Arias, Hansen, and Ohanian (2006) demonstrate how a standard real business cycle model can support the good luck hypothesis. Explanations in the structural change

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[2]Jaimovich and Siu (2007) argue that demographics should be added as a fourth potential explanation for the changes in business cycle fluctuations. Also, see Chapter 1.

category include improvements to inventory management (Kahn, McConnell, and Perez-Quiros 2002, Irvine and Schuh 2005), less restrictive credit constraints (Aghion, Angeletos, Banerjee, and Manova 2005), and changes in the composition of output (Alcala and Sancho 2004). None of these has satisfactorily explained the magnitude and the timing of the decline in business cycle volatility.

The supply of skills in the labor force has been dismissed as a cause of GDP volatility reduction because of an apparent timing problem. The stock of high-skill workers increased gradually, whereas GDP volatility experienced a dramatic break. However, in this chapter I show how a smooth increase in the proportion of high-skill workers can cause an abrupt change in aggregate output volatility. Thus, I offer a new 'change in the structure of the economy' solution to the volatility moderation puzzle. The quantitative exercise in Section 5 indicates the change in the supply of skills can account for a substantial portion of the decline in GDP volatility. The model also generates an increase in wage inequality (see e.g. Katz and Murphy (1992) for empirical evidence of the increase in wage inequality.).

My approach builds on the search models of Mortensen and Pissarides (1994). Models of this type feature a friction in the labor market; it takes time for workers and firms to meet. Rogerson, Shimer, and Wright (2005) offers a review (also see Chapter 1, Shimer (2005), and Hall (2005)). My model is standard in most respects. However, I add worker heterogeneity of the type introduced in Acemoglu (1999).

The analysis begins with the static one-period model from Acemoglu (1999). Then, I extend the basic set-up to include match-specific costs and changes to the aggregate production technology in a multi-period setting. This environment allows me to study the amplification of productivity shocks in regards to the distribution of skills. Introducing heterogeneity into search models makes solutions notoriously difficult to compute. I follow Nagypál (2006) and compare steady state equilibria with different aggregate productivity levels as an approximation to the business cycle. I find a strong relationship between worker skill heterogeneity and aggregate output volatility.

2.3 One-Period Model

I present a simple one-period model in order to introduce the mechanism linking the distribution of skills to aggregate volatility. The set-up closely follows Acemoglu (1999). Ex-ante, two types of workers, high- and low-skill, seek employment. Firms open jobs, meet workers, and then decide whether to hire the worker and produce. When the supply of high-skill workers is large, the economy switches to an equilibrium in which firms create jobs specifically for high-skill workers. These new matches produce more profits and are therefore less likely to be destroyed due to changes in productivity.

2.3.1 Model Environment

A unit mass of workers passively waits to be matched, one-to-one, with an equal number of vacant firms. A fraction, ϕ, of workers possess superior skills, and the rest are low-skill workers. I normalize the productivity of low-skill workers to $h = 1$, and high-skill workers have $h = \eta > 1$. Vacant firms randomly match to a single worker, with no switching allowed. Workers receive share β of output.[3] The firm pays the production costs, Ψk, out of its share. The fees associated with k are the price for rental and operation of the capital; non-productive firms incur no cost.

Firms know ϕ and η; however, they select k prior to learning their match's labor productivity, h. The technology takes a Cobb-Douglas form. I denote the share of labor by α and normalize $\Psi = (1 - \beta)$. To reduce notational clutter, I suppress functional arguments throughout. Superscripts H and L indicate association with high- and low-skill workers, respectively. See Table 7 for a list of notation. The expected value of an unmatched firm with capital k equals:

$$V = (1 - \beta)[\phi x^H (k^{1-\alpha} \eta^\alpha - k) + (1 - \phi) x^L (k^{1-\alpha} - k)]. \tag{10}$$

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[3]The search literature frequently uses a 'Nash bargaining' wage rule (Rogerson, Shimer, and Wright 2005). Shimer (2005) attacks this rule for not delivering the wage rigidity necessary to generate the observed volatility in the vacancy-unemployment ratio. Other ways to set wages have been proposed. For example, Hall (2005) specifies a rule with more wage stickiness. Since neither wage negotiation nor the vacancy-unemployment ratio is central to this paper, I assume matched pairs split each period's output as in Acemoglu (1999). See Chapter 1 for more on this point.

The choice variables x^H and x^L stand for the agent's expected probability, once matched, of actually producing. Thus, a firm expects to produce with a high-skill worker with probability ϕx^H. Firms select k, x^H, and x^L to maximize equation (10). Firms must decide what type of job to create when posting a vacancy and prior to meeting a worker. This irreversible technology decision costs nothing. In the one-period model, workers have no outside option and accept any job. Figure 10 outlines the sequence of events.

2.3.2 Equilibria

As detailed in Acemoglu (1999), the choice of capital depends on the distribution of skills, captured by ϕ and η. When ϕ and η are relatively low, firms create jobs suitable for either type of worker. If enough workers have sufficiently large productivity, then firms open jobs specifically for high-skill workers. Since workers passively accept any match, an equilibrium consists of firms maximizing their expected value (10). Two equilibrium types emerge. A "pooling" equilibrium prevails when ϕ and η have relatively small values. When ϕ and η are large, a "separating" equilibrium prevails, and firms target high-skill workers.[4] The skill condition (11) dictates the prevailing equilibrium.

Skill Condition (Acemoglu 1999)

$$\eta > \left(\frac{1 - \phi}{\phi^\alpha - \phi} \right)^{1/\alpha} = \Omega \tag{11}$$

When $\eta < \Omega$, the skill condition (11) fails, and if $\eta > \Omega$, then the skill condition (11) holds.

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[4] Acemoglu (1999) refers to one type of equilibrium as "separating" because firms select an amount of capital expecting to produce only when matched with a high-skill worker. Firms treat the two worker types in separate ways. In a "pooling" equilibrium, firms select a level of capital expecting to produce with either type of worker. In the multi-period model developed below, idiosyncratic shocks complicate matters somewhat. However, I continue to use the same labels as in Acemoglu (1999). Finally, the equilibria should not be confused with the pooling and separating concepts common to non-cooperative game theory.

I let $\Lambda = (1 - \alpha)^{1/\alpha}$ and $\Pi = [\phi\eta^{\alpha} + 1 - \phi]^{1/\alpha}$. Proposition 1 describes the relationship shared by the skill condition (11), the prevailing equilibrium, and the choice of capital.

Proposition 1 *(Acemoglu 1999)*

If $\eta < \Omega$, then a Pooling Equilibrium prevails.
Firms choose $k = k^P = \Lambda\Pi$ and $x^H = x^L = 1$.

If $\eta > \Omega$, then a Separating Equilibrium prevails.
Firms choose $k = k^H = \Lambda\eta$, $x^H = 1$, and $x^L = 0$.

I take η as given and examine how the economy reacts to an exogenous increase in the supply of high-skill workers, ϕ. Firms select capacity $k = k^P = \Lambda\Pi$ or $k = k^H = \Lambda\eta$ depending on whether the skill condition (11) holds. In a separating equilibrium, low-skill workers do not get hired. Both worker types find jobs in a pooling equilibrium.

2.3.3 Output and Labor's Extensive Margin

A firm with capital k matched to a worker with skill level h produces:

$$y = k^{1-\alpha}h^{\alpha}. \tag{12}$$

Firms decide whether to hire their match and produce (12) at cost Ψk, given h and k. A firm produces whenever revenues exceed costs. I refer to the hiring / production decision as labor's *extensive margin*. Decisions along the extensive margin are the critical mechanism amplifying the aggregate shock.

Figure 11 contains a stylized plot of profits against capacity for a firm with a high-skill worker. The optimal choice of capital is $k^H = \Lambda\eta$. Imagine an aggregate productivity shock shifting the entire profit curve up or down. If a firm selects the right amount of capital for its employee's skill type, then only a large negative shock can drop profits below the shutdown level. When profits are below the shutdown level, the match breaks apart. In a separating equilibrium, firms do pick the optimal capacity for a high-skill worker, $k = k^H = \Lambda\eta$, and profits equal $\frac{\alpha(1-\beta)}{1-\alpha}\Lambda\eta$. The shock would have to annihilate all this profit to disintegrate the match.[5] Only then would the shock generate movement along labor's extensive margin.

In a pooling equilibrium firms select $k = k^P = \Lambda\Pi$. This capacity choice is sub-optimal for both low-skill workers and high-skill workers. When a firm has a sub-optimal (e.g. pooling) amount of capital for its employee's skill type, a relatively small change in productivity can drop profits to shutdown. For example, a match between a firm and a low-skill worker in a pooling equilibrium generates only $\frac{1-\beta}{1-\alpha}\Lambda\Pi\left(\Pi^{-\alpha} - 1 + \alpha\right)$ in profits. An aggregate shock impacts labor's extensive margin at less extreme values than in a separating equilibrium. So, the pooling equilibrium generates more movement on labor's extensive margin.

Labor's extensive margin connects the distribution of skills to aggregate output volatility. Next, I imbed this mechanism in a multi-period matching model and try to quantify the difference in output volatility between the two equilibria. The mechanism works the same way in the multi-period environment as in the one-period model. Firms react to an increase in high-skill workers by creating new types of jobs. Then, worker-firm pairs have better capacity-to-productivity matches. Only large shocks drop productivity below shutdown levels. Hiring decisions stabilize along the extensive margin, reducing the amplification of the aggregate shock. Thus, aggregate output is less volatile in a separating equilibrium.

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[5]See the Appendix at the end of the chapter for a derivation of a firm's profits in each equilibrium.

2.4 Multi-Period Model

In a multi-period setting, the effect of an aggregate productivity shock depends on the distribution of skills in the labor force. When the model economy is in a separating equilibrium, firms exploit the skill distribution by creating different jobs for workers of different skill types (just as in the one-period model and in Acemoglu (1999)). Firms also modify their hiring strategies. Moving from a pooling equilibrium to a separating equilibrium decreases aggregate output volatility because the labor market gains stability along the extensive margin. Employed workers are better suited to their jobs in the separating case. Even low-skill workers encounter less employment variation.

2.4.1 Model Environment

A unit mass of workers lives an infinite number of discrete periods. A period is defined as the amount of time required to find a potential employer. Therefore, every unemployed worker meets a firm in every period, and all vacant firms meet an employee. As in the one-period model, firms choose a capacity, k, before matching. Firms consider a prospective match's lifetime value when deciding whether to hire a worker and produce. Workers also consider a match's expected lifetime value and do not necessarily accept any job. Workers have an outside option; they can wait for a better match. High-skill workers may have different job finding and unemployment rates than low-skill workers. The fraction of unemployed workers possessing superior skills is denoted by q; whereas, the fraction of high-skill workers in the entire population is still denoted by ϕ. Each firm knows q, ϕ, and η, the relative productivity of high-skill workers. If a pair does not mutually agree to produce, then the worker remains unemployed and the vacancy is destroyed. Agents discount future earnings at rate $(1 - \delta)$.

There exists a large number of inactive firms, but only measure one open lots for firms to operate. Inactive firms can pay c to post a vacancy on an open lot.[6]

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[6]This payment can be considered a rental cost for one of the lots. Alternatively, the payment could be a function of a fixed cost and the probability of meeting a worker through a degenerate matching function, where the number of matches equals the number of unemployed workers. Either way, a free entry condition leaves firms indifferent to paying c or remaining inactive.

Posting a vacancy guarantees the firm meets a worker. The price c is determined in equilibrium, leaving firms indifferent between posting a vacancy and remaining inactive. The value of an inactive firm is zero, and the value of a vacant firm equals c. In other respects, the matching process remains the same as in the one-period model. Firms entering the market create jobs and search for workers. Firms select k to maximize the expected value of an unmatched firm.

Firms pay all the costs. The period-by-period rental and operation payments, Ψk, depend on the firm's capacity. Initial set-up fees, $\Phi\epsilon$, are paid only once. The set-up costs could include match-specific training, human resources paperwork, moving fees, etc. This idiosyncratic shock is drawn from a uniform distribution on $[0, \tau]$, denoted by $F(\epsilon)$. All agents face a common aggregate state, z. I interpret changes to the aggregate state as shocks to productivity.

The timing within a period goes as follows. First, a share σ of existing matches are destroyed. This exogenous separation rate does not impact newly formed matches. Next, firms open vacancies and select a level of capital. Then, unemployed workers and vacant firms meet. Every unemployed worker meets a vacancy. Upon learning the properties of the match, agents decide whether to produce. The properties of the match include the worker's skill level, h, the firm's capacity, k, and the idiosyncratic match specific shock, ϵ. If the pair does not produce, then the worker remains unemployed until the next period, and the vacancy ceases to exist. Finally, production (12) occurs. Agents split output, with share β going to the worker.

Next, I summarize the economy in a steady state. The agents' value functions are defined prior to matching. Following Nagypál (2006), and due to computational complexity, only steady state equilibria are analyzed.[7] The value of a vacancy with capacity k is:

$$V = qx^H\delta \int_0^{B_H} \left(J^H - \Phi\epsilon\right) dF(\epsilon) + (1-q) x^L\delta \int_0^{B_L} \left(J^L - \Phi\epsilon\right) dF(\epsilon).$$

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[7]In other words, I compare different steady state equilibria to assess the response of the model to aggregate shocks. Nagypál (2006) argues that in "the standard search model such a comparative static exercise invariably gives results that are very close to the dynamic response of the full stochastic model". See Shimer (2005) for an example.

Firms and workers mutually arrive at x^j, the probability a match with worker type $j \in \{H, L\}$ produces. Additionally, the firm must determine if the match will produce enough to justify paying the up-front fee, $\Phi \epsilon$. I set Φ to $\frac{1-\beta}{1-\delta(1-\sigma)}$. If a match produces, then the firm obtains the value of a matched firm, J^j. For example, an unmatched firm meets a low-skill worker with probability $(1-q)$. The pair agrees to produce with probability x^L, given $\epsilon < B_L$. Then, the firm gets J^L, the value of a matched firm. If the match-specific shock is greater than B_L, then the firm prefers to destroy the match. The terms B_H and B_L stand for the maximum idiosyncratic shocks with which a firm chooses to produce with high- and low-skill workers, respectively. Since the firm's outside option equals zero, a firm facing $\epsilon = B_j$ nets zero profits. The next equation encapsulates the value of a matched firm:

$$J^j \;=\; (1-\beta)\, z \left(k^{1-\alpha} h_j^\alpha - k \right) + (1-\sigma)\, \delta J^j.$$

The value of a matched firm depends on its capacity, k, and the skill level of its worker, h_j. As before, $\Psi = (1-\beta)$. A match falls apart in any future period with probability σ. When a match breaks apart, the firm leaves the market, and the worker becomes unemployed.

Unemployed workers do not receive any payments. Although, it would be straight forward to include unemployment benefits. The next equation applies to unemployed workers:

$$U^j \;=\; \int_\kappa x^j \int_0^{B_j} dF\left(\epsilon\right) \delta W^j dG\left(k\right) + \left(1 - \int_\kappa x^j \int_0^{B_j} dF\left(\epsilon\right) dG\left(k\right) \right) \delta U^j.$$

Again, $j \in \{L, H\}$ represents a worker's skill level. An unemployed worker meets a firm with capacity k randomly drawn from the distribution $G(k)$ with support κ, as in Acemoglu (1999). The term $\int_0^{B_j} dF\left(\epsilon\right)$ is the equilibrium probability of the firm producing. Workers take this probability as given.

The following equation expresses the value of an employed worker producing with a firm of capacity k:

$$W^j = \beta z k^{1-\alpha} h^j + (1-\sigma)\,\delta W^j + \sigma \delta U^j.$$

As in the one-period model, the worker and the firm divide output with the worker obtaining share β. The firm pays the operating costs, Ψk, from its share. Each party must receive at least their outside option.

2.4.2 Pooling and Separating Equilibria

Consider, again, pooling and separating equilibrium. The productivity shock, z, enters aggregate output through the production function, and also via employment levels. The effect from the production function channel is the same across equilibria. The second channel captures the labor market mechanism. Labor's extensive margin responds to changes in the aggregate state. The quantitative analysis in Section 5 confirms that the extensive margin is more volatile in a pooling equilibrium. The capital choice in a pooling equilibrium keeps profits closer to shutdown for both worker types. The equations defining steady state economies in the pooling and separating cases are presented next.

2.4.2.1 Pooling Equilibrium

In a pooling equilibrium, $x^L = x^H = 1$, and κ has only one element, k_P. The percent of unemployed workers with high-skills, q, does not equal the population value, ϕ, because of idiosyncratic shocks. The model must be solved numerically.

The following system of equations (13) defines the economy when in a steady state pooling equilibrium:

$$V^P = q\delta \int_0^{B_H^P} \left(J^H - \Phi\epsilon\right) dF\left(\epsilon\right) + \left(1 - q\right)\delta \int_0^{B_L^P} \left(J^L - \Phi\epsilon\right) dF\left(\epsilon\right) \quad (13)$$

$$J^H = \left(1 - \beta\right) z \left(k_P^{1-\alpha}\eta^\alpha - k_P\right) + \left(1 - \sigma\right)\delta J^H$$

$$U^H = \delta \int_0^{B_H^P} dF\left(\epsilon\right) W^H + \left(1 - \int_0^{B_H^P} dF\left(\epsilon\right)\right)\delta U^H$$

$$W^H = \beta z k_P^{1-\alpha}\eta^\alpha + \left(1 - \sigma\right)\delta W^H + \sigma\delta U^H$$

$$J^L = \left(1 - \beta\right) z \left(k_P^{1-\alpha} - k_P\right) + \left(1 - \sigma\right)\delta J^L$$

$$U^L = \delta \int_0^{B_L^P} dF\left(\epsilon\right) W^L + \left(1 - \int_0^{B_L^P} dF\left(\epsilon\right)\right)\delta U^L$$

$$W^L = \beta z k_P^{1-\alpha} + \left(1 - \sigma\right)\delta W^L + \sigma\delta U^L.$$

In a pooling equilibrium, each firm chooses an optimal amount of capital given the above equations (13).[8] So, k_P is the solution to:

$$\max_{k_P}\left\{V^P\right\} = \max_{k_P}\left\{\frac{\left(1 - \beta\right)\delta}{\tau\left(1 - \left(1 - \sigma\right)\delta\right)}\left\{q\left(B_H^P z\left(k^{1-\alpha}\eta^\alpha - k\right) - \frac{1}{2}\left(B_H^P\right)^2\right)\right.\right. \quad (14)$$
$$\left.\left. + \left(1 - q\right)\left(B_L^P z\left(k^{1-\alpha} - k\right) - \frac{1}{2}\left(B_L^P\right)^2\right)\right\}\right\}.$$

The first-order condition of equation (14) captures the optimal level of capital, k_P. The first-order condition is:

$$0 = q B_H^P\left(\left(1 - \alpha\right)k_P^{-\alpha}\eta^\alpha - 1\right) + \left(1 - q\right) B_L^P\left(\left(1 - \alpha\right)k_P^{-\alpha} - 1\right), \quad (15)$$

where:

$$B_H^P = z\left(k_P^{1-\alpha}\eta^\alpha - k_P\right) \quad (16)$$
$$B_L^P = z\left(k_P^{1-\alpha} - k_P\right).$$

---

[8] The Appendix provides more details on the algebraic derivations.

The flows of workers in and out of employment in the steady state pin down the employment levels and the value of q, the percent of unemployed with high-skills. I denote the employment levels (not percents) of each worker type with e. For a pooling equilibrium in a steady state:

$$e^H = \phi \frac{z\left(k_P^{1-\alpha}\eta^\alpha - k_P\right)}{z\left(k_P^{1-\alpha}\eta^\alpha - k_P\right) + \sigma\tau}$$

$$e^L = (1-\phi)\frac{z\left(k_P^{1-\alpha} - k_P\right)}{z\left(k_P^{1-\alpha} - k_P\right) + \sigma\tau},$$

and:

$$q = \frac{1}{1 + \frac{(1-\phi)\left(z\left(k_P^{1-\alpha}\eta^\alpha - k_P\right) + \sigma\tau\right)}{\phi\left(z\left(k_P^{1-\alpha} - k_P\right) + \sigma\tau\right)}}. \tag{17}$$

Equations (15), (16), and (17) can be combined to find a numerical solution to the model economy in a pooling equilibrium for a given set of parameter values.

The productivity shock, z, enters through the production function and through employment, which is labor's extensive margin. Given a solution for k^P, it is straightforward to calculate aggregate output, Y^P:

$$Y^P = e^H z k_P^{1-\alpha}\eta^\alpha + e^L z k_P^{1-\alpha}$$

$$Y^P = z k_P^{1-\alpha}\left(\phi\frac{k_P^{1-\alpha}\eta^\alpha - k_P}{k_P^{1-\alpha}\eta^\alpha - k_P + \frac{\sigma\tau}{z}}\eta^\alpha + (1-\phi)\frac{k_P^{1-\alpha} - k_P}{k_P^{1-\alpha} - k_P + \frac{\sigma\tau}{z}}\right). \tag{18}$$

2.4.2.2 Separating Equilibrium

Consider a separating equilibrium. Share p of firms target high-skill workers and set $x^H = 1$ and $x^L = 0$. The remaining $(1-p)$ of firms face $x^H = 0$ and $x^L = 1$ and can only hire low-skill workers. Firms looking for high-skill workers select a high-capacity, and firms searching for low-skill workers pick a low level of capital. So κ has two elements, k^L and k^H. The steady state is characterized by the following equations (19):

$$
\begin{aligned}
V_H^S &= q\delta \int_0^{B_H^S} \left(J^H - \Phi\epsilon \right) dF(\epsilon) \qquad\qquad\qquad (19)\\
J^H &= (1-\beta) z \left(k_H^{1-\alpha}\eta^\alpha - k_H \right) + (1-\sigma)\delta J^H \\
U^H &= p\delta \int_0^{B_H^S} dF(\epsilon) W^H + \left(1 - p \int_0^{B_H^S} dF(\epsilon) \right) \delta U^H \\
W^H &= \beta z k_H^{1-\alpha}\eta^\alpha + (1-\sigma)\delta W^H + \sigma\delta U^H \\
V_L^S &= (1-q)\delta \int_0^{B_L^S} \left(J^L - \Phi\epsilon \right) dF(\epsilon) \\
J^L &= (1-\beta) z \left(k_L^{1-\alpha} - k_L \right) + (1-\sigma)\delta J^L \\
U^L &= (1-p)\delta \int_0^{B_L^S} dF(\epsilon) W^L + \left(1 - (1-p) \int_0^{B_L^S} dF(\epsilon) \right) \delta U^L \\
W^L &= \beta z k_L^{1-\alpha} + (1-\sigma)\delta W^L + \sigma\delta U^L.
\end{aligned}
$$

In a separating equilibrium, each firm chooses the optimal amount of capital given the above equations (19). So, k_H is the solution to:

$$
\max_{k_H} \left\{ V_H^S \right\} = \max_{k_H} \left\{ \frac{q(1-\beta)\delta}{\tau(1-(1-\sigma)\delta)} \left(B_H^S z \left(k^{1-\alpha}\eta^\alpha - k \right) - \frac{1}{2} \left(B_H^S \right)^2 \right) \right\},
$$

and k_L solves:

$$
\max_{k_L} \left\{ V_L^S \right\} = \max_{k_L} \left\{ \frac{q(1-\beta)\delta}{\tau(1-(1-\sigma)\delta)} \left(B_L^S z \left(k^{1-\alpha} - k \right) - \frac{1}{2} \left(B_L^S \right)^2 \right) \right\}.
$$

The solution to the firms' problems can be found analytically.[9] The choices are:

$$k_L = \Lambda$$

$$k_H = \Lambda\eta.$$

Also, a technical condition for a separating equilibrium is high-capacity firms should not be willing to hire low-skill workers even with the best possible idiosyncratic shock, $\epsilon = 0$. This implies $\eta > \left(\frac{1}{1-\alpha}\right)^{\frac{1}{\alpha}}$ (see this chapter's Appendix). I assume $\eta > \left(\frac{1}{1-\alpha}\right)^{\frac{1}{\alpha}}$.

The value of creating a low-capacity vacancy must be the same as the value of opening a high-capacity vacancy in equilibrium. In a steady state, the flows in and out of employment are equal. These two conditions pin down q, the percent of unemployed with high-skills, and p, the percent of vacant firms with high-capacities. Thus, q and p are:

$$q = \frac{1}{\eta^2 + 1}$$

$$p = \frac{\phi\eta + \frac{\left(\phi\eta^2 - 1 + \phi\right)\sigma\tau}{\alpha z(1-\alpha)^{\frac{1-\alpha}{\alpha}}\eta}}{(\phi\eta + 1 - \phi)};$$

therefore:

$$e^H = \frac{\phi\left(1 - \sigma\right)}{(1 - \sigma) + \frac{\tau\sigma(\phi\eta+1-\phi)}{\phi\eta^2\alpha z(1-\alpha)^{\frac{1-\alpha}{\alpha}} + (\phi\eta^2 - 1 + \phi)\sigma\tau}}$$

$$e^L = \frac{(1 - \phi)\left(1 - \sigma\right)}{(1 - \sigma) + \frac{\tau\sigma(\phi\eta+1-\phi)}{(1-\phi)\alpha z(1-\alpha)^{\frac{1-\alpha}{\alpha}} + (\phi\eta^2 - 1 + \phi)\frac{\sigma\tau}{\eta}}}.$$

---

[9]See the Appendix at the end of the chapter for the derivation.

The productivity shock, z, enters through the production function and through employment, which is labor's extensive margin. The above equations can be combined into an expression for aggregate output (20):

$$Y^S = e^H z k_H^{1-\alpha} \eta^\alpha + e^L z k_L^{1-\alpha}$$

$$Y^S = z(1-\alpha)^{\frac{1-\alpha}{\alpha}} \{ \frac{\phi(1-\sigma)}{(1-\sigma) + \frac{\tau\sigma(\phi\eta+1-\phi)}{\phi\eta^2\alpha z(1-\alpha)^{\frac{1-\alpha}{\alpha}}+(\phi\eta^2-1+\phi)\sigma\tau}} \eta$$
$$+ \frac{(1-\phi)(1-\sigma)}{(1-\sigma) + \frac{\tau\sigma(\phi\eta+1-\phi)}{(1-\phi)\alpha z(1-\alpha)^{\frac{1-\alpha}{\alpha}}+(\phi\eta^2-1+\phi)\frac{\sigma\tau}{\eta}}} \}. \tag{20}$$

2.4.3 Dynamic Skill Condition

In a pooling equilibrium, all firms choose capacity $k = k^P$. Firms agree to produce with any worker as long as the match-specific costs do not exceed the boundary B. Workers' outside options do not bind because $\kappa = \{k^P\}$. When $V^S = V^L > V^P$, the economy is in a separating equilibrium. In a separating equilibrium, firms only produce with one of the two types of workers. A high-capacity firm will not hire a low-skill worker, and a high-skill worker would rather wait than produce with a low-capacity firm. Thus, $\kappa = \{k^P, k^H\}$.

The multi-period version of the skill condition is found by setting $V^S = V^P$. This must be calculated numerically for a given set of parameter values.

2.5   Quantitative Results

In this section I report the results from a simple quantitative exercise in order to get a sense of how much of the drop in aggregate output volatility can be attributed to changes in the skill distribution.

2.5.1   Parameter Values

There are only a few parameters to choose. Each period lasts one quarter. I set the exogenous separation rate σ equal to 0.1. This value generates the average job duration of about 2.5 years quoted in Shimer (2005). The supply of high-skill workers, ϕ, is set equal to the percentage of the labor force with college degrees as reported in Acemoglu (2002).[10] The production function parameter α is set to 0.64 to match the long-run share of output going to labor (Kydland and Prescott 1982). Given α, the model implies that η must be 5 or higher for a separating equilibrium to exist (see Section 4 and the Appendix). The share of output going to workers β and the discount rate δ simply act to normalize the value of a matched firm (as in Chapter 1); I set these parameters to 0.64 and 0.95, respectively. Table 8 lists the relevant parameter value choices. I discuss alternative parameter values below.

2.5.2   Results

The separating case can be directly evaluated. To solve for the pooling equilibrium, I search over a coarse grid to find starting points. Then, I use a simple hill climber. Table 9 details firms' equilibrium capital choices.

The results from the multi-period model agree with the theory built up with the one-period model. In the pooling equilibrium, it is optimal for firms to select a middling amount of capital, $k^P = 0.471$. This capital choice is sub-optimal for either worker type and generates lower profits. The value of a firm matched with a high- or low-skill worker is larger in a separating equilibrium than the value of a firm matched with the same worker in a pooling equilibrium. In the separating case,

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[10]As already noted, I use the supply of college graduates as a proxy for the exogenous increase in the supply of high-skill workers. Acemoglu (2002) lists this number at about 19.2% in 1980 and 24.0% in 1990.

workers produce with the optimal amount of capital for their skill type. High-skill workers produce with more capital, $k^H = 1.013$, while low-skill workers produce with less, $k^L = 0.203$. When the supply of high-skill workers gets large enough, firms have a profit incentive to design new types of jobs. Aggregate output volatility declines because matches are more stable on the extensive margin. The value, J, of being matched goes up for the firm.

The model also features a change in the skill premium or wage inequality. This result follows directly from Acemoglu (1999). Wage inequality is η^α in the pooling case and increases to η in a separating equilibrium. It is difficult to know what to compare the skill premium to. There exists a large body of evidence on increasing wage inequality, increasing college premium, and increasing residual income inequality. However, these measures do not directly correspond to the skill premium concept present in my model economy.

Table 10 presents the model output and employment results with U.S. data in parentheses.[11] To examine output volatility, I changed the aggregate productivity variable z by 5 percent. When subjected to this 'shock', aggregate output changed by 6.9 percent less in the separating equilibrium than in the pooling equilibrium. Again, I compare steady state equilibria as in Nagypál (2006). I interpret the percent change in output as a measure of volatility. Thus, the change in equilibrium can generate about 16 percent of the observed reduction in aggregate output volatility.

2.5.3 Alternative Parameter Values

Given the other parameter values, I constrain the parameter η to be above 5 (again, see Section 4 and the Appendix). The relative productivity of high-skill workers could take on higher values, but if η is too high, then the pooling equilibrium will fall apart (some firms will target high-skill workers, only). Thus, increasing η moves the economy closer to the threshold (i.e. the skill condition) at which firms begin to treat workers separately because η increases the value of high-skill workers.

---

[11] Table 10 reports the difference in output and employment across steady state equilibria, where the productivity shock has been changed by 5%. The U.S. data from 1980 (for pooling) and 1990 (for separating) are given in parentheses. The U.S. data are the standard deviation of the logged, de-trended time series over the appropriate time period.

Similarly, higher values of ϕ move the economy closer to a separating equilibrium because this change makes high-skill workers easier to find.

In Table 11, I present the results using alternate parameter value choices. The parameters α and σ remain at their previous values, and ϕ still equals 0.24 in the separating case. I provide only the final results (i.e. the percent difference in 'volatility' between the two equilibria types). The difference between output volatility in the pooling case and separating case gets larger as the initial (pooling) value of ϕ gets smaller and as η grows larger. Thus, the benchmark results presented in Table 10 are a lower bound. Across the different parameter value choices, the mechanism developed in this chapter explains $16 - 28$ percent of the 43 percent decline in aggregate output volatility.

2.6 Discussion

The main finding can be restated as follows. A gradual increase in the supply of skills induces firms to open new types of jobs. When the composition of jobs changes, the economy shifts to a separating equilibrium. In the new equilibrium, there is a better match between labor and capital. Output volatility falls because shocks have less impact on hiring and production decisions. Thus, changes in the distribution of skills affects aggregate output volatility. In addition to this result, the model has several other implications.

2.6.1 Static Implications

If the model economy changes from a pooling to a separating equilibrium, then wage inequality increases and firms create different types of jobs, regardless of business cycle fluctuations. Acemoglu (1999) documents these implications in detail. The wages of low-skill workers react non-monotonically to the supply of skills, ϕ, and to skill-biased technical change, captured by η. In a pooling equilibrium, an increase in ϕ has little impact on wages. In a separating equilibrium, the average wage for low-skill workers drops because low-skill workers produce with less capital. An increase in η always amplifies wage inequality. Thus, an exogenous increase in η or ϕ tends to exacerbate the wage inequality between high- and low-skill workers. Wage inequality

goes up because low-skill workers produce with less capital than high-skill workers (again see Acemoglu (1999)). In my main quantitative example, high-skill workers produce with $k^H = 1.013$, while low-skill workers produce with $k^L = 0.203$. Wage inequality among workers grew (Katz and Murphy 1992, Karoly 1992) over roughly the same time period as GDP volatility shrank, so it is tempting to imagine a connection between output volatility and income inequality. In my model, an exogenous progression in skills increases both macroeconomic stability and the skill premium.

The feature of the model that generates the wage premium increase is the change in the composition of jobs and the associated change in hiring practices by firms. Acemoglu (1999) lists several pieces of evidence in this regard. The evidence includes measurable changes in recruitment practices, the capital-to-labor ratio, the distribution of jobs, the distribution of on the job training, and better employee-employer matching. The U.S. economy has also been moving away from manufacturing and towards service based industries.

2.6.2 Business Cycle Implications

Consider again the two time series in Figure 8 and Figure 9. First, the volatility of GDP dramatically decreased during the early 1980's (Kim and Nelson 1999, McConnell and Perez-Quiros 2000). Second, the skill level of the labor force increased throughout the past three decades (Acemoglu 2002). Most notably, the large, well-educated, baby-boom generation entered the workforce beginning around 1970. I have conjectured a link between the supply of high-skill workers and aggregate output volatility.

My story goes as follows. The economy gained skilled workers throughout the 1970's. By the mid-1980's, firms reacted by creating jobs tailored to workers of different skill types. The average worker became better suited to his or her job. The labor market's ability to amplify the aggregate shock declined, so GDP volatility suddenly fell. This drop corresponds to the switch from a pooling equilibrium to a separating equilibrium in the model economy.

Consider a pooling equilibrium. The proportion of high-skill workers, ϕ, is relatively small, and firms select $k = k^P$. Firms expect to produce with workers of either skill type. Small increases in ϕ or η lead to small changes in output. When

ϕ exogenously increases enough, the economy moves into a separating equilibrium. Firms select a level of capital suited to producing with only one type of worker, and the economy's aggregate output volatility decreases.

The decline in output volatility occurs just as the economy moves from a pooling equilibrium to a separating equilibrium. The equilibrium switch happens because firms respond to profit incentives created by increases in ϕ. Firms open new high-capacity jobs and modify their hiring strategies. Workers in a separating equilibrium produce with the optimal amount of capital for their skill type, altering the economy's responsiveness to aggregate shocks along labor's extensive margin. Only large shocks disintegrate a match. Aggregate output volatility falls. Thus, the model economy generates the sudden and sustained business cycle moderation observed in the data.

2.6.2.1   Evidence from U.S. States

According to the model, output volatility decreases when the supply of high-skill workers gets high enough to pass a threshold (i.e. the skill condition). Data from the U.S. states provides evidence on this hypothesis. I split the states into two equal-sized groups based on the percent of college graduates within each state before 1984. Then, I calculated state-specific GDP volatility for two sub-periods using BEA data from 1963–1983 and 1984–1997.[12] The group of states with more college graduates pre-1984 experienced only a small decline in GDP volatility between the two sub-periods; the decline in GDP volatility across these states averaged 2.5 percent of the pre-1984 level. Possibly, these 'high-education states' had passed the threshold for the supply of high-skill workers *before* 1984, so the decline in output volatility had already occurred within these states.

Meanwhile, most of the decline in U.S. GDP volatility associated with the Great Moderation occurred in states that had low concentrations of high-skill workers pre-1984. The intuition from the model is that as these states gained high-skill workers (enough to satisfy the skill condition), firms reacted and aggregate output volatility decreased within these states. All of the states in this second group had large increases

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[12]I include DC, but drop Alaska; this does not appreciably affect the results. I only use GDP data up to 1997 because the methodology used to calculate state GDP changed. See the BEA web site for details. Also, see Chapter 1 for more on measuring GDP volatility.

in the share of college graduates between the two sub-periods. The average decline in GDP volatility (from pre-1984 levels) between the two sub-periods in these states was over 35 percent, about fifteen times larger than for the states that had higher concentrations of college graduates before 1984.[13] The states with the largest declines in volatility also tended to have higher unemployment rates post-1984, which follows another implication of the model (unemployment rates increase when the economy moves from a pooling equilibrium to a separating equilibrium; see Acemoglu (1999)).

2.6.2.2   Other Implications for the Business Cycle

The model predicts that the GDP volatility decrease will be accompanied by a decrease in employment volatility when the economy switches from the pooling case to a separating equilibrium (see Table 10). As already noted, employment fluctuations have declined in the U.S. aggregate data. However, the drop in employment volatility has not been the same across skill groups. Castro and Coen-Pirani (2008) report that the decline has been greater for low-skill workers. In my model simulation from last section, employment volatility fell by 25 percent more for low-skill workers than for high-skill workers. In fact, when the economy switched to a separating equilibrium, employment volatility among high-skill workers did not fall appreciably *relative to the observed decline in GDP volatility.* These results are not inconsistent with the observed changes in cyclical employment volatility by skill group reported in Castro and Coen-Pirani (2008).

Finally, wages tend to be weakly pro-cyclical and unemployment moves counter-cyclically in the U.S. data. In the model, wages equal a share of output, and output co-moves with the aggregate shock. Similarly, the employment rate moves in tandem with the aggregate shock because firms react to high realizations of z by becoming less selective employers. Thus, the model economy features both pro-cyclical wages and counter-cyclical unemployment.

---

[13]I have also re-done the calculations in this section with the states weighted by state-wide GDP. The results are striking. When weighted, the states with the higher concentrations of college graduates pre-1984 actually show an increase in GDP volatility, while the reduction among the remaining states is even higher. Finally, this general finding remains when output net of manufacturing is used instead of total state GDP.

2.7   Conclusion

In this chapter, I hypothesized a connection between the decrease in U.S. GDP volatility and the increase in wage inequality. Other explanations for these phenomena have been suggested. My labor market based theory is unique in offering a single explanation for both. The theory relies on skill heterogeneity and an employment search friction, which are widely used assumptions.

In summary, amplification of the aggregate shock depends on the distribution of skills in the labor force. I extend the labor search model developed in Acemoglu (1999) to demonstrate how a gradual increase in the supply of high-skill workers can cause a sudden decrease in aggregate output volatility. In the model, firms react to an influx of skills by changing the composition of jobs and by modifying their hiring strategies. The labor market's responsiveness to the aggregate productivity shock changes when firms alter these extensive margin decisions. The economy moves to a separating equilibrium and enters a state of quiescence. This corresponds to the sudden and sustained drop in U.S. GDP volatility, which occurred in the early 1980's. The model also predicts pro-cyclical wages and output and an increase in residual wage inequality.

The results of a simple quantitative exercise indicate that the relationship between the supply of skills and aggregate output volatility is important. The labor market mechanism developed in this chapter can account for over 15 percent of the recent moderation in GDP volatility.

2.8 Appendix to Chapter 2

This Appendix contains algebraic derivations referenced throughout Chapter 2.

2.8.1 Proposition 1 and the Skill Condition

Acemoglu (1999) contains a proof of Proposition 1. I replicate the proof using my notation for the sake of completeness, and I also derive the skill condition (11).

Workers accept all jobs because their outside option equals zero and wages are strictly positive. Thus, an equilibrium is a set, $\{k, x^H, x^L\}$, maximizing each firms expected value (10). Firms maximize (10) according to the first-order condition:

$$\frac{\partial}{\partial k}V(k, x^H, x^L) \;=\; (1-\beta)[\phi x^H((1-\alpha)k^{-\alpha}\eta^\alpha - 1) + (1-\phi)x^L((1-\alpha)k^{-\alpha} - 1)] = 0, \tag{21}$$

where x^H and x^L are considered fixed. Setting $x^H = x^L = 1$ and solving equation (21) for k^P gives:

$$
\begin{aligned}
(1-\beta)[\phi((1-\alpha)k^{-\alpha}\eta^\alpha - 1) + (1-\phi)((1-\alpha)k^{-\alpha} - 1)] &= 0 \\
\phi((1-\alpha)k^{-\alpha}\eta^\alpha - 1) + (1-\phi)((1-\alpha)k^{-\alpha} - 1) &= 0 \\
\phi(1-\alpha)k^{-\alpha}\eta^\alpha - \phi + (1-\alpha)k^{-\alpha} - 1 - \phi(1-\alpha)k^{-\alpha} + \phi &= 0 \\
(1-\alpha)^{1/\alpha}[\phi\eta^\alpha - \phi + 1]^{1/\alpha} &= k \\
k^P &= \Lambda\Pi.
\end{aligned}
$$

With $x^H = x^L = 1$ and $k = k^P$, the expected value of an unmatched firm is:

$$
\begin{aligned}
V^P(k = \Lambda\Pi, x^H = 1, x^L = 1) &= (1-\beta)[\phi((\Lambda\Pi)^{1-\alpha}\eta^\alpha - \Lambda\Pi) + (1-\phi)((\Lambda\Pi)^{1-\alpha} - \Lambda\Pi)] \\
&= (1-\beta)[\phi(\Lambda\Pi)^{1-\alpha}\eta^\alpha + (\Lambda\Pi)^{1-\alpha} - \Lambda\Pi - \phi(\Lambda\Pi)^{1-\alpha}] \\
&= \Lambda\Pi(1-\beta)[\phi(\Lambda\Pi)^{-\alpha}\eta^\alpha + (\Lambda\Pi)^{-\alpha} - 1 - \phi(\Lambda\Pi)^{-\alpha}] \\
V^P &= \Lambda\Pi\alpha(1-\beta)/(1-\alpha).
\end{aligned}
$$

Setting $x^H = 1$ and $x^L = 0$ and solving equation (21) for k^S gives:

$$
\begin{aligned}
(1 - \beta)[\phi((1 - \alpha)k^{-\alpha}\eta^\alpha - 1)] &= 0 \\
(1 - \alpha)k^{-\alpha}\eta^\alpha - 1 &= 0 \\
(1 - \alpha)^{1/\alpha}\eta &= k \\
k^S &= \Lambda\eta.
\end{aligned}
$$

With $x^H = 1$, $x^L = 0$, and $k = k^S$ the expected value of an unmatched firm equals:

$$
\begin{aligned}
V^H(k = \Lambda\eta, x^H = 1, x^L = 0) &= (1 - \beta)[\phi((\Lambda\eta)^{1-\alpha}\eta^\alpha - \Lambda\eta)] \\
&= \Lambda(1 - \beta)\eta\phi[\Lambda^{-\alpha} - 1] \\
&= \Lambda(1 - \beta)\eta\phi[1 - 1 + \alpha]/(1 - \alpha) \\
V^H &= \Lambda\alpha(1 - \beta)\eta\phi/(1 - \alpha).
\end{aligned}
$$

Note that $V(k^P, x^H < 1, x^L = 1) < V^P$ and $V(k^S, x^H < 1, x^L = 0) < V^H$. Setting $V^P = V^H$ and solving for η gives the skill condition (11) :

$$
\begin{aligned}
\Lambda\Pi\alpha(1 - \beta)/(1 - \alpha) &= \Lambda\alpha(1 - \beta)\eta\phi/(1 - \alpha) \\
\Pi &= \eta\phi \\
[\phi\eta^\alpha + 1 - \phi]^{1/\alpha} &= \eta\phi \\
1 - \phi &= (\eta\phi)^\alpha - \phi\eta^\alpha \\
\eta &= \left(\frac{1 - \phi}{\phi^\alpha - \phi}\right)^{1/\alpha} \\
\eta &= \Omega.
\end{aligned}
$$

When the skill condition (11) does not hold (i.e. $\eta < d$), then $V(k^P, x^H \leq 1, x^L < 1) < V^P$; also, when the skill condition (11) holds (i.e. $\eta > d$), then $V(k^S, x^H \leq 1, x^L < 1) < V^H$. Thus, either the pooling equilibrium is the unique equilibrium or the separating equilibrium is the unique equilibrium in the one-period model.

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2.8.2 Firm Profits in the One-Period Model

Firm profits in a one-period model can be calculated by subbing in the firm's choice of capital. Consider first a pooling equilibrium:

$$\text{Profit} \quad = \quad (1 - \beta) \left(k_P^{1-\alpha} h^\alpha - k_P \right)$$

$$\text{note:} \qquad k_p = \Lambda\Pi, \quad \Lambda = (1-\alpha)^{\frac{1}{\alpha}}, \quad \Pi = (\phi\eta^\alpha + 1 - \phi)^{\frac{1}{\alpha}}$$

$$\text{Profit} \quad = \quad (1 - \beta) \left((\Lambda\Pi)^{1-\alpha} h^\alpha - \Lambda\Pi \right)$$

$$= \quad (1 - \beta) \Lambda\Pi \left((\Lambda\Pi)^{-\alpha} h^\alpha - 1 \right)$$

$$= \quad \frac{1-\beta}{1-\alpha} \Lambda\Pi \left(\Pi^{-\alpha} h^\alpha - 1 + \alpha \right)$$

$$\text{Profit} \quad = \quad \frac{1-\beta}{1-\alpha} \Lambda \left(\phi\eta^\alpha + 1 - \phi \right)^{\frac{1}{\alpha}} \left(\frac{h^\alpha}{\phi\eta^\alpha + 1 - \phi} - 1 + \alpha \right).$$

Similarly, in a separating equilibrium profits are:

$$\text{Profit} \quad = \quad (1 - \beta) z \left(k_H^{1-\alpha} \eta^\alpha - k_H \right)$$

$$\text{note:} \qquad k_H = \Lambda\eta, \quad \Lambda = (1-\alpha)^{\frac{1}{\alpha}}$$

$$\text{Profit} \quad = \quad (1 - \beta) z \left((\Lambda\eta)^{1-\alpha} \eta^\alpha - \Lambda\eta \right)$$

$$= \quad (1 - \beta) z \Lambda\eta \left((\Lambda\eta)^{-\alpha} \eta^\alpha - 1 \right)$$

$$\text{Profit} \quad = \quad \frac{\alpha (1-\beta)}{1-\alpha} \Lambda\eta.$$

The claim in the main body of the chapter is that minimum profits in a separating equilibrium are larger than in a pooling equilibrium. This fact can be shown analytically as follows:

$$\frac{\alpha\left(1-\beta\right)}{1-\alpha}\Lambda\eta \; > \; \frac{1-\beta}{1-\alpha}\Lambda\left(\phi\eta^{\alpha}+1-\phi\right)^{\frac{1}{\alpha}}\left(\frac{1}{\phi\eta^{\alpha}+1-\phi}-1+\alpha\right)$$

$$\alpha\eta \; > \; \left(\phi\eta^{\alpha}+1-\phi\right)^{\frac{1}{\alpha}}\left(\frac{1}{\phi\eta^{\alpha}+1-\phi}-1+\alpha\right)$$

$$\text{note} \quad : \quad 1 < \left(\phi\eta^{\alpha}+1-\phi\right)^{\frac{1}{\alpha}} < \eta.$$

The result follows immediately.

The result can also be seen by using the parameter values from the first numerical example in Section 5:

$$\alpha\eta \; > \; \left(\phi\eta^{\alpha}+1-\phi\right)^{\frac{1}{\alpha}}\left(\frac{1}{\phi\eta^{\alpha}+1-\phi}-1+\alpha\right)$$

$$(.64)\,5 \; > \; \left((.192)\,5^{.64}+1-.192\right)^{\frac{1}{.64}}\left(\frac{1}{(.192)\,5^{.64}+1-.192}-1+.64\right)$$

$$3.20 \; > \; .61 \, .$$

So, in the simple one-period model, a separating equilibrium requires a shock of about five times the magnitude to generate movement on the extensive margin.

2.8.3 Solution to the Pooling Equilibrium

The firm's choice of capital in a pooling equilibrium can only be found numerically in the multi-period model. In this section, I derive the equations used to find the numerical solution.

In equilibrium, each firm must be choosing the optimal amount of capital given the steady state equations (13). This level of capital can be found by letting $k_P = k$ and substituting:

$$J^H = \frac{(1 - \beta) z (k^{1-\alpha} \eta^\alpha - k)}{(1 - (1 - \sigma) \delta)}$$

$$J^L = \frac{(1 - \beta) z (k^{1-\alpha} - k)}{(1 - (1 - \sigma) \delta)}$$

into V^P and integrating. The idiosyncratic shock is uniformly distributed between zero and τ. Thus:

$$V^P = q \int_0^{B_H^P} \delta \left(J^H - \frac{(1 - \beta) \epsilon}{(1 - (1 - \sigma) \delta)} \right) dF(\epsilon) + (1 - q) \int_0^{B_L^P} \delta \left(J^L - \frac{(1 - \beta) \epsilon}{(1 - (1 - \sigma) \delta)} \right) dF(\epsilon)$$

$$V^P = \frac{(1 - \beta) \delta}{\tau (1 - (1 - \sigma) \delta)} \left(q \left(B_H^P z \left(k^{1-\alpha} \eta^\alpha - k \right) - \frac{1}{2} \left(B_H^P \right)^2 \right) \right)$$
$$+ (1 - q) \left(B_L^P z \left(k^{1-\alpha} - k \right) - \frac{1}{2} \left(B_L^P \right)^2 \right).$$

The firm's choice of k solves the first-order condition:

$$0 = q B_H^P \left((1 - \alpha) k^{-\alpha} \eta^\alpha - 1 \right) + (1 - q) B_L^P \left((1 - \alpha) k^{-\alpha} - 1 \right).$$

Not every match produces. A firm hires its match and produces for idiosyncratic shocks, ϵ, where $J^j - \Phi\epsilon$ is greater than zero (the outside option). In other words, a firm only hires a worker and produces if the idiosyncratic shock is low enough. The threshold values, B, are given by:

$$
\begin{aligned}
J^j - \Phi B_H^P &= 0 \\
\frac{(1-\beta)z\left(k^{1-\alpha}\eta^\alpha - k\right)}{(1-(1-\sigma)\delta)} - \Phi B_H^P &= 0 \\
z\left(k^{1-\alpha}\eta^\alpha - k\right) - B_H^P &= 0
\end{aligned}
$$

$$
B_H^P = z\left(k^{1-\alpha}\eta^\alpha - k\right).
$$

Similarly:

$$
B_L^P = z\left(k^{1-\alpha} - k\right).
$$

The steady state value of the percent of unemployed with high-skills, q, in a pooling equilibrium can be derived from the flow equations. Let e^j and u^j denote the number (not percent) of employed and unemployed, respectively.

By definition:

$$
1 - \phi = u^L + e^L
$$

$$
\phi = u^H + e^H
$$

$$
q = \frac{u^H}{u^H + u^L}.
$$

The flow equations in steady state are:

$$e^H = e^H + u^H \int_0^{B_H^P} dF(\epsilon) - \sigma e^H$$

$$e^L = e^L + u^L \int_0^{B_L^P} dF(\epsilon) - \sigma e^L.$$

Thus:

$$e^H = \phi \frac{z\left(k^{1-\alpha}\eta^\alpha - k\right)}{z\left(k^{1-\alpha}\eta^\alpha - k\right) + \sigma\tau}$$

$$e^L = (1-\phi) \frac{z\left(k^{1-\alpha} - k\right)}{z\left(k^{1-\alpha} - k\right) + \sigma\tau},$$

and:

$$q = \frac{1}{1 + \frac{(1-\phi)(z(k^{1-\alpha}\eta^\alpha - k) + \sigma\tau)}{\phi(z(k^{1-\alpha} - k) + \sigma\tau)}}.$$

Equations (15), (16), and (17) can be combined to find a numerical solution for the model economy in a pooling equilibrium.

2.8.4 Solution to the Separating Equilibrium

When in a separating equilibrium the model can be solved analytically.

In equilibrium, each firm must be choosing the optimal amount of capital given the steady state equations (19).

2.8.4.1 High-Capacity Firm

The level of capital can be found by letting $k_H = k$ and $\Phi = \frac{(1-\beta)}{(1-(1-\sigma)\delta)}$. Then:

$$V_H^S = q \int_0^{B_H^S} \delta \left(J^H - \frac{(1-\beta)}{(1-(1-\sigma)\delta)} \epsilon \right) dF(\epsilon)$$

$$J^H = \frac{(1-\beta) z \left(k^{1-\alpha} \eta^\alpha - k \right)}{(1-(1-\sigma)\delta)}.$$

Subbing in and evaluating the integral gives the following:

$$V_H^S = q\delta \int_0^{B_H^S} \left(\frac{(1-\beta) z \left(k^{1-\alpha} \eta^\alpha - k \right)}{(1-(1-\sigma)\delta)} - \frac{(1-\beta)}{(1-(1-\sigma)\delta)} \epsilon \right) dF(\epsilon)$$

$$V_H^S = \frac{q(1-\beta)\delta}{\tau(1-(1-\sigma)\delta)} \left(B_H^S z \left(k^{1-\alpha} \eta^\alpha - k \right) - \frac{1}{2} \left(B_H^S \right)^2 \right).$$

Then, from the first-order condition:

$$1 = (1-\alpha) k^{-\alpha} \eta^\alpha$$

$$k_H^S = (1-\alpha)^{\frac{1}{\alpha}} \eta.$$

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2.8.4.2 Low-Capacity Firm

Let $k_L = x$ and $\Phi = \frac{(1-\beta)}{(1-(1-\sigma)\delta)}$. Then, from the steady-state equations (19) :

$$V_L^S = (1-q) \int_0^{B_L^S} \delta \left(J^L - \frac{(1-\beta)}{(1-(1-\sigma)\delta)} \epsilon \right) dF(\epsilon)$$

$$J^L = \frac{(1-\beta)}{(1-(1-\sigma)\delta)} z \left(x^{1-\alpha} - x \right).$$

Combining and evaluating the integral gives the following:

$$V_L^S = \frac{(1-q)(1-\beta)\delta}{(1-(1-\sigma)\delta)} \int_0^{B_L^S} \left(z \left(x^{1-\alpha} - x \right) - \epsilon \right) dF(\epsilon)$$

$$V_L^S = \frac{(1-q)(1-\beta)\delta}{(1-(1-\sigma)\delta)\tau} \left(B_L^S z \left(x^{1-\alpha} - x \right) - \frac{1}{2} \left(B_L^S \right)^2 \right).$$

The first-order condition implies:

$$0 = (1-\alpha) x^{-\alpha} - 1$$

$$k_L^S = (1-\alpha)^{\frac{1}{\alpha}}.$$

Not every match produces. A firm hires its match when the idiosyncratic shock ϵ is such that $J^j - \Phi\epsilon$ is greater than zero (the outside option). In other words, a

firm only hires a worker and produces if the idiosyncratic shock is low enough. The threshold values, B, are given by:

$$
\begin{aligned}
0 &= zk^{1-\alpha}\eta^\alpha - zk - B_H^S \\
B_H^S &= z\left(k^{1-\alpha}\eta^\alpha - k\right) \\
B_H^S &= \alpha z \left(1-\alpha\right)^{\frac{1-\alpha}{\alpha}} \eta
\end{aligned}
$$

$$
B_L^S = \alpha z \left(1-\alpha\right)^{\frac{1-\alpha}{\alpha}}.
$$

Also, a technical condition for a separating equilibrium is high-capacity firms must not be willing to hire low-skill workers even with the best possible idiosyncratic shock, $\epsilon = 0$ (the firm's outside option). This implies the following:

$$
(1-\beta)\, z \left(k_S^{1-\alpha} - k_S\right) < 0
$$

$$
\text{note} \quad : \quad k_S = (1-\alpha)^{\frac{1}{\alpha}}\eta.
$$

So, it must be that:

$$
\begin{aligned}
(1-\alpha)^{\frac{1-\alpha}{\alpha}}\eta^{1-\alpha} - (1-\alpha)^{\frac{1}{\alpha}}\eta &< 0 \\
1 - (1-\alpha)\eta^\alpha &< 0
\end{aligned}
$$

$$
\left(\frac{1}{1-\alpha}\right)^{\frac{1}{\alpha}} < \eta.
$$

In equilibrium, a firm is indifferent between choosing a low capacity and attracting only low-skill workers and choosing a high-capacity and targeting high-skill workers. This condition pins down q, the percent of the unemployed that have high-skills.

Note:

$$V_L^S = \frac{(1-q)(1-\beta)\delta}{(1-(1-\sigma)\delta)\tau} \frac{1}{2} \left(\alpha z (1-\alpha)^{\frac{1-\alpha}{\alpha}}\right)^2$$

$$V_H^S = \frac{q(1-\beta)\delta}{\tau(1-(1-\sigma)\delta)} \frac{1}{2} \left(\alpha z (1-\alpha)^{\frac{1-\alpha}{\alpha}}\right)^2 \eta^2.$$

Setting $V_L^S = V_H^S$ requires:

$$\frac{(1-q)(1-\beta)\delta}{(1-(1-\sigma)\delta)\tau} \frac{1}{2} \left(\alpha z (1-\alpha)^{\frac{1-\alpha}{\alpha}}\right)^2 = \frac{q(1-\beta)\delta}{\tau(1-(1-\sigma)\delta)} \frac{1}{2} \left(\alpha z (1-\alpha)^{\frac{1-\alpha}{\alpha}}\right)^2 \eta^2$$

$$q = \frac{1}{\eta^2 + 1}.$$

The flow equations in steady state can be used to calculate the percent p of vacant firms with a high-capacity level of capital, k_H^S.

By definition:

$$1 - \phi = u^L + e^L$$

$$\phi = u^H + e^H$$

$$q = \frac{u^H}{u^H + u^L}.$$

The steady state flow equations are:

$$e^H = e^H + u^H p \int_0^{B_H^S} dF(\epsilon) - \sigma e^H$$

$$e^L = e^L + u^L (1 - p) \int_0^{B_L^S} dF(\epsilon) - \sigma e^L.$$

Thus:

$$u^H = \frac{\sigma \phi}{(1 - \sigma) p \frac{B_H^S}{\tau} + \sigma}$$

$$u^L = \frac{\sigma (1 - \phi)}{(1 - \sigma)(1 - p)\frac{B_L^S}{\tau} + \sigma}$$

$$e^H = \frac{\phi(1 - \sigma)}{(1 - \sigma) + \frac{\tau \sigma}{p B_H^S}}$$

$$e^L = \frac{(1 - \phi)(1 - \sigma)}{(1 - \sigma) + \frac{\tau \sigma}{(1 - p) B_L^S}},$$

and:

$$q = \frac{\frac{\sigma \phi}{p \frac{B_H^S}{\tau} + \sigma}}{\frac{\sigma \phi}{p \frac{B_H^S}{\tau} + \sigma} + \frac{\sigma (1 - \phi)}{(1 - p)\frac{B_L^S}{\tau} + \sigma}}.$$

Subbing in p and solving:

$$\frac{1}{\eta^2 + 1} = \frac{1}{1 + \frac{(1-\phi)pB_H^S + (1-\phi)\sigma\tau}{\phi(1-p)B_L^S + \phi\sigma\tau}}$$

$$(1-\phi)\,pB_H^S + (1-\phi)\,\sigma\tau = \eta^2\phi\,(1-p)\,B_L^S + \eta^2\phi\sigma\tau$$

$$p = \frac{\phi\eta + \frac{\left(\phi\eta^2 - 1 + \phi\right)\sigma\tau}{\alpha z(1-\alpha)^{\frac{1-\alpha}{\alpha}}\eta}}{(\phi\eta + 1 - \phi)}.$$

Finally:

$$e^H = \frac{\phi\,(1-\sigma)}{(1-\sigma) + \frac{\tau\sigma(\phi\eta+1-\phi)}{\phi\eta^2\alpha z(1-\alpha)^{\frac{1-\alpha}{\alpha}} + (\phi\eta^2 - 1 + \phi)\sigma\tau}}$$

$$e^L = \frac{(1-\phi)\,(1-\sigma)}{(1-\sigma) + \frac{\tau\sigma(\phi\eta+1-\phi)}{(1-\phi)\alpha z(1-\alpha)^{\frac{1-\alpha}{\alpha}} + (\phi\eta^2 - 1 + \phi)\frac{\sigma\tau}{\eta}}}.$$

CHAPTER III

THE EFFECT OF HOUSEHOLD APPLIANCES ON FEMALE LABOR FORCE PARTICIPATION: EVIDENCE FROM MICRO DATA

with Daniele Coen-Pirani and Alexis León

Chapter Abstract

We estimate the effect of household appliance ownership on the labor force participation rate of married women using micro-level data from the 1960 and 1970 U.S. Censuses. In order to identify the causal effect of home appliance ownership on married women's labor force participation rates, our empirical strategy exploits both time-series and cross-sectional variation in these two variables. To control for endogeneity, we instrument a married woman's ownership of an appliance by the average ownership rate for that appliance among single women living in the same U.S. state. Single women's labor force participation rates did not increase between 1960 and 1970. By our estimation, the diffusion of household appliances accounts for over one-third of the observed increase in married women's labor force participation rates during the 1960's.

3.1 Introduction

In the last few decades women's labor force participation rates have increased dramatically. This increase has been especially pronounced for married women. In 1950, about 25 percent of married women participated in the workforce; by 2000, nearly 60 percent of married women participated. An extensive literature has investigated the possible causes of this increase.[1] Greenwood, Seshadri, and Yorukoglu (2005) [from now on GSY] argue that the diffusion of household appliances such as washing machines, freezers, etc. in the post-WWII period played an important role in "liberating" women from housework and in propelling them into the workforce. According to GSY, the adoption of time-saving technologies occurred because of a surge in the rate of technological progress in the home durable goods sector. Consequently, the quality-adjusted relative price of home appliances declined. Building on Becker (1965) and Gronau (1977), GSY develop a dynamic equilibrium model in which a household jointly determines female labor force participation and home appliance purchases. GSY calibrate a version of their model and show that the observed decline in the relative price of home appliances can explain about 50 percent of the increase in married women's labor force participation rates between 1900 and 1980.

Despite the intuitive appeal of GSY's story and the quantitative results of their model, there is little independent empirical evidence in favor of their hypothesis. Moreover, from a theoretical perspective, improvements in the productivity of home durable goods could lead married women to increase rather than decrease their time allocated to housework. The sign of this effect depends on the elasticity of substitution between home and market goods in the household's utility function (Jones, Manuelli, and McGrattan 2003).

The goal of this paper is to provide empirical evidence on GSY's hypothesis using micro-level data on women's labor force participation and households' ownership of

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[1]In addition to the "liberation hypothesis" discussed in this paper, other explanations for the increase in women's labor force participation include: 1. A reduction in fertility (Evans and Angrist 1998) 2. The diffusion of the oral contraceptive (Goldin and Katz 2002) which reduced the pregnancy-related uncertainty faced by young women enrolling in professional programs 3. The indirect effect of WWII on men's attitudes toward working women (Fernandez, Fogli, and Olivetti 2004) 4. The reduction in the gender wage gap (Smith and Ward 1985; Jones, Manuelli, and McGrattan 2003; Gayle and Golan 2006).

appliances. The data comes from the 1960 and 1970 U.S. Census of Population. In only those years, households were asked to provide information on their ownership of some home appliances (freezers, washers and dryers), in addition to the standard demographic variables. Women's labor force participation rates and households' ownership of appliances both increased dramatically during the 1960's. The labor force participation rate for white married women increased by 10 percentage points, and the fraction of households with all three of the appliances mentioned above increased from 11 to 28 percent (see Table 12).

In order to identify the causal effect of home appliance ownership on married women's labor force participation, our empirical strategy exploits time-series and cross-sectional variation in these two variables. Ordinary least squares (OLS) will not, in general, provide consistent estimates of the causal effect of appliance ownership on women's labor force participation because of the endogeneity of home appliance ownership. Instead, we employ an instrumental variable (IV) strategy by using the state-level ownership rate of an appliance among *single* women as an instrument for a *married* woman's ownership of that appliance.

We assume that the observed temporal and cross-sectional variation in single women's ownership of home appliances is driven by the (unobserved) appliance prices rather than by autonomous changes in women's labor force participation rates. Two key observations corroborate this assumption. First, differently from married women, the labor force participation rate of single women did not change appreciably from 1960 to 1970 (see Table 13). Second, the instruments based on single women's appliance ownership rates at the state level do not explain differential changes in *single* women's labor force participation rates across states and over time. The results also survive a number of other specification and robustness checks.

Our estimates, based on the instruments described above, provide strong empirical support for GSY's hypothesis. The diffusion of home appliances in the decade between 1960 and 1970 explains about one-third of the observed increase in married women's labor force participation rates according to our results.

As far as we know, our study is the first to examine micro data for evidence on GSY's hypothesis. There is related work in both economics and sociology. In the economics literature, Cavalcanti and Tavares (2008) use country-level panel data

for OECD countries for the period 1975–1999 to show the existence of a statistically significant relationship between the relative price of home appliances and female labor force participation rates across countries. Our approach, based on micro data for a single country and a different time period, complements the analysis in Cavalcanti and Tavares (2008).[2]

Sociologists have also studied the relationship between home technology and women's allocation of time to housework, sometimes reaching different conclusions than GSY. For example, Cowan (1983) considers the relationship between household technology and housework during the last two centuries in the U.S. and argues that the amount of time spent by the average American woman in housework in 1965 and at the beginning of the twentieth century are comparable in magnitude (see Cowan, 1983, page 199, for example). The lack of representative time-use data for the earlier part of the twentieth century makes such comparisons difficult. Recent research by Roberts and Rupert (1995) and Aguiar and Hurst (2006) based on time-use surveys and the Michigan Panel Study on Income Dynamics clearly shows that the time allocated by women, and especially married working women, to home production has fallen considerably in the last 40 years. This trend is consistent with GSY's hypothesis.[3]

In Section 2 we introduce a simple model of home production and female labor supply, which is used to organize the discussion of the empirical evidence and our identification strategy. In Section 3 we describe the Census data, and we present our main econometric results in Section 4. Section 5 details several robustness checks and the results from alternative specifications. Section 6 concludes.

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[2]Cortes and Tessada (2007) focus on increased immigration, as opposed to declining prices of home appliances, as a determinant of female labor supply. They observe that immigrant labor often substitutes for female labor in home production (e.g. child care and housekeeping) and find evidence that immigration affects the labor supply of highly-skilled native women.

[3]In addition, the empirical literature on this topic in sociology suffers from potentially serious endogeneity problems. For example, Bittman, Rice, and Wajcman (2004) use a cross-section of micro-level time-use data from Australia in 1997 to study the association between time spent in different homework activities by men and women and their ownership of household appliances. They claim that "domestic technology rarely reduces women's unpaid working time and even, paradoxically, produces some increases in domestic labour." This conclusion is reached by regressing measures of time spent in housework activities on a series of dummy variables for appliance ownership and demographic controls. While the authors tend to interpret their associations as causal, unobserved heterogeneity across individuals in the sample probably accounts for their results.

3.2 Model and Identification Strategy

In this section we introduce a simple model of female labor supply meant to capture the essence of GSY's argument and to help explain our identification strategy.

3.2.1 A Simple Model

We start from the labor supply decision of a married woman in a household where preferences for consumption of a market (c) and home-produced (x) good are described by the following additively-separable utility function:

$$U = u(c) + g(x). \tag{22}$$

The functions u and g are strictly increasing, strictly concave, and differentiable.

In the household, the husband always works in the market and earns wage income y. If the woman works in the market she earns wage income $w\overline{h}$, where w is the hourly wage and $\overline{h}$ is the exogenous number of hours worked.[4] Her endowment of time per period is normalized to one. There is no leisure in the model. The home good x is produced using a woman's non-market time $(1 - \overline{h})$ and units of household capital (appliances), denoted by k. The household can obtain home capital at a unit rental rate of q. The production function for the home good can be written as:

$$x = f\left(1 - \overline{h}I^w, k\right), \tag{23}$$

where I^w equals one if the woman works and zero otherwise. The production function f satisfies standard assumptions. We assume f is strictly increasing in its two arguments, concave in k, and such that $f_k(1, k) > f_k\left(1 - \overline{h}, k\right)$, i.e. the marginal product of home capital increases with a woman's time allocated to home production. Below we discuss additional restrictions on f necessary to capture GSY's link between appliance prices and married women's labor force participation.

---

[4]We focus on labor force participation as the measure of a woman's labor supply in our empirical analysis. Section 5 considers alternative outcome variables.

The household maximizes utility (equation 22) by choosing c, k, and whether the woman works in the market, subject to the home-production function (23) and the household's budget constraint:

$$c = y + w\overline{h}I^w - qk. \tag{24}$$

Placing the budget constraint (24) into the objective function allows us to eliminate c and write the first-order condition with respect to k as:

$$u'(y + w\overline{h}I^w - qk)q = g'(f\left(1 - \overline{h}I^w, k\right))f_k\left(1 - \overline{h}I^w, k\right). \tag{25}$$

Denote the optimal choice of appliances by k^{m}:

$$k^{\mathrm{m}} = K\left(q, y, I^w\right). \tag{26}$$

For a given labor force participation decision by the woman, it is straightforward to show that lower appliance prices and higher household income both increase the quantity of appliances demanded by the household:

$$K_q\left(q, y, I^w\right) \quad < \quad 0, \tag{27}$$

$$K_y\left(q, y, I^w\right) \quad > \quad 0, \tag{28}$$

for all triples $\left(q, y, I^w\right)$.

The optimal choice of appliances depends on the indicator variable I^w through two channels. First, since the household's total income inclusive of the woman's wage income is higher if $I^w = 1$, the household chooses a higher level of k when the woman works. Second, if $I^w = 1$, then the woman has less time for home production, which affects the marginal utility of an extra unit of k (the right-hand side of equation 25). The second channel has an ambiguous impact on the optimal choice of k. On the one hand, for a given k, the quantity of the home good produced by the household is lower when $I^w = 1$, increasing both the marginal utility of the home good and the demand for household capital. On the other hand, the marginal product of home capital is smaller when the woman works, decreasing the incentive to purchase household capital.

We now impose further restrictions on the primitives of the model in order to obtain two additional results, which facilitate the discussion of our identification strategy. We start by postulating sufficient conditions to guarantee that a household with a working woman purchases more appliances than a household where the woman does not work, all else constant. This result is not necessary for the validity of GSY's argument, but it allows us to formalize a plausible alternative interpretation of their time-series evidence; one in which exogenous variation in the female labor supply can lead to higher investment in home capital.

To help state these assumptions, let the function $F(k, I^w)$ denote the right-hand side of equation (25):

$$F(k, I^w) \equiv g'(f\left(1 - \overline{h} I^w, k\right)) f_k \left(1 - \overline{h} I^w, k\right).$$

Sufficient conditions for a household with a working woman to buy more appliances than a household without a working woman $(K(q, y, 1) > K(q, y, 0))$ are:[5]

Assumption 1 $F(k_2, I^w) < F(k_1, I^w)$ for $k_2 > k_1$.

Assumption 2 $F(k, 1) > F(k, 0)$ for all k.

We would also like to show that a married woman is more likely to participate in the workforce when the relative price of appliances q declines; this result is the essence of GSY's story. Assumption 2 and Assumption 3 are sufficient:

Assumption 3 $k_2 F(k_2, I^w) > k_1 F(k_1, I^w)$ for $k_2 > k_1$.

---

[5]Assumptions 1 and 2 imply that the marginal utility of an extra unit of k declines as k increases (assumption 1) and increases if the woman spends less time in home production (assumption 2). These two assumptions are sufficient (but not necessary) to guarantee that a household with a working woman buys more appliances because the marginal utility of market consumption is lower for such a household (due to the additional income).

To see this result, let $V(I^w)$ denote the household's indirect utility function, conditional on a labor supply choice I^w :

$$V(I^w) = u\left(y + w\overline{h}I^w - qK\left(q, y, I^w\right)\right) + g\left(f\left(1 - \overline{h}I^w, K\left(q, y, I^w\right)\right)\right).$$

The woman in the household participates in the workforce if:

$$V(1) - V(0) - \gamma + \varepsilon > 0, \tag{29}$$

where, following a standard discrete-choice model, ε denotes a mean-zero random variable independently distributed across households and independent of the other variables in the model. Let G denote the cumulative distribution function of ε. The non-negative parameter γ in equation (29) captures other aggregate - possibly location and year specific - factors that might affect a married woman's labor force participation decision, over and above those already mentioned. The fraction of married women in the labor force (LFP) is then:

$$\text{LFP} = 1 - G\left(\gamma + V(0) - V(1)\right). \tag{30}$$

According to GSY, a drop in q led to an increase in LFP. Showing that LFP is decreasing in q amounts to showing that the sign of the following derivative is negative:

$$\frac{\partial\left(V(1) - V(0)\right)}{\partial q} = F(K(q, y, 0), 0)K(q, y, 0) - F(K(q, y, 1), 1)K(q, y, 1).$$

The expression on the right-hand side follows from the envelope theorem and the first-order condition (25). Assumptions 2 and 3 immediately imply the sign of this derivative is indeed negative.

In the following example, we select specific functional forms to illustrate the restrictions imposed by Assumptions 1-3.

Example Let:

$$
\begin{aligned}
g(x) &= \log x, \\
f\left(1 - \overline{h} I^w, k\right) &= \left[\delta \left(1 - I\overline{h}\right)^\theta + (1 - \delta) k^\theta\right]^{\frac{1}{\theta}}, \ \theta \leq 1.
\end{aligned}
$$

Then, the function $F(k, I^w)$ takes the following form:

$$
F(k, I^w) = \frac{(1 - \delta) k^{\theta-1}}{\delta \left(1 - \overline{h} I^w\right)^\theta + (1 - \delta) k^\theta}.
$$

Assumptions 1-3 are satisfied if $\theta > 0$, i.e. if home capital and labor are *gross substitutes* in the home-production function.[6] This interpretation of the parameter is consistent with GSY's view that a reduction in the relative price of home capital led to a substitution of home capital for female labor in household production.

3.2.2 Discussion of the Identification Strategy

As the model just developed makes clear, simply regressing the labor force participation indicator I^w on a set of controls and the household's observed ownership of appliances using cross-sectional data will lead to inconsistent estimates. Households with relatively large ε are more likely to be characterized by a working woman and will own more appliances.

Information on appliance ownership was collected in both 1960 and 1970, so we can exploit the time-series dimension of the Census data. However, the endogeneity problem remains because aggregate unobserved (to the econometrician) factors, captured by shifts in the parameter γ in equation (30), might lead to changes in married women's labor supply decisions, which in turn feed back into the household's choice of appliances. An example of a change in γ which would generate this time-series pattern is the evolution of society's view of married women's role in the household.

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[6]The condition, $\theta > 0$, is sufficient but not necessary.

Ideally, we would use exogenous cross-sectional and time-series variation in the appliance price q to identify the causal effect of appliances on female labor force participation. To the best of our knowledge, such information is not available for the period of interest, 1960–1970. Since we do not have disaggregated price information for our empirical analysis, we instead construct an instrument for a married woman's ownership of appliances from appliance ownership rates among single women. The optimal choice of appliances k^{s} by an single woman is given by:

$$k^{s} = K\left(q, 0, 1\right),$$

where the function K has been defined above. We use the average observed value of k^{s} among *single* women in a given state as an instrument for ownership of appliances by a *married* woman living in that state. In selecting this instrument we think that state-year variation in the prices and operation and maintenance costs of appliances, possibly induced by differences in sales taxes, transportation costs, competition in the local durable goods market, and electricity prices, generates similar variation in appliance ownership among households with married women and households of only single women. In our model, a lower rental price q leads to higher demand for appliances by both single and married women (equation 27).

Additionally, we view our instrument as unlikely to be affected by unobserved determinants of the participation decisions of married women, such as shifts in the parameter γ in equation (29). We make this assertion because the labor force participation rates of single women remained literally constant during the 1960's, while their appliance ownership rates increased in a similar way to those of married women.[7] These facts suggest that single women's labor supply around 1960 was already close to its upper bound, so the diffusion of appliances did not affect their employment choices. Instead, single women purchased new home technologies when q declined. Even though we cannot directly observe time-series and cross-sectional variation in q, we interpret the changes in appliance ownership among single women as reflecting those trends. We test the validity of our approach in Section 5.

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[7]This point is documented in Table 13. We discuss the data further in Section 3. Also, the marked differences in participation trends between married and single women continued after 1970.

3.3   Data

We use the Integrated Public Use Microdata Series (IPUMS) from the U.S. Census of the Population for 1960, one-percent sample, and 1970, Form 1 State, one-percent sample (Ruggles et al. 2004).[8] This data has several advantages. The 1960 and 1970 (Form 1) Censuses collected information on household ownership of washing machines, dryers, and freezers.[9] As far as we know, the Census samples are the only large micro data set containing appliance ownership information over the period of rapid increase in the labor force participation of married women. Also, the Census samples provide demographic, employment, and income details. Unfortunately, individual observations cannot be linked across years. We focus on U.S. states because the smallest identifiable geographic region in the 1960 sample is a state.[10]

Our primary sample includes white, U.S.-born, married women of prime working age (18–55 years old), with non-missing information on state of residence and appliance ownership, and with working husbands. In the 1960 Census only 20 percent of households were surveyed about appliance ownership, leaving 53, 347 households that satisfy our sample selection criteria. The 1970 sample contains 273, 118 observations.

Summary statistics for married women can be found in Table 12. The labor force participation rate of married women increased from about 33 percent in 1960 to 43 percent in 1970. Labor force participation is our main outcome variable. Employment (share of married women in the labor force and holding a job), full-time employment (share of married women working at least 35 hours in the past week), and year-round employment (share of married women working at least 48 weeks in the past year) also indicate a large increase in female labor supply during the 1960's. These outcome variables are used to check the robustness of our results; see Section 5. Notice, the average hours worked by a married woman in the labor force did not change

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[8]The Census samples can be found at http://usa.ipums.org/usa.

[9]The 1970 Census also asked about dishwashers, but the 1960 Census did not. For this reason we do not use the dishwasher variable in our analysis in Section 4. Section 5 discusses possible ways to use the information contained in this variable and the associated results.

[10]Information about a household's metropolitan area of residence is not available in the 1960 Census. In our empirical analysis we also cannot use information regarding the urban / rural location of the household or whether the household was located in a metropolitan area because, due to confidentiality concerns, this information is not available in the 1960 and 1970 samples.

appreciably from 1960 to 1970.

The appliance ownership dummies are the explanatory variables of interest. We recoded these appliance variables as binary indicators. For example, the WASHER variable in the Census takes on 0 (no washer), 1 (yes - automatic washer), or 2 (yes - separate spinner). We collapsed the first two categories into one category. Aggregate appliance ownership rates for freezers and dryers increased substantially for married women between 1960 and 1970. Ownership of washing machines stayed roughly constant during this period most likely because this appliance had already reached a relatively high degree of diffusion in 1960.[11] The share of married women owning all three appliances increased 17 percentage points, from 10.8 percent to 27.8 percent, between 1960 and 1970.

Table 12 also summarizes the other covariates used in our analysis. Annual wage and family total incomes were adjusted for top-coding by multiplying the censored values by 1.4. We converted all dollar amounts to 1970 dollars with the consumer price index (CPI All Urban Consumers series CUUR0000SA0). Household income net of female earnings is defined as family total income minus a woman's wage income. State-level average annual wage income was calculated using both married and single working women.

The sample we use to construct our instruments includes white, U.S.-born, single women of prime working age (18–55 years old).[12] Table 13 reports summary statistics for single women. Unlike married women, the labor force participation rate of single women did not increase in the 1960's. However, appliance ownership rates for single women did increase in a way similar to the appliance ownership rates for married women.

Table 14 provides more detail on appliance ownership rates by year and for selected states. For both married and single women, the change in appliance ownership rates varies widely across states. As detailed in the next section, we exploit this variation in our estimation strategy.

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[11] The appliance ownership rates reported in Table 12 and Table 13 agree with those reported in GSY and Lebergott (1976).

[12] We use the term "single" to mean both women who are single because they never married and women who were married at a previous point in their life and who are now either divorced or widows.

3.4 Results

Next, we introduce the benchmark regression equation and discuss the OLS estimates. Then, we present the results based on the IV approach.

3.4.1 OLS Estimates

Consider the following regression equation:

$$\text{lfp}_{ist} = \beta \text{appl}_{ist} + x'_{ist}\gamma + \delta_s + \delta_t + \delta_{st} + \varepsilon_{ist}, \tag{31}$$

For each woman i observed in state s at time t, the dependent variable lfp_{ist} is a binary indicator for labor force participation;[13] x_{ist} is a vector of individual covariates including demographic characteristics such as education, potential experience, household income, and number of children; δ_s, δ_t and δ_{st} represent state-of-residence main effects, Census year main effects, and their interactions, respectively; ε_{ist} is a disturbance term; and the dummy variable appl_{ist} captures the presence of household appliances. The variable appl_{ist} is the key regressor of interest. We experiment with three alternative specifications for this regressor. First, we include one appliance dummy at a time in equation (31). Second, we simultaneously include all three appliance dummies for which we have data for both Census years (washing machines, dryers, and freezers). Third, we use a single dummy that takes a value of 1 if the household owns all three appliances and zero otherwise. Each of these alternative versions of the independent variable represents an imperfect empirical counterpart for the variable k in the model of Section 2 because the Census data only contains information about a limited set of home durable goods. Our preferred specification is the one that employs the binary indicator of ownership of all three appliances. This variable conveniently summarizes the information on appliance ownership by implicitly assigning the same degree of importance to each appliance for which information is available.

Table 15, columns 1-5, reports the OLS estimates of the parameter β in equation (31). Labor force participation for married women has a negative correlation with the ownership of washers and freezers and a positive association with the ownership

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[13]In Section 5 we provide results using alternative measures of labor supply.

of dryers. The signs of these correlations are the same whether all three appliance regressors are included in the regression equation at the same time or separately. Ownership of all three appliances is positively associated with female labor force participation, but the relationship is statistically insignificant. Taken together, the OLS estimates in Table 15 do not support GSY's hypothesis. The estimated magnitude of β is relatively small and sometimes of the wrong sign. Estimates of the marginal effects implied by a probit model (reported in Table 15, column 6) are similar to the OLS results, indicating the linear probability model is a reasonable approximation.

The last six columns of Table 15 report estimates from models where we have replaced the set of state-year interactions with the average log female wage in the state that year, w_{st}. Both specifications attempt to capture potential state-year shocks affecting the labor market for women, but only the latter allows for a direct comparison with the IV estimates in the next section. This change is necessary because our instrument does not vary within a state-year cell; hence, it would be perfectly collinear with a full set of state-year fixed effects in the estimating equation. The OLS results do not depend on which one of these two specifications is used, which suggests that mean wages are a good proxy for state-year market conditions.[14]

As argued in Section 2, caution must be exercised in interpreting the OLS results because the appliance regressor is likely endogenous. At least three potential sources of bias exist. First, households with a working woman are more likely to purchase appliances. Reverse causation could induce a positive bias in the estimate of β. Second, households with strong tastes for home-produced goods might invest heavily in both inputs of home production, namely household work (traditionally carried out by the wife) and household appliances. These unobserved preference shifters (which cannot be fully captured by the covariates) may induce a negative correlation between appliance ownership and female labor participation, creating a downward bias in the OLS estimate of β. Third, in the presence of measurement error in $appl_{ist}$ the OLS estimator of its coefficient will be attenuated toward zero, as is well known. Given these potential sources of bias, we turn to an IV approach.

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[14]The results are quantitatively similar in both the OLS and two-stage least-squares approaches when we do not control for variation in average female wages at the state-level. These results are not reported in this chapter but are available upon request.

3.4.2 IV Estimates and Main Results

To consistently estimate the parameter β in equation (31) we need a variable that is correlated with appl_{ist} but not with the error term ε_{ist}. As mentioned in Section 2 we instrument the endogenous regressor appl_{ist} with the state-year mean appliance ownership rate among *single* women, denoted by appl-sin_{st}. Table 16 displays estimates of the first-stage regression models:[15]

$$\text{appl}_{ist} = \pi\text{appl-sin}_{st} + x'_{ist}\varphi + \eta w_{st} + \lambda_s + \lambda_t + u_{ist}. \qquad (32)$$

In all specifications, we find a sizable, positive, and statistically significant relationship between appl_{ist} and its corresponding instrumental variable appl-sin_{st}. For example, the entry in the first column of Table 16 indicates that a 10 percentage point increase in ownership of washers among single women is associated with a 2.6 percentage point increase in the fraction of married women owning washers. An even stronger positive relationship is illustrated in Figure 12a, which plots ownership rates of all three appliances (washers, dryers and freezers) among single women against the same measure for married women, net of covariates, state and year effects. The F-statistics for the significance of the estimated coefficients on the instruments are 14 or higher in all cases; this strong first stage dispels any concerns about serious finite-sample bias problems in the IV estimates (Bound, Jaeger, and Baker 1995).

The two-stage least-squares (2SLS) estimates of equation (31) represent our main results (see Table 17). The findings are generally consistent with the existence of a positive statistically and economically significant causal effect of appliance ownership on female labor force participation of married women. For example, the 2SLS estimate reported in Table 17, column 5 (our preferred specification) implies that owning all three appliances raises the likelihood of labor force participation by married women by almost 21 percentage points (with a standard error of 4.3 percentage points).

Figure 12b provides visual evidence of the reduced-form relationship between the outcome variable of interest and our instrument. The fitted line slopes upward, indicating that higher rates of ownership of all three appliances among single women

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[15]Recall that when all three appliances are included in the regression at the same time, π is a three-dimensional vector.

coincide with higher labor force participation rates for married women. The 2SLS estimate of β is identical to the indirect least squares estimate obtained from taking the ratio between the reduced-form regression coefficient (slope of the line in Figure 12b) and the first-stage coefficient estimate of π (slope of the regression line in Figure 12a) because equation (31) is just-identified.

The share of married women owning all three appliances increased by 17 percentage points from 1960 to 1970 (see Table 12). Therefore, our results suggest that the adoption of household appliances accounts for a 3.55 percentage point (0.21×0.17) increase in female participation during the 1960's, about one-third of the observed 10 percentage point increase in the labor force participation rate of married women.

Using only the variable "freezer" as a measure of appliance ownership produces a near-identical result. Using the variable "dryer" indicates a larger effect, with an 8.35 percentage point increase in the labor force participation rate of married women predicted in the decade between 1960 and 1970.

The variable "washer" leads to an insignificant estimate. This finding is not entirely surprising because the share of households with a washer was already relatively high in 1960 and actually slightly declined during the following decade.

When we simultaneously introduce all three appliances into the regression equation, none of the 2SLS estimates is individually significant, but they are jointly statistically significant (the F-statistic has a p-value smaller than 0.01). The estimates that turn out to be positive in this regression are associated with the variables "dryer" and "freezer" whose ownership rates display a sizable increase over the sample period.

The 2SLS approach generates uniformly larger estimates for the parameter β (see Table 17) than the OLS estimates of Table 15. This discrepancy does not seem to be due to the endogeneity of appliance ownership. Endogeneity would have led to the opposite ranking. As described above, these results are consistent with attenuation bias due to measurement error in the endogenous regressor appl_{ist} and with negative bias because of unobservable tastes for home-produced goods causing both high appliance ownership and low female participation rates.

3.5 Alternative Specifications and Robustness Checks

In this section, we describe the results from robustness checks and falsification exercises. The purpose is to show the consistency of the findings reported in Table 17 and to demonstrate the validity of our IV strategy.

3.5.1 Falsification Exercises

This section presents two falsification exercises whose goal is to test the validity of our IV strategy. The first exercise checks whether our instrument (appl-sin$_{st}$) also predicts changes in the participation of single women. The concern is that unobservable state-year specific shocks might lead to higher labor force participation by married and single women, leading both groups of women to purchase more appliances.[16] In this case our instrument would be correlated with the residual in equation (31) violating the fundamental condition for its validity. Table 18, columns 1-5, displays the 2SLS estimates of the parameter β in the regression (31) obtained using data on single women only. The instrument for single women appliance ownership is built using appl-sin$_{st}$, as before. Figures 13a and 13b display the first-stage and reduced-form counterparts to Figures 12a and 12b, with the appliance ownership of single women instead of that of married women. The estimate of β is not statistically significant in any of the different specifications of this regression, supporting the assertion that reverse causation is unlikely to account for our findings.

Admittedly, this falsification exercise only rules out interpretations of our results based on unobserved state and year specific shocks that cause women - both single and married - to join the work force and, *through* this channel, decide to purchase more appliances.[17] The falsification exercise does not address situations in which unobserved state and year specific shocks have a positive independent effect on both a woman's incentive to join the labor force and on her decision to own appliances. In this case, the fact that single women's labor force participation did not increase jointly with their ownership of appliances could simply reflect the fact that in 1960 their rates of participation were already relatively high. We cannot rule out the existence

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[16]These shocks can be interpreted as shifts in the parameter γ in equation (30).

[17]Recall from the model of Section 2, appliance ownership is higher for women that are employed.

of shocks that have an independent effect on each of these two margins; however, it is difficult to think of an example capable of explaining the contemporaneous rise in married women's labor force participation and in their ownership of household appliances.[18]

The second falsification exercise checks whether including a non-productive appliance, a television, to our set of endogenous regressors generates additional predictive power. The existence of such an effect induced by a non-productive appliance would diminish the plausibility of interpreting our main results as evidence of a *causal* link between ownership of home appliances and married women's labor force participation. Table 18, columns 6-11, presents the 2SLS estimates from this exercise; ownership of a television at the household level is instrumented, as above, by the state-year specific ownership rate by single women. Ownership of a television is not significantly associated with the dependent variable in any of the different versions of our regression equation, after including one of the original productive appliances in the specification of the regression.

Ownership of a television set does have a positive and statistically significant (although only at the 10 percent level) effect on female labor force participation when it is the only endogenous regressor in equation (31) (see Table 18, column 10). We do not believe this result falsifies our IV strategy because if productive appliances do indeed have an effect on female labor force participation, then a model based solely on a non-productive appliance would be misspecified. Leaving out the original regressor(s) artificially creates an omitted variable problem, as state level ownership rates of different appliances are likely correlated among themselves.[19] Thus, *adding* the non-productive appliance to the existing endogenous regressor(s) in equation (31)

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[18]A candidate shock would be a change in preferences for the home-produced good. Preferences directly affect both a household's decision to purchase appliances and a married woman's decision to participate in the labor force. However, this kind of shock cannot rationalize the simultaneous increase in appliance ownership and female labor supply observed in the data. A lower weight on home goods in the utility function increases women's labor force participation but decreases their willingness to own consumer durables. An increase in appliance ownership by married women might occur but it would be the result of increased participation, instead of a direct implication of the underlying shock. Our falsification exercise already rules out this possibility.

[19]The partial correlation coefficient between ownership of a television and ownership of other appliances in our sample is positive and statistically significant after controlling for the covariates in our regression specifications.

is the relevant test. We conclude this section by noting that neither of the two falsification exercises invalidates our IV approach.

3.5.2 Changing School Enrollment and Marriage Selection

In 1960, the female college enrollment rate among 16–24 year-olds was 37.9 percent. A decade later, this statistic had increased to 48.5 percent. This increase in schooling could be a problem for our identification strategy. Differential trends in school enrollment rates can mechanically affect labor force participation rates (through an "incapacitation effect") and make the use of single women as an instrument potentially problematic. To address this concern, we re-estimate our main regressions excluding college-age women. Table 19 reports estimates from OLS and 2SLS models with the sample restricted to 24–55 year-olds. The results are largely unchanged from the ones discussed so far.

Differential selection into the labor force due to changing college enrollment also could undermine our first falsification exercise. In particular, if the single young women in our sample are more likely to be full-time students in 1970 than a decade earlier, we would expect this "incapacitation effect" to have mechanically reduced the observed labor force participation of single women in 1970. This reduction could have masked any increases in the participation of non-college-going single women between 1960 and 1970. Our estimates in Table 19 would be biased downwards, rendering our first falsification exercise uninformative. However, excluding 18–23 year-olds does not change the results of the falsification exercise (see Table 20), further reinforcing our conclusion that reverse causality cannot explain our main findings.

The declining marriage rate over the period of study may result in a selection bias in our sample of married women. To account for this, we use a selection correction procedure, which was originally suggested by Hunt (2002) to adjust for differential selectivity into employment and more recently used by Blau and Kahn (2007) to correct for self-selection into marriage in the estimation of labor supply elasticities. We first estimate marriage probit models so as to assign each individual a "marriage score". These models are run separately by year and include age, schooling, and a full set of state dummies. Then we use that score to remove our least marriage-prone

individuals in 1960, the sample year with the highest marriage rate. The procedure forces the sample of married women in each year to represent the same share of the overall population.[20] Finally, we estimate our OLS and 2SLS models on the new sample. The results remain largely unchanged, as reported in Table 21.

3.5.3 Incorporating Data on Dishwashers

Our preferred specification employs the binary indicator of ownership of all three appliances as the key explanatory variable. This variable summarizes the ownership of the three appliances observed in the Census data and proxies for the likely, but unobserved, ownership of all other relevant new household technologies that also may have encouraged greater labor force participation among married women. The Census reports information on dishwasher ownership in 1970 (but not 1960). Ownership of a dishwasher in 1970 is positively correlated with ownership of a washer, dryer and freezer. Thus, it is reasonable to treat the estimated coefficient on "owning all three appliances" as a proxy for the overall effect of all the main time-saving household appliances available.[21]

Moreover, we have estimated models where the dummy variable indicating ownership of all three appliances is replaced with ownership of all four appliances (i.e. including dishwashers) for 1970 households. Table 22 lists the results. Not surprisingly given the high correlation between dishwashers and other appliances, the estimates are similar to our previous results in Table 17. The 2SLS estimate of the effect from owning all observable appliances (3 in 1960, 4 in 1970) is 0.185 compared to 0.209 obtained without accounting for dishwashers.

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[20]Since 79.21 percent of white women aged 18–55 were married in 1960, but only 73.91 percent were married in 1960, we eliminate the lowest 7.1 percent ([0.7921-0.7391]/0.7391) of the distribution of "marriage scores" from the sample of married women in 1960.

[21]The partial correlation coefficient between ownership of a dishwasher in 1970 and ownership of all three appliances, after controlling for the covariates in our main regression, is 0.1574 and statistically significant.

3.5.4 Alternative Outcome Variables

Until now we have focused on female labor force participation as the outcome variable of interest; next, we evaluate the effect of appliance ownership on alternative measures of labor supply. We have estimated three additional versions of the basic model. The dependent variable is either a woman's employment status (1 if employed, 0 otherwise) or whether she is working full-time (1 if working 35+ hours per week) or whether she is working year-round (1 if working 48+ weeks per year). In all the specifications, appliance ownership has a positive and statistically significant impact on female labor supply. The results for employment status (see Table 23) are basically the same as for labor force participation. The estimated versions of the model with the two other dependent variables (see Table 24) suggest that the increase in the ownership of all three appliances accounts for the entire observed increase in the fraction of married women who work full-time and for about 40 percent of the increase in the share of married women working year-round. Taken together these results confirm the main findings in Table 17.

3.6   Conclusion

In this chapter, we used micro data from the U.S. Census to evaluate the contribution of household appliances to the increase in female labor force participation during the 1960's. According to our estimates, household appliances account for about one-third of the increase in participation by married women. These empirical results support the idea that technological progress in the household sector played an important role in the "liberation" of women from housework and in increasing labor force participation.

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Tables and Figures

Table 1: *Cyclical Volatility*

Description	*1962–2006*	*1962–1984*	*1985–2006*
U.S. GDP	1.49%	1.88%	0.91%
Employment volatility by age group:			
16–54	1.02%	1.24%	0.72%
16–34	1.35%	1.66%	0.93%
35–54	0.72%	0.83%	0.59%

I constructed Table 1 using quarterly CPS and BEA data from 1962–2007. Cyclical volatility equals the standard deviation of the entire HP filtered, logged, quarterly series expressed in levels. I removed the trend from each series using the HP filter with smoothing parameter 1600. See Chapter 1, Section 2 for more details.

Table 2: *Notation for Chapter 1*

Exogenous			*Endogenous*	
Symbol	Description		Symbol	Description
a	Age of worker		e_a	Employed aged a
$\bar{a}$	Retirement age		J^e	Expected value matched firm
A	Matching function scale		J	Value matched firm
c	Cost to post vacancy		m	Number of matches
$\widehat{c}$	$\frac{c}{A\beta}$, normalized posting cost		p	Job-finding rate
T	Tenure		q	Matching rate
z	Aggregate productivity shock		s_a	Searchers aged a
β	Firm's share of output		S	Total number of searchers
δ	Time discount parameter		U	Value unemployed worker
θ	Match survival rate		v	Number of vacancies
λ	Survival rate		W	Value employed worker
ξ_a	Productivity by age			
π	Markov transition probability			
σ	Matching function parameter			
ϕ	Good match probability			

Table 3: *Parameter Values for Chapter 1*

Symbol	Description	Value	Target / Reason
$\bar{a}$	Retirement age	468	Work for 39 years
$\widehat{c}$	Normalized posting cost	9.4550	42% job-finding rate
z	Aggregate productivity	1.0000	Normalization
δ	Discount factor	0.9959	4.8% annual discount rate
θ^b	Match survival rate	0.7101	7% separation rate
λ	Survival rate	0.9998	Mortality rate
ξ_a	Productivity by age	*	Fit to CPS data, 1962–2006
σ	Matching function elasticity	0.7200	Shimer (2005)
ϕ	Probability good match	0.0335	6.1% unemployment rate
	Youth share	0.4998	

Table 3 lists the parameter values used in the steady state analysis and dynamic simulations reported on in Chapter 1. See Chapter 1 for more details.

Table 4: *Unemployment Rates by Age Group*

Age Group	U.S. Data	Steady State Model
16–19	16.1%	17.8%
20–24	9.4%	10.2%
25–34	5.6%	6.0%
35–44	4.2%	3.2%
45–54	3.7%	2.1%
16–54	6.1%	6.1%

I calculated the unemployment rate for each age group using CPS data from 1948 through the second quarter of 2007. The parameter value choices for the steady state model developed in Chapter 1 can be found in Table 3.

Table 5: *Separation Rates by Age Group*

Age Group	U.S. Data	Steady State Model
15–19	20.2%	16.6%
20–24	11.6%	12.1%
25–29	6.9%	8.3%
30–34	5.7%	5.9%
35–44	4.8%	3.9%
45–54	4.3%	2.6%
15–54	7.0%	7.0%

Table 5 reports the average monthly separations as a fraction of employment by age group. The U.S. data originates from Table 1 in Nagypál (2004), which was created from CPS data. Note the first age group for the model is aged 16–19. In the model, separations include retirements, deaths, and match destructions. The parameter value choices for the steady state model developed in Chapter 1 can be found in Table 3.

Table 6: *Employment Volatility by Age Group*

Age Group	U.S. Data	Model
16–19	0.0357	0.0303
20–24	0.0223	0.0264
25–34	0.0112	0.0121
35–44	0.0093	0.0100
45–54	0.0093	0.0068

I constructed Table 6 using CPS data from 1948–2007 and the data generated from the model as detailed in Chapter 1, Section 5. Employment volatility is the standard deviation of the detrended, logged, quarterly employment series expressed in levels. I remove the trend from each series using the HP filter with smoothing parameter 1600.

Table 7: Notation for Chapter 2

Symbol	Description	Symbol	Description
B	Boundary for producing	α	Production function parameter
c	Cost to meet worker	β	Worker's share of output
e	Employment level	δ	Time discounting parameter
F	Idiosyncratic shock distribution	ϵ	Match-specific idiosyncratic shock
G	Firm capacity distribution	η	High-skill productivity
h	Worker skill level	κ	Support of capacity distribution
H	High-skill worker	σ	Exogenous separation rate
J	Value of active firm	τ	Maximum idiosyncratic cost
k	Capital or firm capacity	ϕ	% High-skill in population
L	Low-skill worker	Φ	$\frac{1-\beta}{1-\delta(1-\sigma)}$, set-up price
P	Pooling equilibrium	Λ	$(1-\alpha)^{\frac{1}{\alpha}}$
p	% vacant firms w/ high-capacity	Π	$(\phi\eta^\alpha + 1 - \phi)^{\frac{1}{\alpha}}$
q	% of unemployed w/ high-skill	Ψ	$1 - \beta$, rental price
S	Separating equilibrium	Ω	$\left[(1-\phi)\left(\phi^\alpha - \phi\right)^{-1}\right]^{\frac{1}{\alpha}}$
U	Value of unemployed worker		
u	Unemployment level		
V	Value of vacant firm		
W	Value of employed worker		
x	Probability of producing		
Y	Aggregate output		
z	Aggregate state		

Table 8: *Parameter Values for Chapter 2*

Symbol	Description	1980	1990
α	Production function parameter	.64	.64
η	High-skill productivity	5	5
σ	Exogenous separation rate	.1	.1
ϕ	% High-skill in population	19.2	24.0

Table 8 lists the parameter values used in the benchmark analysis for the model developed in Chapter 2. Only steady states of the model economy are considered. The 1980 column represents the economy in a pooling equilibrium, and the 1990 column captures the separating case. See Chapter 2 for more details.

Table 9: *Solutions for Pooling and Separating Equilibria*

Symbol	Description	Pooling	Separating
k^P	Capital - employ all	0.471	-
k^H	Capital - employ high-skill	-	1.013
k^L	Capital - employ low-skill	-	0.203
J^L	Value of matched firm	0.292	0.360
J^H	Value of matched firm	1.665	1.801
	Skill Premium	2.8	5.0

Table 9 lists the firms' capital choices and associated valuations in pooling and separating equilibria. See Table 8 for the parameter values used to obtain these results. More details can be found in Chapter 2.

Table 10: *Results - Pooling and Separating Equilibrium*

	Pooling	Separating	Decline in Volatility
Change in Output	6.23%	5.80%	6.90%
(U.S. Data)	(2.20%)	(1.25%)	(43.18%)
Change in Employment	6.33%	4.40%	30.49%
(U.S. Data)	(1.36%)	(0.76%)	(44.12%)

Table 10 reports the percent decline in aggregate output and total employment after reducing the aggregate productivity variable z by 5% for both the pooling and separating equilibrium. The U.S. data row (in parentheses) provides the standard deviation of the deviations from trend over the relevant time period. The last column lists the percent decline in aggregate cyclical volatility that occurs after moving from the pooling equilibrium to the separating case. See Chapter 2 for more details.

Table 11: *Results using Alternate Parameter Values*

η	ϕ (pooling)	Percent decline in Output Volatility
5.0	0.192	6.90%
5.5	0.192	7.06%
6.0	0.192	7.78%
5.0	0.150	9.38%
5.0	0.100	11.04%
6.0	0.100	11.92%

This table presents the results for alternative parameter value choices. See Chapter 2 and Table 10 for more on how these results were calculated.

Table 12: Summary Statistics for Married Women Aged 18-55

Variables	All	1960	1970
	Outcome Variables		
Participation Rate	0.410	0.327	0.426
	(0.492)	(0.469)	(0.495)
Employment Rate	0.391	0.312	0.406
	(0.488)	(0.463)	(0.491)
Share Working Full-Time	0.253	0.215	0.261
(35+ Hours/Week)	(0.435)	(0.410)	(0.439)
Share at Work Year-Round	0.238	0.181	0.249
(48+ Weeks in Prior Year)	(0.426)	(0.385)	(0.433)
Hours Worked per Week	34.1	35.0	34.0
(Conditional on Working)	(10.5)	(10.6)	(10.5)
	Endogenous Regressors of Interest		
Washer Present	0.854	0.872	0.851
in the Household	(0.353)	(0.334)	(0.356)
Dryer Present	0.563	0.291	0.616
in the Household	(0.496)	(0.454)	(0.486)
Freezer Present	0.351	0.254	0.370
in the Household	(0.477)	(0.435)	(0.483)
All 3 Appliances Present	0.250	0.108	0.278
in the Household	(0.433)	(0.310)	(0.448)
	Covariates		
Age	36.7	36.7	36.7
	(10.2)	(9.7)	(10.3)
Number of Children Under	0.44	0.56	0.41
Age 5	(0.73)	(0.84)	(0.70)
Number of Children Over	1.42	1.30	1.44
Age 5	(1.48)	(1.35)	(1.50)
Potential Experience	19.0	19.5	18.9
(Years)	(10.8)	(10.3)	(10.8)

Table 12 (continued): Summary Statistics for Married Women Aged 18-55

Variables	All	1960	1970
Share with 0-11 Years of Schooling	0.325 (0.468)	0.433 (0.495)	0.304 (0.460)
Share with 12 Years of Schooling	0.467 (0.499)	0.399 (0.490)	0.480 (0.500)
Share with 13-15 Years of Schooling	0.124 (0.329)	0.109 (0.311)	0.127 (0.333)
Share with 16 or More Years of Schooling	0.085 (0.279)	0.060 (0.238)	0.090 (0.286)
Household Income (minus own earnings)	10,737 (8,059)	8,712 (6,470)	11,133 (8,277)
Log of State Mean Wage	1.04 (0.16)	0.83 (0.15)	1.08 (0.12)
Instruments			
Share of Single Women in State Owning a Washer	0.717 (0.069)	0.726 (0.094)	0.716 (0.063)
Share of Single Women in State Owning a Dryer	0.385 (0.144)	0.155 (0.084)	0.429 (0.105)
Share of Single Women in State Owning a Freezer	0.252 (0.087)	0.159 (0.061)	0.270 (0.079)
Share of Single Women in State Owning All Three Appliances	0.157 (0.074)	0.054 (0.036)	0.177 (0.062)
Number of Observations	326,465	53,347	273,118

Notes: Entries are means with standard deviations reported in parentheses. The data are from the Census IPUMS for 1960 and 1970 (State Form 1), with the sample restricted to white, U.S.-born, married women of prime working age (18 to 55 years old), with state information, and working husbands. Dollar amounts are in 1970 dollars.

Table 13: Summary Statistics for Single Women Aged 18-55

Variables	All	1960	1970
	Outcome Variables		
Participation Rate	0.729	0.748	0.727
	(0.444)	(0.434)	(0.446)
Employment Rate	0.693	0.709	0.691
	(0.461)	(0.454)	(0.462)
Share Working Full-Time	0.527	0.591	0.518
(35+ Hours/Week)	(0.499)	(0.492)	(0.500)
Share at Work Year-Round	0.447	0.466	0.444
(48+ Weeks in Prior Year)	(0.497)	(0.499)	(0.497)
Hours Worked per Week	36.3	37.7	36.1
(Conditional on Working)	(9.2)	(8.3)	(9.3)
	Endogenous Regressors of Interest		
Washer Present	0.714	0.723	0.712
in the Household	(0.452)	(0.448)	(0.453)
Dryer Present	0.392	0.154	0.427
in the Household	(0.488)	(0.360)	(0.495)
Freezer Present	0.245	0.150	0.259
in the Household	(0.430)	(0.357)	(0.438)
All 3 Appliances Present	0.156	0.052	0.171
in the Household	(0.363)	(0.222)	(0.377)

Table 13 (continued): Summary Statistics for Single Women Aged 18-55

Variables	All	1960	1970
	Covariates		
Age	31.7	33.9	31.4
	(12.6)	(12.6)	(12.5)
Number of Children Under Age 5	0.09	0.08	0.09
	(0.36)	(0.35)	(0.36)
Number of Children Over Age 5	0.45	0.39	0.46
	(1.03)	(0.91)	(1.04)
Potential Experience (Years)	13.9	16.6	13.5
	(13.1)	(13.2)	(13.1)
Share with 0-11 Years of Schooling	0.323	0.420	0.308
	(0.467)	(0.494)	(0.462)
Share with 12 Years of Schooling	0.412	0.377	0.417
	(0.492)	(0.485)	(0.493)
Share with 13-15 Years of Schooling	0.170	0.123	0.176
	(0.375)	(0.328)	(0.381)
Share with 16 or More Years of Schooling	0.096	0.080	0.099
	(0.295)	(0.272)	(0.298)
Household Income (minus own earnings)	6,810	5,557	6,991
	(8,596)	(6,787)	(8,813)
Number of Observations	102,105	12,899	89,206

Notes: Entries are means with standard deviations reported in parentheses. The data are from the Census IPUMS for 1960 and 1970 (State Form 1), with the sample restricted to white, U.S.-born, single women of prime working age (18 to 55 years old), and with state information. Dollar amounts are in 1970 dollars.

Table 14: Mean State Appliance Ownership Rates by Demographic Group, 1960-1970

Variables	Married Women Aged 18-55		Single Women Aged 18-55	
	1960	1970	1960	1970
Percent with Clothes Washer in Household:				
Overall Average	0.875	0.852	0.714	0.718
	(0.068)	(0.051)	(0.133)	(0.077)
Lowest State Average	0.600	0.599	0.224	0.372
	[DC]	[DC]	[DC]	[DC]
Highest State Average	0.982	0.919	0.912	0.821
	[VT]	[LA]	[WV]	[PA]
Percent with Clothes Dryer in Household:				
Overall Average	0.269	0.604	0.142	0.422
	(0.132)	(0.116)	(0.091)	(0.107)
Lowest State Average	0.070	0.376	0.000	0.241
	[AZ]	[AZ]	[HI, VT]	[SC]
Highest State Average	0.558	0.804	0.333	0.612
	[OR]	[WA]	[AK]	[MI]
Percent with Freezer in Household:				
Overall Average	0.288	0.410	0.181	0.303
	(0.101)	(0.124)	(0.090)	(0.100)
Lowest State Average	0.094	0.161	0.000	0.078
	[MA]	[RI]	[RI]	[DC]
Highest State Average	0.571	0.673	0.529	0.496
	[ND]	[ND]	[ND]	[WY]
Percent with All 3 Appliances in Household:				
Overall Average	0.113	0.300	0.059	0.192
	(0.072)	(0.115)	(0.060)	(0.084)
Lowest State Average	0.031	0.117	0.000	0.041
	[AL]	[RI]	[DC, HI, NV, RI, VT]	[DC]
Highest State Average	0.308	0.568	0.333	0.379
	[ND]	[ND]	[AK]	[ND]
Number of Observations	51	51	51	51

Notes: Entries are means with standard deviations reported in parentheses. See notes to Tables 12 and 13.

Table 15: OLS and Probit Estimates of the Effect of Household Appliances on the Labor Force Participation of Married Women

	OLS (1)	OLS (2)	OLS (3)	OLS (4)	OLS (5)	Probit (6)	OLS (7)	OLS (8)	OLS (9)	OLS (10)	OLS (11)	Probit (12)
Washer Present in the Household	-0.054*** (0.003)			-0.067*** (0.003)			-0.054*** (0.003)			-0.067*** (0.003)		
Dryer Present in the Household		0.002 (0.003)		0.024*** (0.003)				0.002 (0.003)		0.024*** (0.003)		
Freezer Present in the Household			-0.005* (0.003)	-0.002 (0.003)					-0.005* (0.003)	-0.002 (0.003)		
All Three Appliances Present in Household					0.003 (0.002)	0.004 (0.002)					0.003 (0.002)	0.004 (0.002)
Controls for state×year fixed effects?	Yes	Yes	Yes	Yes	Yes	Yes	No	No	No	No	No	No
Controls for the mean state female wage?	No	No	No	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Standard errors corrected for state-year clustering are reported in parentheses. The data are from the Census IPUMS for 1960 and 1970 (State Form 1), with the sample restricted to white, U.S.-born, married women of prime working age (18 to 55 years old), with state information, and working husbands. The sample size is 326,465. All regressions include four education dummies, a quartic in potential experience, household income (in 1970 dollars), number of children under age 5, number of children over age 5, and a full set of state and year dummies. * denotes significance at the 10% level, ** denotes significance at the 5% level, and *** denotes significance at the 1% level. Probit entries are estimates of the implied marginal effects on the probability of a positive outcome (labor force participation).

Table 16: First Stage Estimates of the Effect of Mean Appliance Ownership Rates among Singles in the State on the Appliance Ownership of Married Women

	Owns Washer (1)	Owns Washer (2)	Owns Dryer (3)	Owns Dryer (4)	Owns Freezer (5)	Owns Freezer (6)	Owns All Three (7)
Share of Single Women in State Owning a Washer	0.264*** (0.045)	0.240*** (0.050)		0.324*** (0.095)		-0.066 (0.062)	
Share of Single Women in State Owning a Dryer		-0.106 (0.068)	0.435*** (0.105)	0.397*** (0.085)		0.002 (0.072)	
Share of Single Women in State Owning a Freezer		0.102 (0.068)		0.281*** (0.100)	0.499*** (0.070)	0.508*** (0.082)	
Share of Single Women in State Owning All Three Appliances							1.028*** (0.075)
F-statistic	34.22	14.09	17.11	20.23	50.33	19.73	186.17

Notes: Standard errors corrected for state-year clustering are reported in parentheses. The data are from the Census IPUMS for 1960 and 1970 (State Form 1), with the sample restricted to white, U.S.-born, married women of prime working age (18 to 55 years old), with state information, and working husbands. All regressions include four education dummies; a quartic in potential experience; household income (in 1970 dollars); number of children under age 5; number of children over age 5; mean log female wages in the state and year; and a full set of state and year dummies. The F-statistic corresponds to the test of joint significance of the coefficients on the instruments in each model. The sample size is 326,465. * denotes significance at the 10% level, ** denotes significance at the 5% level, and *** denotes significance at the 1% level.

Table 17: 2SLS Estimates of the Effect of Household Appliance Ownership on the Labor Force Participation of Married Women

	2SLS (1)	2SLS (2)	2SLS (3)	2SLS (4)	2SLS (5)	IVProbit (6)
Washer Present in the Household	0.134 (0.191)			-0.073 (0.156)		
Dryer Present in the Household		0.257** (0.129)		0.184 (0.126)		
Freezer Present in the Household			0.308*** (0.083)	0.153 (0.123)		
All Three Appliances Present in the Household					0.209*** (0.043)	0.245*** (0.041)
F-statistic	0.49	3.97	13.69	4.69	23.92	

Notes: Standard errors corrected for state-year clustering are reported in parentheses. The data are from the Census IPUMS for 1960 and 1970 (State Form 1), with the sample restricted to white, U.S.-born, married women of prime working age (18 to 55 years old), with state information, and working husbands. All regressions include four education dummies; a quartic in potential experience; household income (in 1970 dollars); number of children under age 5; number of children over age 5; mean log female wages in the state and year; and a full set of state and year dummies. The state's contemporaneous mean appliance ownership rates among single women are used as instruments for the endogenous regressors listed on each row. The F-statistic corresponds to the test of joint significance of the coefficients on the endogenous regressors in each model. The sample size is 326,465. * denotes significance at the 10% level, ** denotes significance at the 5% level, and *** denotes significance at the 1% level. Probit entries are estimates of the implied marginal effects on the probability of a positive outcome (labor force participation).

Table 18: Falsification Exercises: Estimation Results from Alternative Specifications

	Outcome variable: Labor Force Participation of *Single Women*					*Outcome variable: Labor Force Participation of* *Married Women*					
	2SLS (1)	2SLS (2)	2SLS (3)	2SLS (4)	2SLS (5)	2SLS (6)	2SLS (7)	2SLS (8)	2SLS (9)	2SLS (10)	OLS (11)
Washer Present in the Household	-0.048 (0.084)			-0.062 (0.086)		0.039 (0.247)					
Dryer Present in the Household		0.003 (0.112)		-0.042 (0.120)			0.272** (0.126)				
Freezer Present in the Household			0.115 (0.090)	0.137 (0.101)				0.277*** (0.106)			
All Three Appliances Present in Household					0.062 (0.096)				0.202*** (0.054)		
TV Set Present in the Household						0.194 (0.190)	0.113 (0.132)	0. 059 (0.143)	0.044 (0.140)	0.219* (0.113)	0.059*** (0.007)

Notes: Entries are estimates of the implied marginal effects on the probability of a positive outcome (labor force participation). Standard errors corrected for state-year clustering are reported in parentheses. The data are from the Census IPUMS for 1960 and 1970 (State Form 1), with the sample restricted to white, U.S.-born, married women of prime working age (18 to 55 years old), with state information, and working husbands. The sample size is 102,105 for columns 1–5, and 326,465 for columns 6–10. All regressions include four education dummies; a quartic in potential experience; household income (in 1970 dollars); number of children under age 5; number of children over age 5; mean log female wages in the state and year; and a full set of state and year dummies. IV models use the state's contemporaneous mean appliance ownership rates among single women as instruments for the endogenous regressors listed on each row. * denotes significance at the 10% level, ** denotes significance at the 5% level, and *** denotes significance at the 1% level.

Table 19: Robustness Checks: Estimation Results Excluding College-Age Women

	OLS (1)	OLS (2)	OLS (3)	OLS (4)	OLS (5)	2SLS (6)	2SLS (7)	2SLS (8)	2SLS (9)	2SLS (10)
Washer Present in the Household	-0.058*** (0.003)			-0.072*** (0.004)		0.220 (0.227)			-0.208 (0.339)	
Dryer Present in the Household		0.004 (0.003)		0.024*** (0.004)			0.576 (0.447)		0.277 (0.337)	
Freezer Present in the Household			-0.004 (0.003)	-0.001 (0.003)				0.306*** (0.073)	0.133 (0.228)	
All Three Appliances Present in Household					0.004 (0.002)					0.200*** (0.048)

Notes: Standard errors corrected for state-year clustering are reported in parentheses. The data are from the Census IPUMS for 1960 and 1970 (State Form 1), with the sample restricted to white, U.S.-born, married women aged 24 to 55, with state information, and working husbands. The sample size is 287,473. All regressions include four education dummies; a quartic in potential experience; household income (in 1970 dollars); number of children under age 5; number of children over age 5; mean log female wages in the state and year; and a full set of state and year dummies. * denotes significance at the 10% level, ** denotes significance at the 5% level, and *** denotes significance at the 1% level.

Table 20: Robustness Check of First Falsification Exercise: 2SLS Estimates of the Effect of Household Appliance Ownership on the Labor Force Participation of Single Women, Restricting the Sample to Exclude College-Age Women

	2SLS	2SLS	2SLS	2SLS	2SLS
	(1)	(2)	(3)	(4)	(5)
Washer Present in the Household	-0.018 (0.091)			-0.042 (0.086)	
Dryer Present in the Household		-0.068 (0.143)		-0.109 (0.153)	
Freezer Present in the Household			0.096 (0.148)	0.153 (0.158)	
All Three Appliances Present in Household					-0.003 (0.139)

Notes: Standard errors corrected for state-year clustering are reported in parentheses. The data are from the Census IPUMS for 1960 and 1970 (State Form 1), with the sample restricted to white, U.S.-born, married women aged 24 to 55, with state information, and working husbands. The sample size is 59,966. All regressions include four education dummies; a quartic in potential experience; household income (in 1970 dollars); number of children under age 5; number of children over age 5; mean log female wages in the state and year; and a full set of state and year dummies. * denotes significance at the 10% level, ** denotes significance at the 5% level, and *** denotes significance at the 1% level.

Table 21: Robustness Check: Estimation Results with Corrections for Marriage Selection

|	OLS	OLS	OLS	OLS	OLS	2SLS	2SLS	2SLS	2SLS	2SLS
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Washer Present in the Household	-0.054*** (0.003)			-0.067*** (0.003)		0.153 (0.189)			-0.701 (0.153)	
Dryer Present in the Household		0.023 (0.003)		0.024*** (0.004)			0.257* (0.134)		0.188 (0.129)	
Freezer Present in the Household			-0.005* (0.003)	-0.002 (0.003)				0.306*** (0.085)	0.144 (0.127)	
All Three Appliances Present in Household					0.003 (0.002)					0.207*** (0.045)

Notes: Standard errors corrected for state-year clustering are reported in parentheses. The data are from the Census IPUMS for 1960 and 1970 (State Form 1), with the sample restricted to white, U.S.-born, married women aged 24 to 55, with state information, and working husbands. The sample size is 326,075 (See text for details on the marriage selection adjustment procedure). All regressions include four education dummies; a quartic in potential experience; household income (in 1970 dollars); number of children under age 5; number of children over age 5; mean log female wages in the state and year; and a full set of state and year dummies. * denotes significance at the 10% level, ** denotes significance at the 5% level, and *** denotes significance at the 1% level.

Table 22: Robustness Check: The Effect of All Observable Household Appliances on the Participation of Married Women

	OLS	2SLS
	(1)	(2)
All Observable Appliances Present in the Household (Washer, Dryer and Freezer in 1960; Washer, Dryer, Freezer and Dishwasher in 1970)	-0.008*** (0.002)	0.185*** (0.065)

First Stage Regression for 'All Observable Appliances Present'

| Share of Single Women in State Owning All Observable Appliances (Washer, Dryer and Freezer in 1960; Washer, Dryer, Freezer and Dishwasher in 1970) | | 0.780*** (0.086) |

Notes: Standard errors corrected for state-year clustering are reported in parentheses. The data are from the Census IPUMS for 1960 and 1970 (State Form 1), with the sample restricted to white, U.S.-born, married women of prime working age (18 to 55 years old), and with state information. The sample size is 326,465. All regressions include four education dummies; a quartic in potential experience; household income (in 1970 dollars); number of children under age 5; number of children over age 5; mean log female wages in the state and year; and a full set of state and year dummies. 2SLS models use the state's contemporaneous mean appliance ownership rates among single women as instruments for the endogenous regressors listed on each row. * denotes significance at the 10% level, ** denotes significance at the 5% level, and *** denotes significance at the 1% level.

Table 23: OLS and 2SLS Estimates of the Effect of Household Appliance Ownership on Employment of Married Women

	OLS (1)	OLS (2)	OLS (3)	OLS (4)	OLS (5)	2SLS (6)	2SLS (7)	2SLS (8)	2SLS (9)	2SLS (10)
Washer Present in the Household	-0.047*** (0.003)			-0.062*** (0.003)		0.168 (0.183)			-0.088 (0.156)	
Dryer Present in the Household		0.007** (0.003)		0.027*** (0.034)			0.287** (0.136)		0.224* (0.125)	
Freezer Present in the Household			-0.003 (0.003)	-0.001 (0.003)				0.301*** (0.082)	0.112 (0.119)	
All Three Appliances Present in Household					0.006*** (0.002)					0.194*** (0.043)

Notes: Standard errors corrected for state-year clustering are reported in parentheses. The data are from the Census IPUMS for 1960 and 1970 (State Form 1), with the sample restricted to white, U.S.-born, married women of prime working age (18 to 55 years old), with state information, and working husbands. The sample size is 326,465. In all models, the dependent variable is a binary indicator for whether the individual was employed in the previous week. All regressions include four education dummies; a quartic in potential experience; household income (in 1970 dollars); number of children under age 5; number of children over age 5; mean log female wages in the state and year; and a full set of state and year dummies. 2SLS models use the state's contemporaneous mean appliance ownership rates among single women as instruments for the endogenous regressors listed on each row. * denotes significance at the 10% level, ** denotes significance at the 5% level, and *** denotes significance at the 1% level.

Table 24: OLS and 2SLS Estimates of the Effect of Appliances on Full-Time and Year-Round Employment of Married Women

	OLS (1)	OLS (2)	OLS (3)	OLS (4)	OLS (5)	2SLS (6)	2SLS (7)	2SLS (8)	2SLS (9)	2SLS (10)
Outcome variable: Worked Full-Time Last Week										
Washer Present in the Household	-0.059*** (0.003)			-0.069*** (0.003)		0.435** (0.189)			0.310** (0.148)	
Dryer Present in the Household		-0.004 (0.003)		0.018*** (0.003)			0.174* (0.096)		0.122 (0.108)	
Freezer Present in the Household			-0.009* (0.002)	-0.005* (0.003)				0.534*** (0.095)	0.359*** (0.129)	
All Three Appliances Present in Household					-0.003* (0.002)					0.278*** (0.039)
Outcome variable: Worked Year-Round Last Year										
Washer Present in the Household	-0.047*** (0.004)			-0.059*** (0.004)		0.195 (0.150)			0.184 (0.130)	
Dryer Present in the Household		0.004 (0.003)		0.023*** (0.003)			0.053 (0.077)		0.018 (0.085)	
Freezer Present in the Household			-0.008*** (0.002)	-0.006** (0.002)				0.279*** (0.079)	0.226** (0.112)	
All Three Appliances Present in Household					-0.001 (0.002)					0.152*** (0.036)

Notes: See notes to Table 20. 'Worked Full-Time Last Week' is a dummy variable indicating whether the individual worked at least 35 hours the previous week; 'Worked Year-Round Last Year' is an indicator for whether the individual worked at least 48 weeks in the previous year. The sample size is 326,465.

Figure 1: *Youth Share and GDP Volatility* *(1967—2001)*
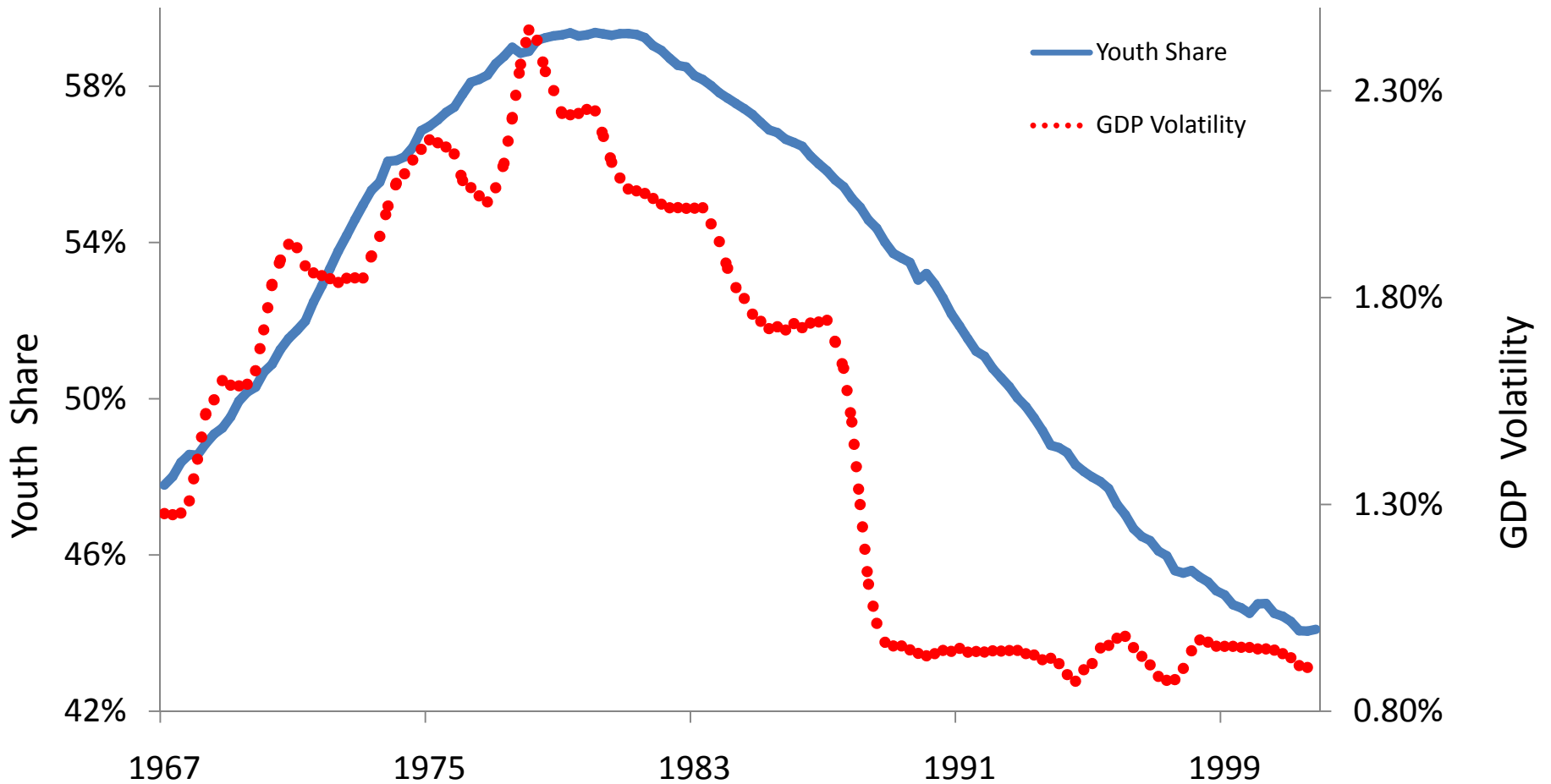
I constructed Figure 1 using CPS and BEA data from 1962—2006. The youth share equals the fraction of workers aged 16—54 under the age of 35. GDP volatility at quarter *t* is the standard deviation of a 41-quarter window centered around quarter *t* of the de-trended, logged, quarterly series of U.S. GDP. I removed the trend using the HP filter with the smoothing parameter set to 1600.

Figure 2: *Youth Share and Hours Volatility* *(1966—2002)*
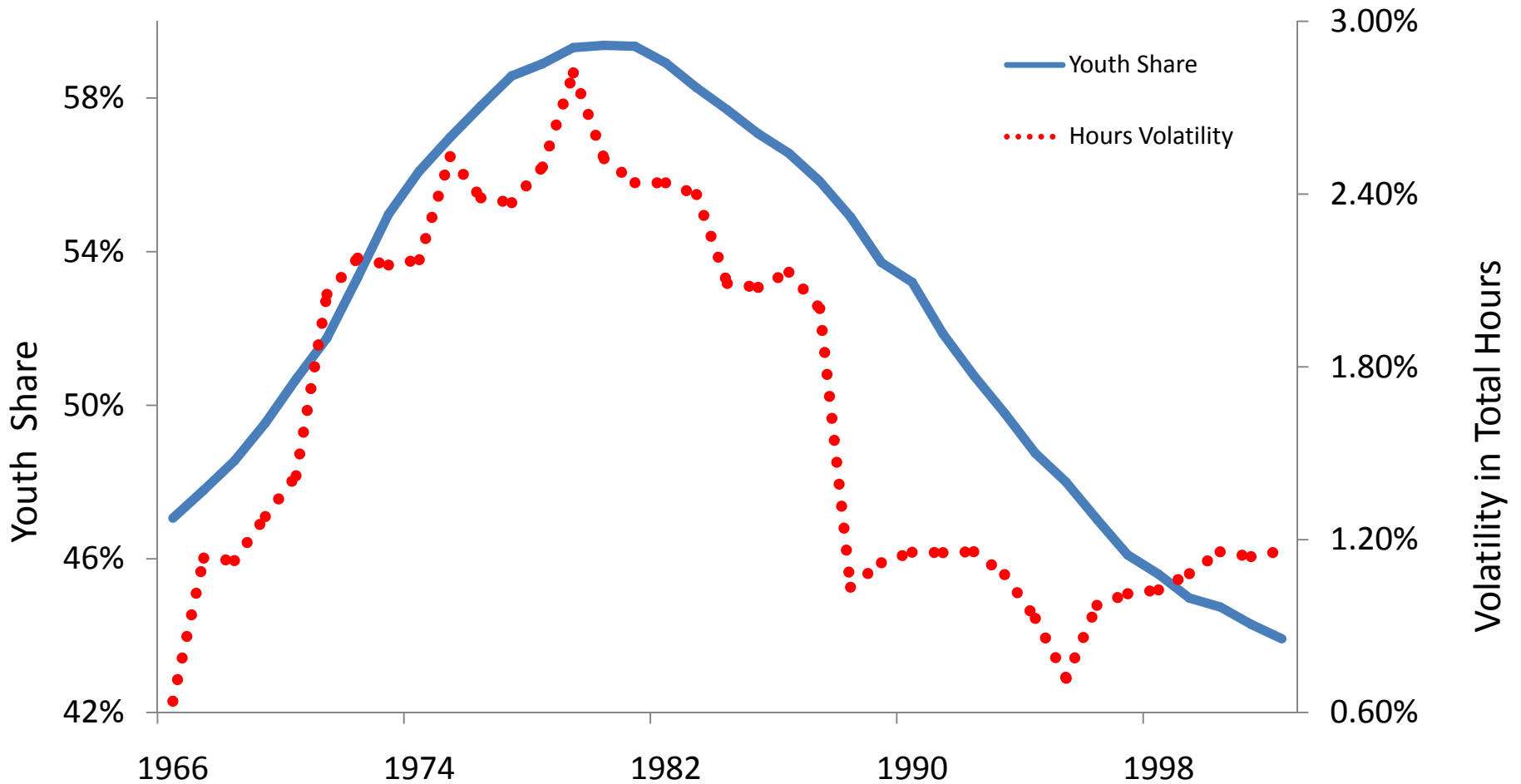
I constructed Figure 2 using CPS data from 1962—2006. The youth share equals the fraction of workers aged 16—54 under the age of 35. Hours volatility at year *t* is the standard deviation of a 9-year window centered around year *t* of the de-trended, logged, annual series of aggregate hours. I removed the trend using the HP filter with the smoothing parameter set to 10.

Figure 3: *Youth Share and Employment Volatility*
by Demographic Group
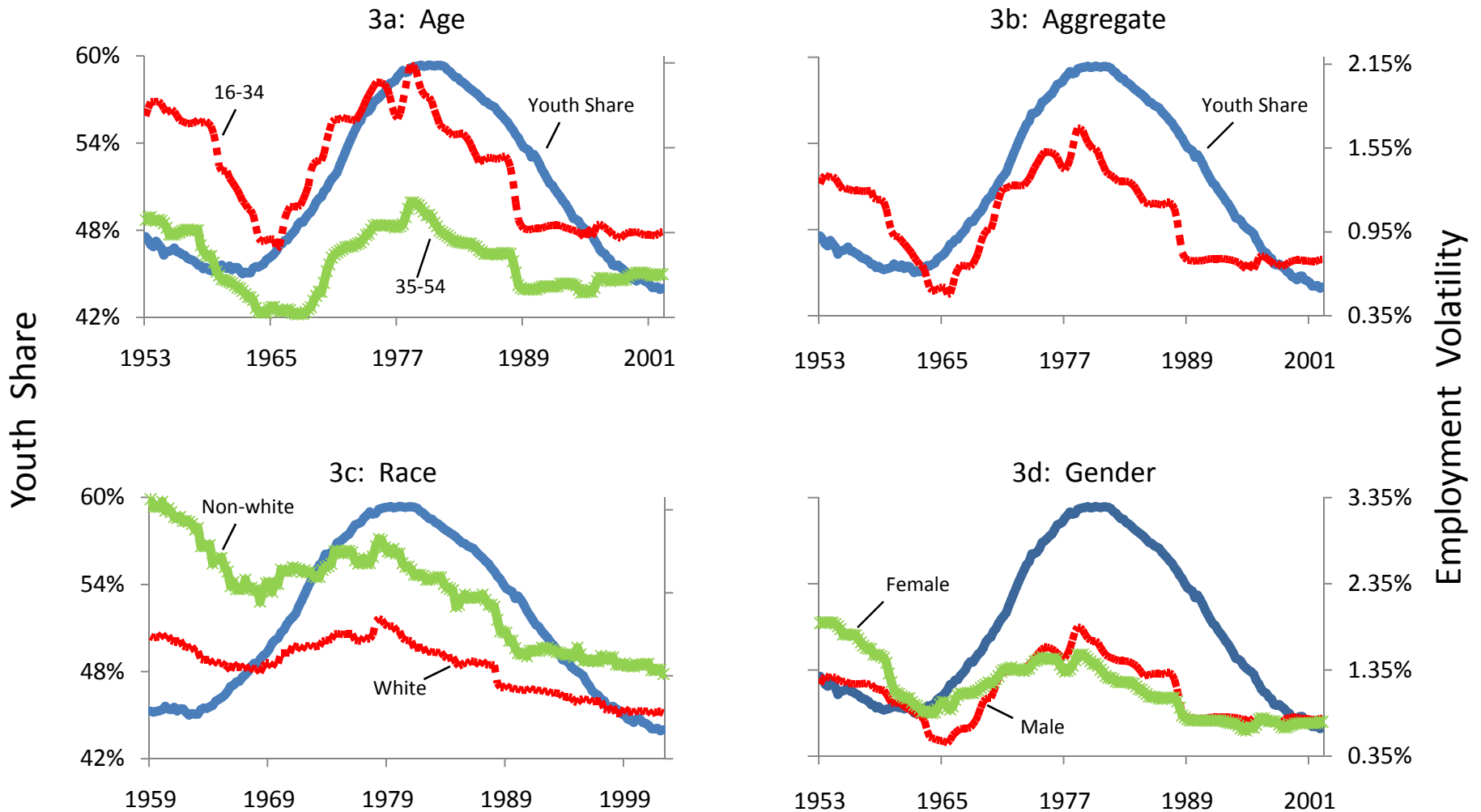
Figures 3a-d were constructed using CPS data from 1948—2007. The youth share (solid line) equals the fraction of workers aged 16—54 under the age of 35. Employment volatility at quarter *t* is the standard deviation of a 41-quarter window centered around quarter *t* of the HP filtered, logged, quarterly total employment series.

Figure 4: *Productivity by Age*
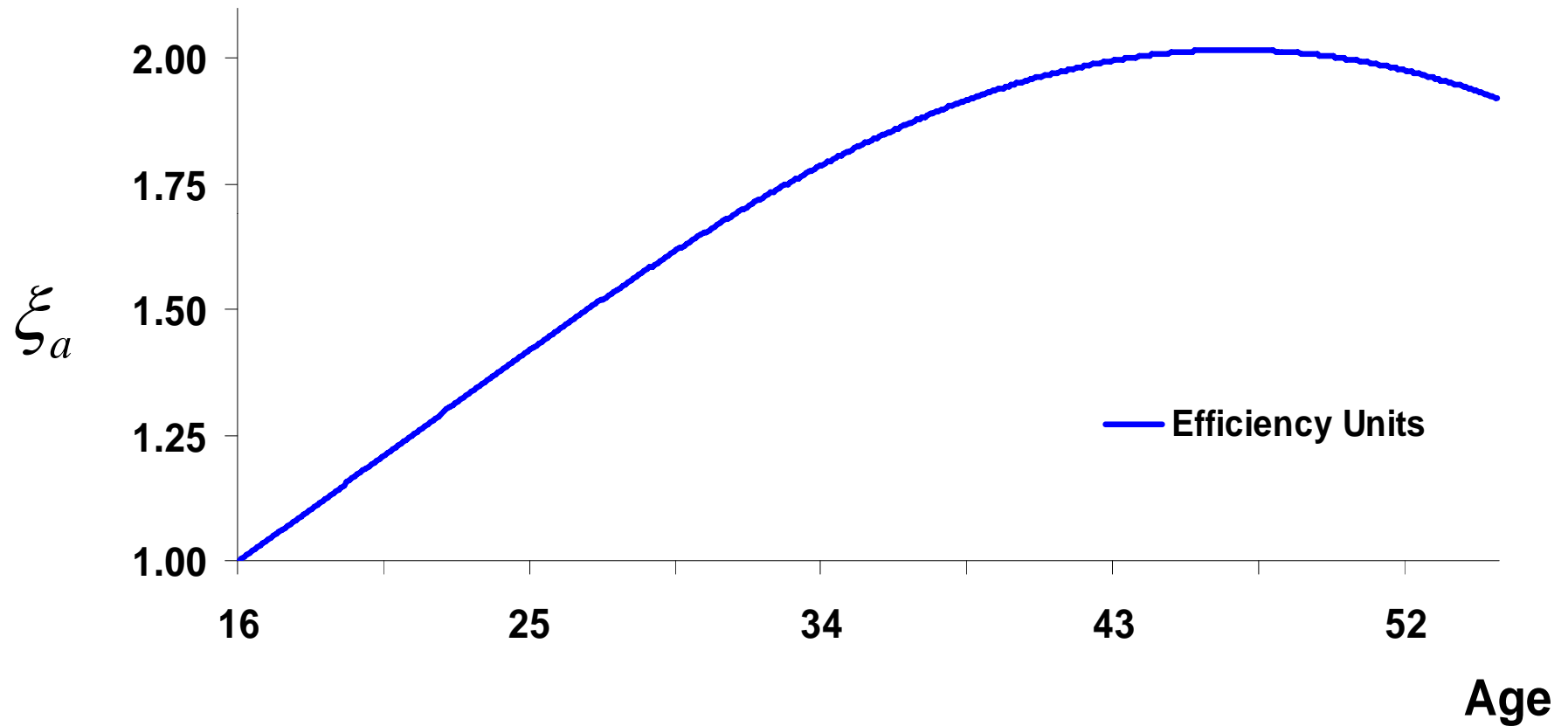
Figure 4 depicts the labor inputs by age used in the simulations detailed in Chapter 1. See Chapter 1 for more details.

Figure 5: *Youth Share and Output Volatility*
(aggregate output; model versus data)
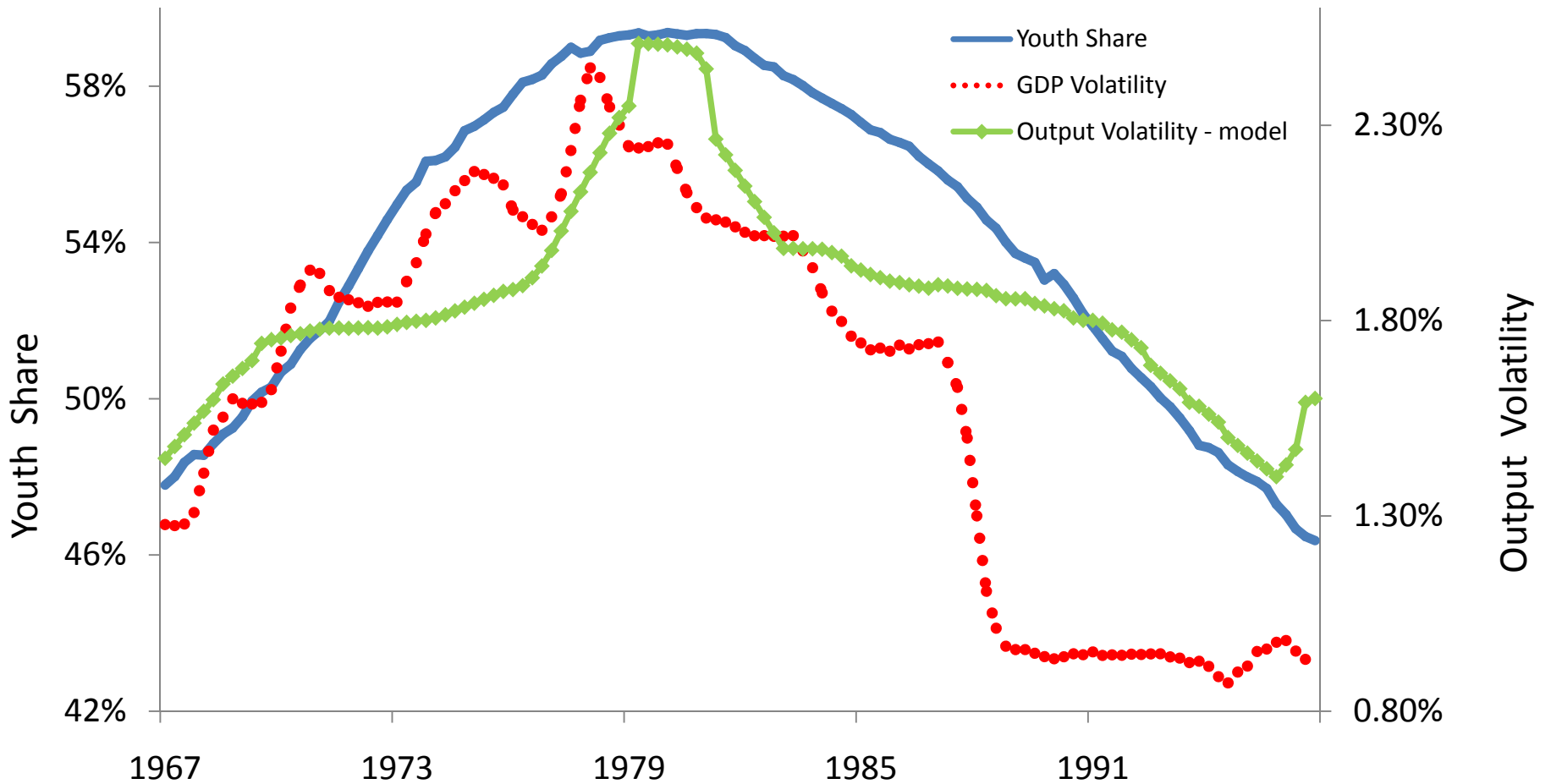
I constructed Figure 5 using the same method and data as Figure 1, plus 160 quarters of model generated data. The size of the youngest cohort in the model was chosen to match the observed youth share (% of labor force under 35) pattern. Output volatility at quarter t is the standard deviation of a 41-quarter window centered around quarter t of the HP filtered, logged, quarterly series of total aggregate output.

Figure 6: *Youth Share and Employment Volatility*
by Age Group (model)
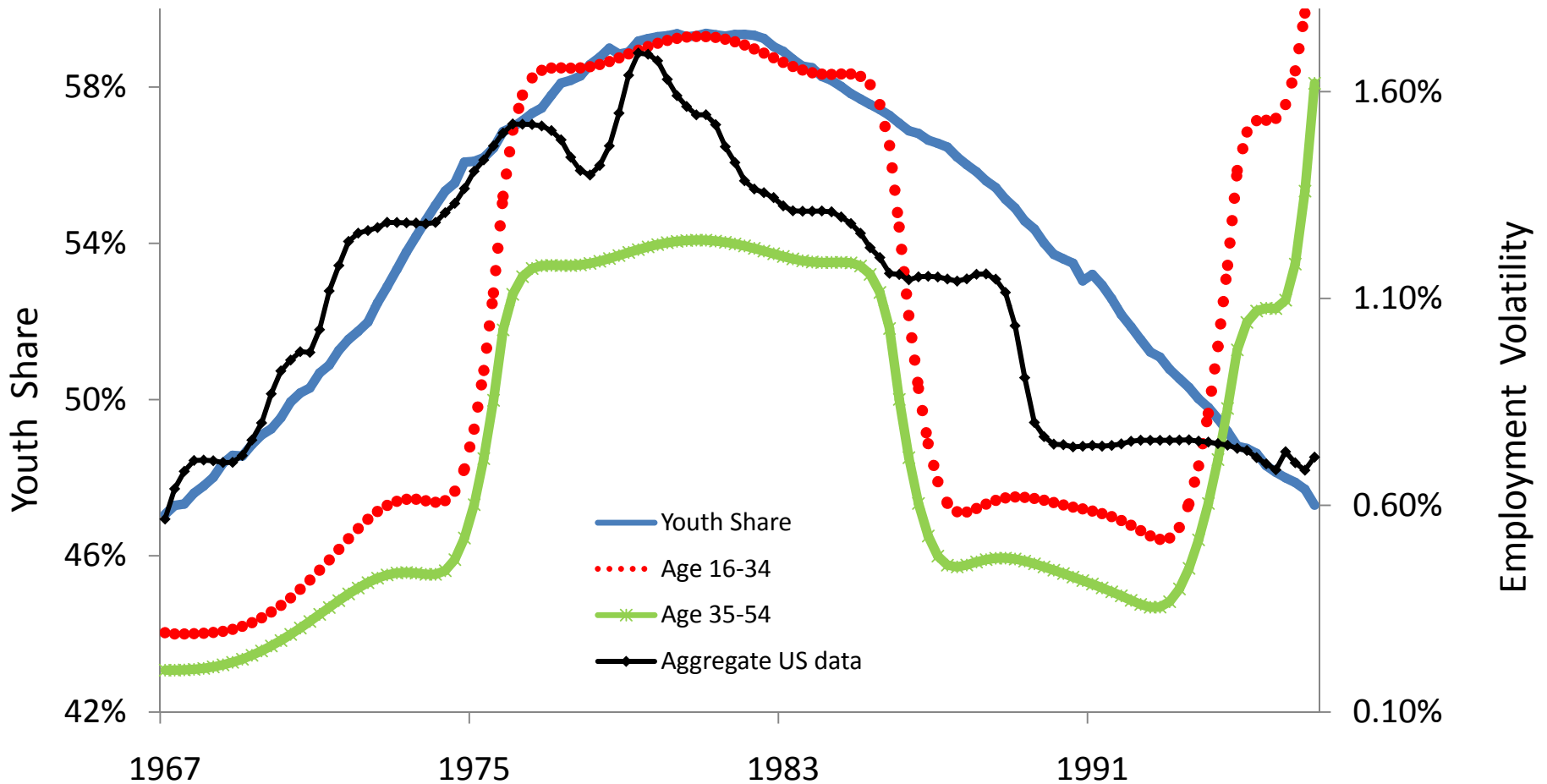
Figure 6 was constructed from CPS data and 160 model generated quarterly observations, with the youngest cohort in the model chosen to match the observed youth share (% of labor force under 35) pattern. Employment volatility at quarter *t* is the standard deviation of a 41-quarter window centered around quarter *t* of the HP filtered, logged, series. The dotted line measures employment volatility for 16—34 years olds, and the crossed line is volatility for those aged 35—54.

Figure 7: *Response to Productivity Increase*
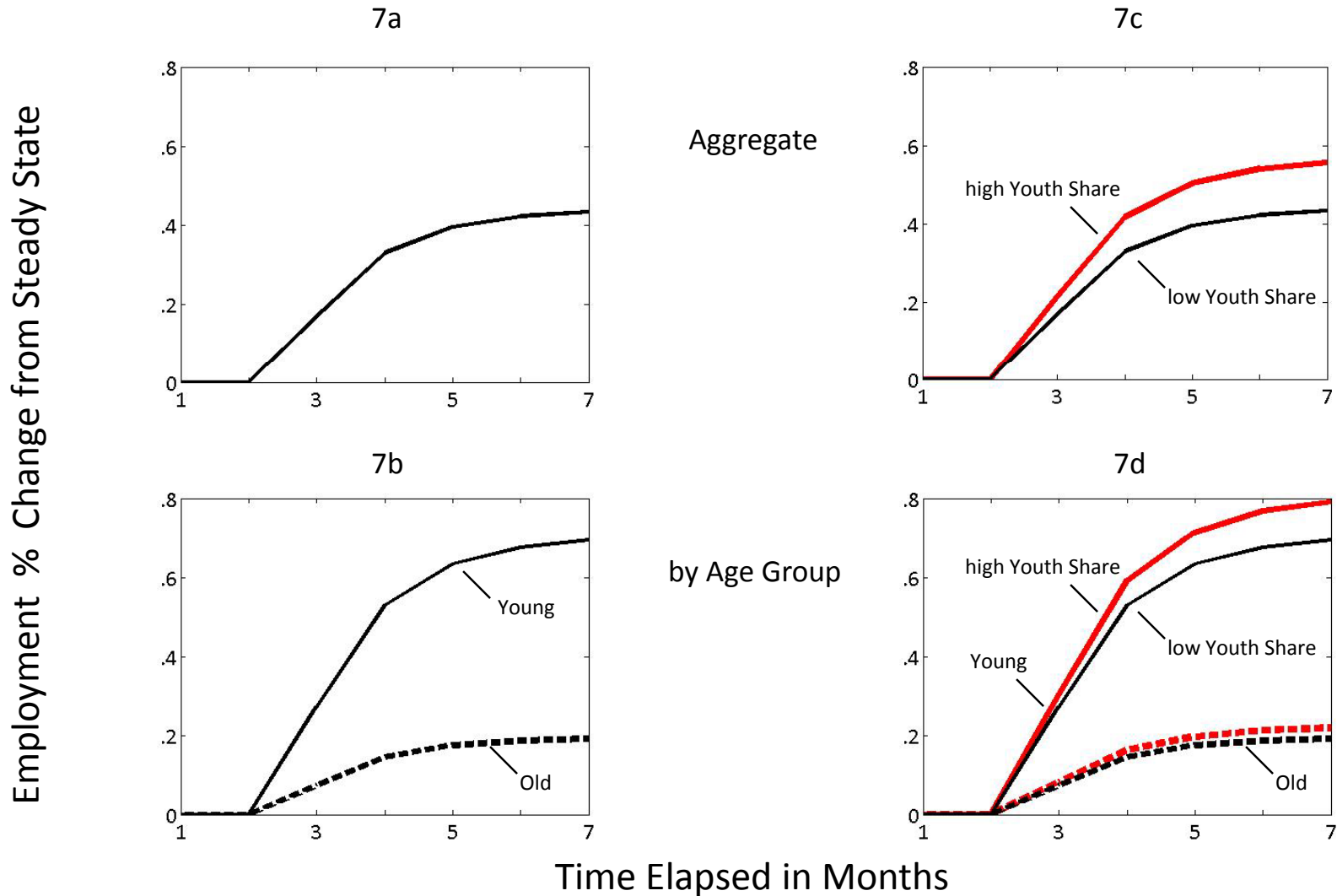
Figures 7a-b track the percent change in employment (from a steady state with youth share 49.98%) after a permanent 1% increase in productivity. The change occurs in month 3. The youth are aged 16—34; the old (dashed line) are 35—54. Figures 7c-d also contain the response of an economy with a higher youth share. The red (lighter / thicker) lines track the employment response when the youth share is 61.37%. The black (darker / thinner) lines track the response in an economy with youth share 49.98%.

Figure 8: *Real GDP Growth*
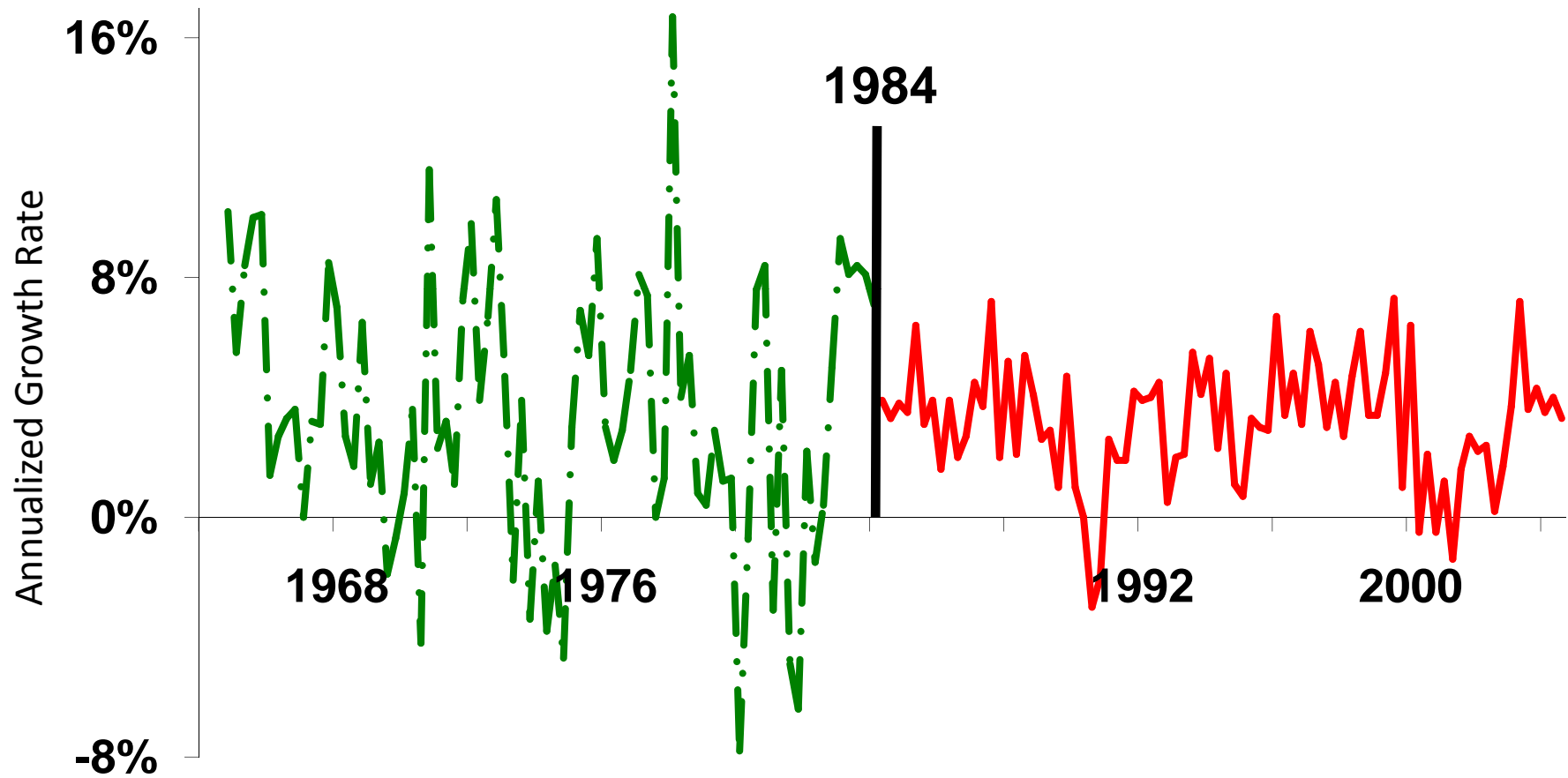
Figure 8 was created using U.S. GDP data from the BEA.

Figure 9: *Supply of College Graduates*
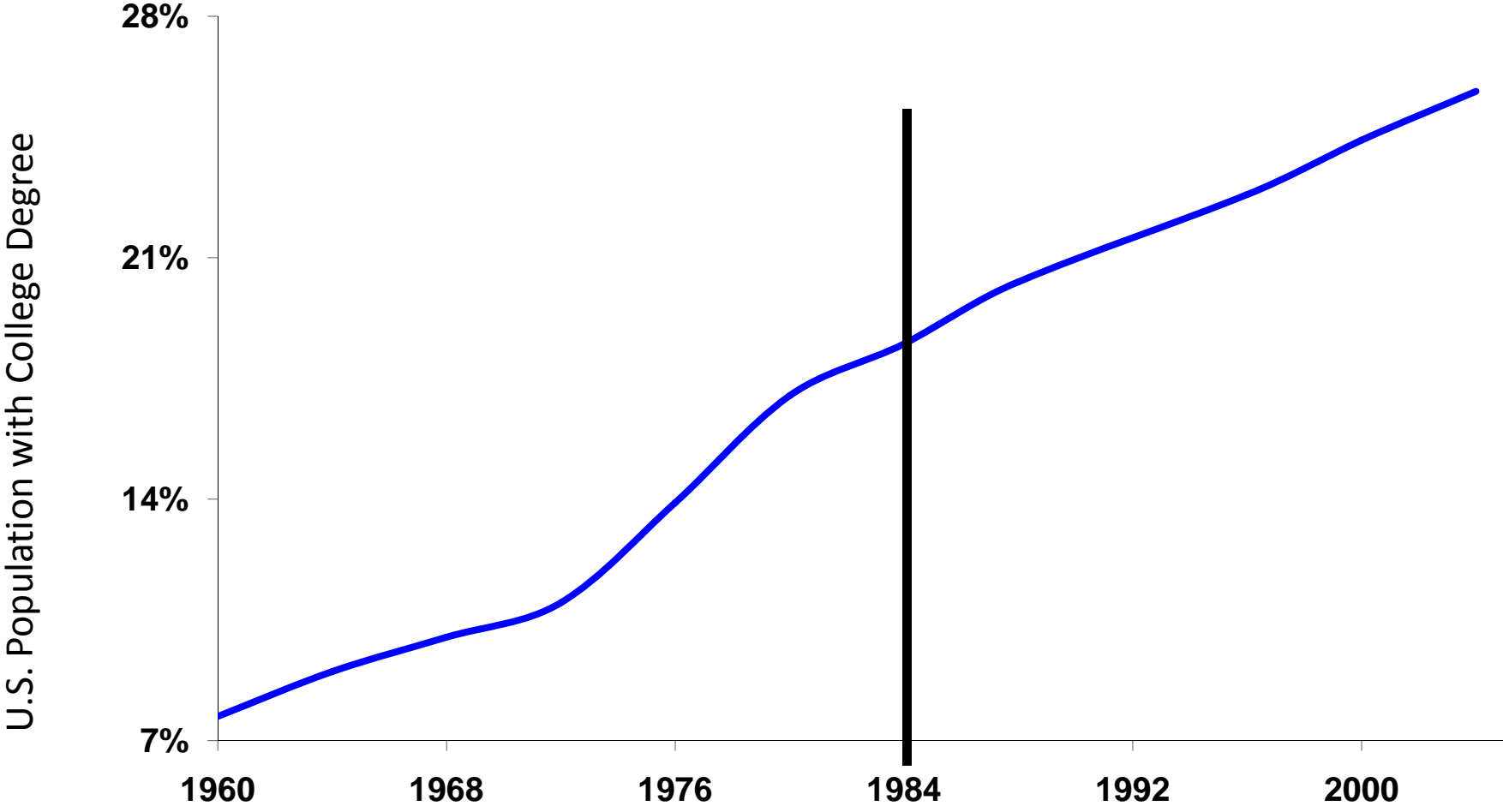
Figure 9 was created from CPS and BLS data.

Figure 10: *Sequence of Events*

| Observe | Select | Match | Learn | Choose to | Pay all Costs |
| φ & η | k | | z, h, & ∈ | Produce | Collect Profits |
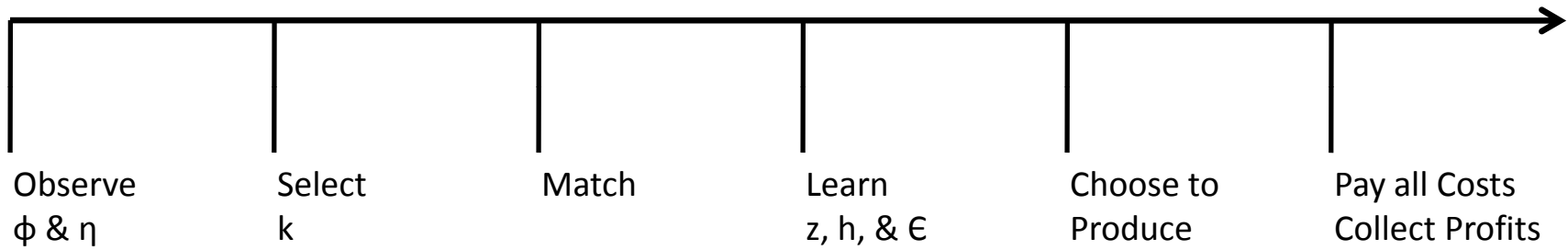
Figure 10 details the timing of events within a period for the model developed in Chapter 2.
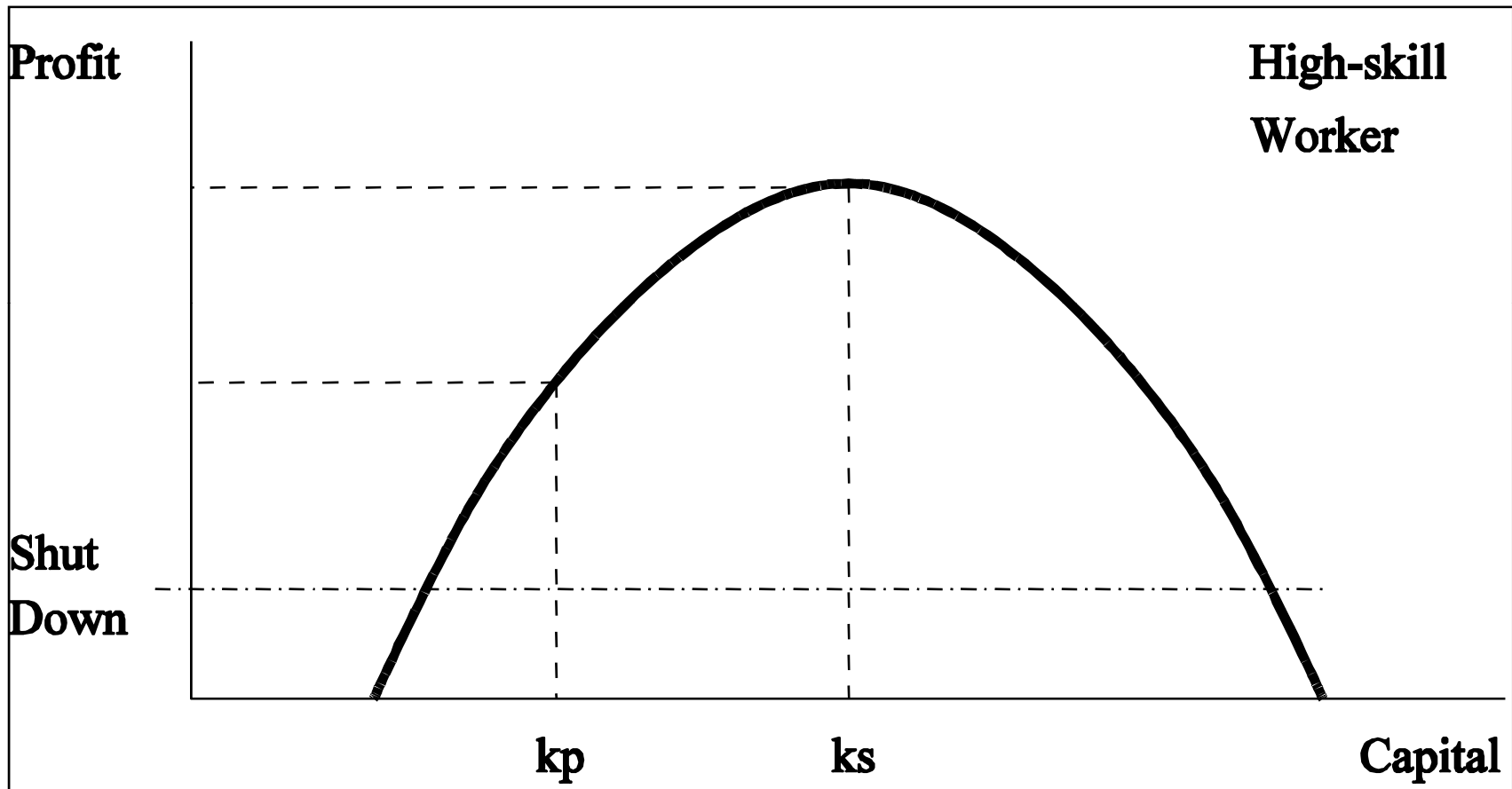
Figure 11: *Firm Profits*

Figure 11 depicts the potential profits for a firm with different choices of capital when matched with a high-skill worker. See Chapter 2 for more details.

Figure 12a: *First-Stage Relationship between Ownership (all 3 appliances) by Married Women and Ownership Among Single Women, by State and Year*
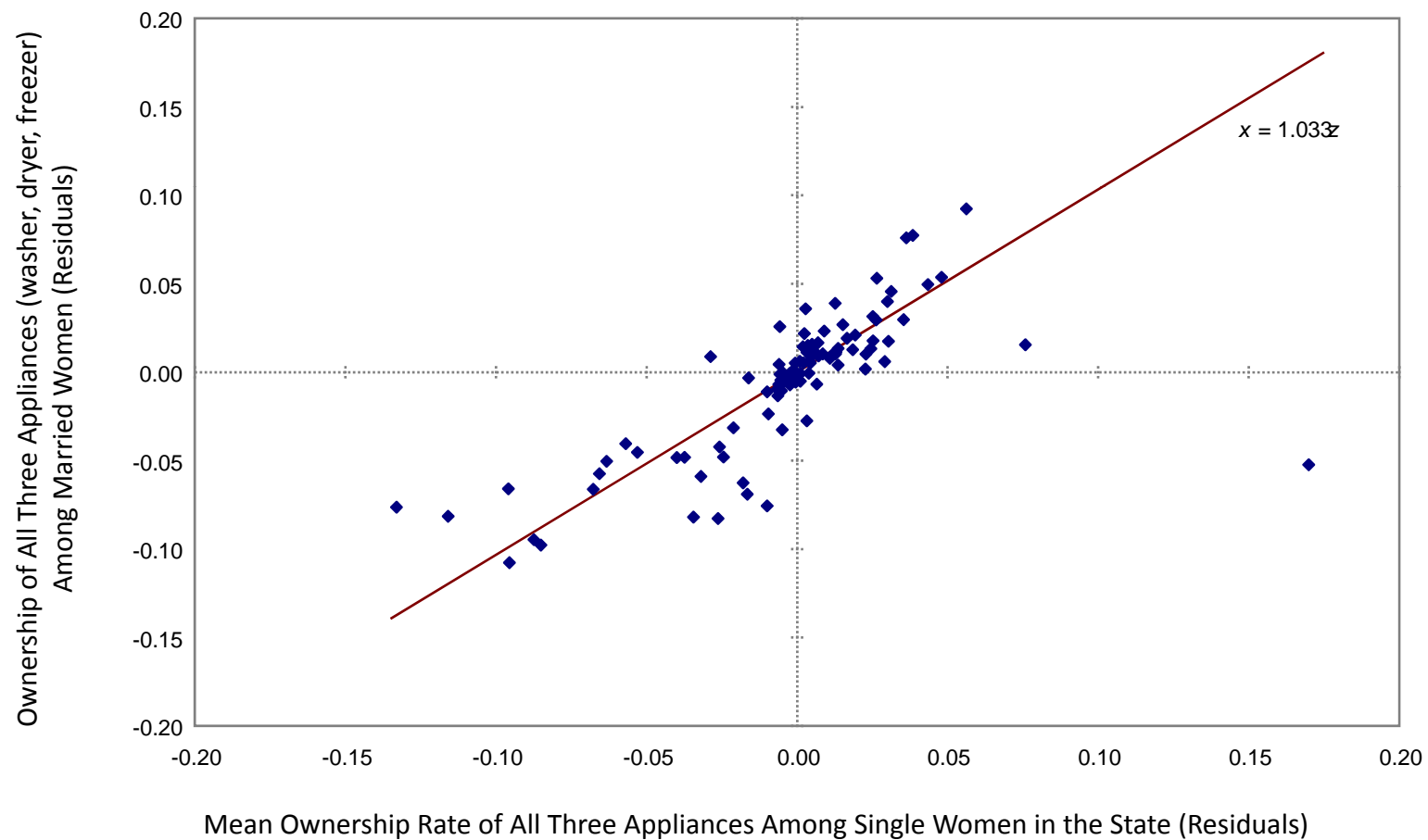
Figure 12b: *Reduced Form Relationship between Labor Force Participation by Married Women and Ownership Among Single Women, by State and Year*
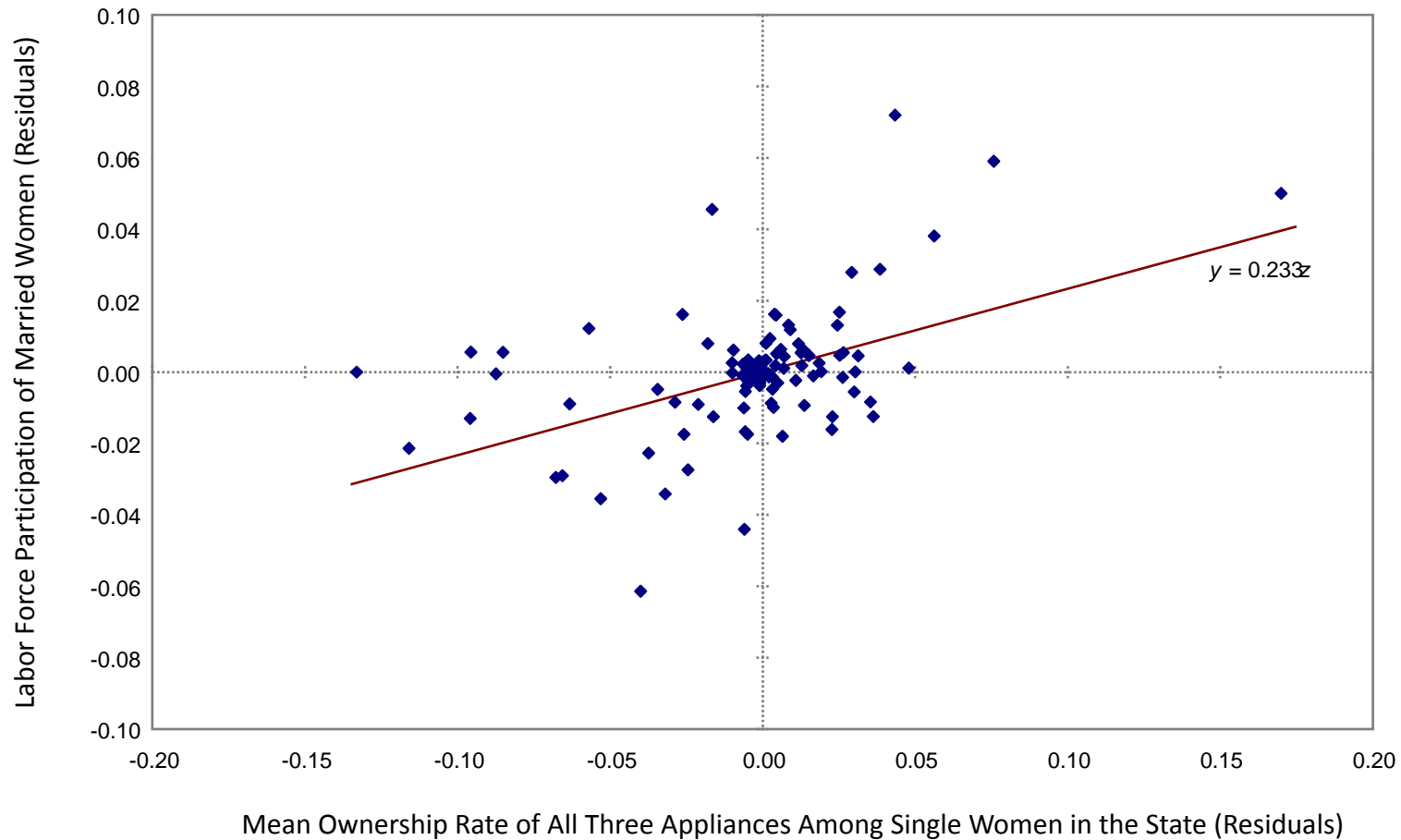
Figure 13a: *First-Stage Relationship between Ownership (all 3 appliances) by Single Women and Ownership Among Single Women, by State and Year*
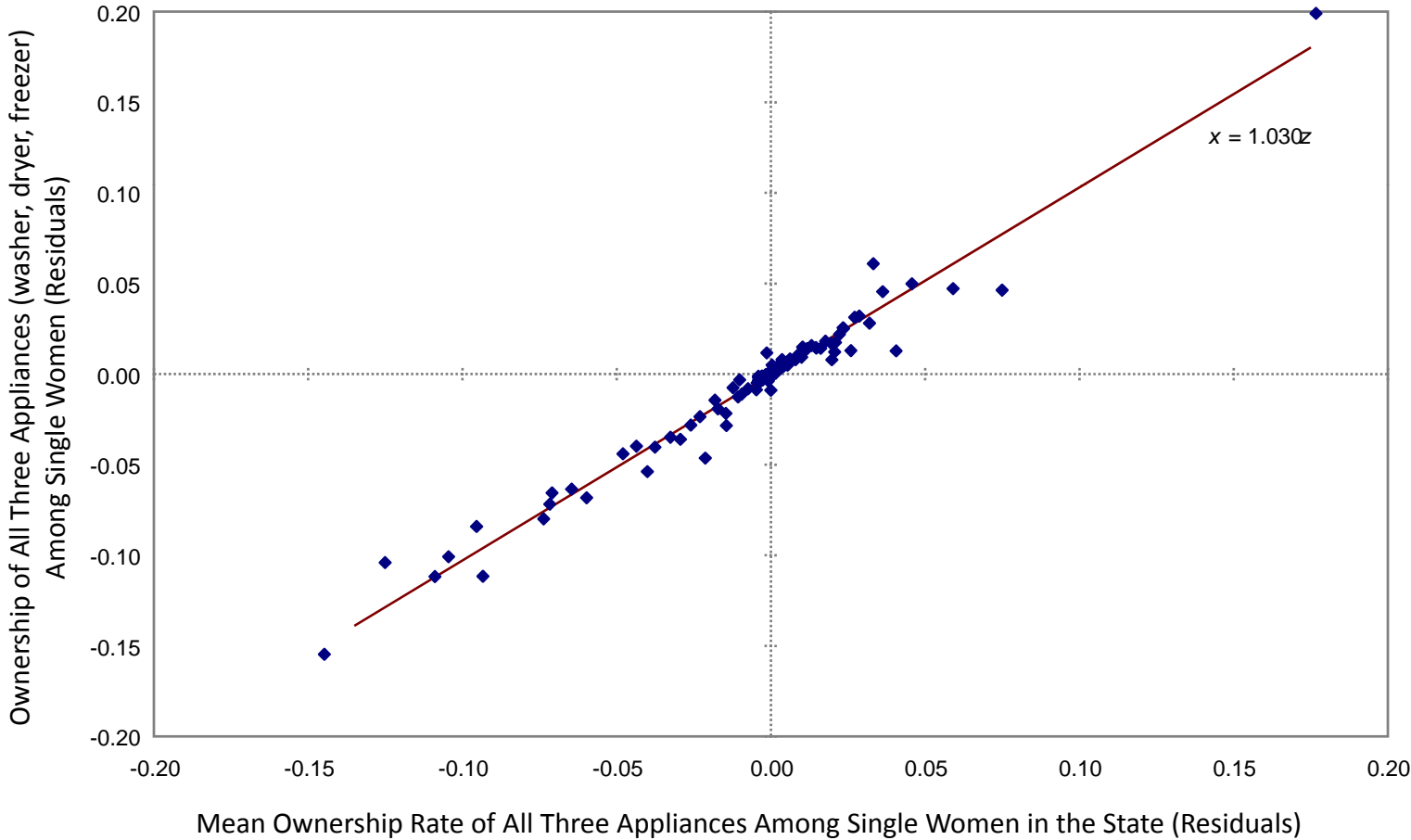
Figure 13b: *Reduced Form Relationship between Labor Force Participation by Single Women and Ownership Among Single Women, by State and Year*