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Abstract: The purpose of this paper is to explore the microfoundations of the observed asymmetric movement in aggregate unemployment rates. Using U.S. data, we find that individual labor force participation responds asymmetrically to changes in local labor market conditions, consistent with the pattern of movements in the aggregate unemployment rate. Differences in the asymmetry and sensitivity of labor force participation decisions are found across gender, age, and education groups, and these differences are used to anticipate changes in the aggregate movements as population characteristics change over time.

JEL classification: J21, J22, E24, E32

Key words: asymmetric labor force participation decision, unemployment rate, business cycle, gender, education, age

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I. Introduction

The tendency for the proportion of labor market participants who are unemployed to increase quickly during periods of economic weakness and to fall slowly during the subsequent recovery is a well-documented phenomenon (for example, see Neftci 1984 and Koop and Potter 1999). Figure 1 illustrates the asymmetric movement of the unemployment rate in the U.S., Canada, Australia and the U.K. In each case, large upswings in the unemployment rate tend to be much steeper than the ensuing declines.[1] Various explanations of this phenomenon have been postulated, including behavioral inertia (Gay and Washer 1989), structural changes in the labor market (Groshen and Potter 2003), differential response of firms to shocks across the business cycle (Burgess and Turon 2005), and economic shocks affecting different aspects of the labor market depending on the direction of the shock (Bardsen et al. 2003). Several statistical descriptions of the asymmetric time series pattern have also been proposed, including Hamilton (2005), Moshiri and Brown (2004), Rothman (2000), van Dijk et al. (2000), and Montgomery et al. (1998).

[Figure 1 here]

The purpose of this paper is to identify and to explore the behavioral foundations of the asymmetric movement of the unemployment rate by modeling individual labor supply responses to changing labor market conditions. If an individual's labor supply decision is different when their employment prospects weaken than when they improve, then that asymmetric response

[1] Similar asymmetric movement can be seen in the unemployment rate of other countries, as well (for example see Moshiri and Brown 2004). Darby et al. (2001) document an opposite asymmetric movement of the unemployment rate across the business cycle in Japan.

will, in turn, contribute to the nonlinearity observed in the aggregate unemployment rate over time. Identifying the micro-foundations for the observed aggregate time-series relationship will allow policy analysts to explain, and perhaps anticipate, changes to that relationship as individual characteristics of the population change. Of course, because demand factors play an important role in determining the flow into and out of unemployment, changes in labor force participation behavior across the business cycle will not fully explain movements in the unemployment rate. However, this paper does identify the role that labor supply decisions could play in accounting for the observed asymmetry in aggregate unemployment rates.

The next section of the paper outlines the link between labor force participation decisions and the unemployment rate, and describes theoretical reasons why individual labor force sensitivity to labor market conditions could be expected to be asymmetric. An empirical analysis of whether individual labor force participation decisions respond asymmetrically to changes in employment prospects is presented in section three, using micro-data on U.S. regional labor markets. The fourth section summarizes the results and suggests various empirical implications for the aggregate unemployment rate. The fifth section concludes.

II. Theoretical Background

The basis for identifying the role that individual behavior plays in determining the source of asymmetric movements in the unemployment rate is the well-known inverse relationship between labor market conditions and individual labor force participation decisions. In a weak labor market, unemployed individuals become discouraged and drop out of the labor market, reducing the labor force participation rate (LFPR). Non-participants are also less likely to enter the labor market under these conditions. In tight labor markets, individuals enter the labor market to take advantage of promising employment opportunities, increasing the LFPR. The so-called "discouraged worker" effect provides the theoretical foundation for the observed counter-cyclicality of labor force participation rates (Long 1958).[2] The question remains, however, as to whether the labor force participation response to the relative strength of the labor market is different depending on whether the labor market is weakening or strengthening. Evidence of asymmetric labor force responses to changing labor market conditions would be the basis for linking asymmetric movement in the aggregate unemployment rate to individual labor supply decisions.

The standard labor/leisure choice model suggests why individual labor force sensitivity to labor market conditions might be expected to be asymmetric. Assume that a person maximizes utility over two goods, income and leisure:

$$\max_{L} U = U(Y, L).$$

Utility is increasing in both expected income (*Y*) and leisure (*L*), but there is a tradeoff between income and leisure summarized by the budget constraint:

$$Y = Y_0 + (T - L)W^*,$$

where Y_0 is a person's non-labor income, *T* is the total amount of time a person has available to work, and W^* is the person's expected wage and reflects the cost of one hour of leisure. The expected wage can be thought of as the product of the value of the person's human capital (the actual market wage for that person, *W*) and the probability that the person can find a job offering a certain number of hours of work (π):

[2] While the potential of an opposing "added worker" effect (Woytinsky 1940) is acknowledged, quantitatively the discouraged worker almost uniformly dominates any added worker influences, resulting in the counter-cyclicality of labor force participation. The added worker effect contends that when a worker in a family loses his/her job during a recession, other members will enter the labor market (additional workers) to make up for the lost income. See Borrow (2004) for further empirical evidence of the inverse relationship between the LFPR and the unemployment rate.

$$W^* = \pi W \ .$$

For someone in the labor market but unemployed, a deterioration of employment prospects signals a reduction in π and hence a lower expected wage.[3] This reduction in the price of leisure has both a substitution and income effect.[4] Other things equal, the lower expected wage means leisure is now less expensive, causing the person to seek fewer hours of work (reducing $T-L$), and in the extreme, to exit the labor market ($T=L$). However, the lower expected wage also reduces expected income, causing the person to seek more hours of work. The desired number of hours of work will decline if the substitution effect dominates the income effect, and the discouraged worker will be one for whom the substitution effect is so large that the individual exits the labor market.

Conversely, a strengthening of the labor market signals an increase in π, which will raise the expected wage. For someone out of the labor market, this higher expected wage will have only a substitution effect, raising the price of leisure and acting to pull the person into the labor market. The key is that in this situation, there is no countervailing income effect; the entire pressure is to pull non-participants into the labor market.

Consequently, during periods when the labor market is weakening the resulting reduction in expected income lessens the pressure for unemployed workers to exit the labor market, but during periods of strengthening labor markets there is no such opposing force on individuals who are currently out of the labor force. The implication is that the impact of changes in labor market conditions on exits from the labor market will be more sluggish than the impact on entrances. This is consistent with the finding of Gay and Wascher (1989), who find persistence in labor

[3] There is also some evidence that weaker labor market conditions also directly, and negatively, affect the market wage (see Macis 2006).

[4] The income effect is clearly not literal since a change in the expected wage does not literally affect a person's income, but, rather, the person's expected income.

supply (once in the market, it takes longer for a person to leave, relative to how quickly a person enters), although they attribute the persistence to high entry costs and accumulated human capital, which they argue makes workers more insulated from transitory changes in labor demand.[5]

Of course, labor force decisions have a feedback effect to the unemployment rate itself. The prediction of weaker exit and stronger entrance pressures suggests that the unemployment rate will rise relatively quickly during periods of economic weakness as people linger in unemployment, and fall more slowly when the economy recovers as people pour into the labor market to take advantage of new opportunities. This scenario results in the asymmetric movement of the unemployment rate depicted in Figure 1.

III. Empirical Method

The first goal of the empirical analysis is to establish whether individual labor force participation decisions respond asymmetrically to changes in the probability of finding employment (π). In other words, does a given decline in employment prospects decrease a person's tendency to be a labor market participant differently than it would increase if employment prospects improved by the same amount? If so, then we know that at least some of the observed asymmetric movement of the unemployment rate across the business cycle has foundation in individual behavioral decisions.

[5] Gay and Wascher (1989) also find greater persistence among those demographic groups for whom we find *greater* sensitivity to labor market conditions.

A. Estimation Strategy

The baseline model is a standard probit model of individual labor force participation decisions, modified to incorporate movements in local labor market conditions. The unemployment rate is used as the measure of labor market conditions because it is arguably the most direct measure of the difficulty labor force participants have in finding employment (π). Other measures that might be considered are not nearly as desirable for this investigation. For example, it would be difficult to argue that individuals can easily digest reports of GDP and what its movement means for their employment prospects. In addition, the popular Employment-to-Population ratio confounds the labor supply decision with worker demand. The unemployment rate (which specifically measures among workers who want a job the percent that can't get one, and is widely reported and easily understood by the general population) is the closest measure of π as it was defined in the previous section.

In the baseline model an individual's labor force participation decision at a particular point in time is specified as a function of a number of individual demographic and human capital characteristics, as well as the observed local unemployment rate in the previous period:

$$LFP_i = \phi\left(\beta + \mathrm{B}' X_i + \gamma UR_i\right) + \varepsilon_i , \qquad (1)$$

where X_i are individual demographic and human capital characteristics, UR_i is the lagged state-level unemployment rate, ε_i is the random error component that is assumed to be Bernoulli distributed, $\phi(\cdot)$ is the normal density function, and

$LFP_i = \begin{Bmatrix} 1 \text{ if } U(Y_i, L_i < T) \; > \; U(Y_i, L_i = T) \\ 0 \text{ otherwise} \end{Bmatrix}$. In other words, a person is in the labor force

($LFP_i = 1$) if the utility of supplying a positive number of hours ($L_i < T$) is greater than not working at all ($L_i = T$).

The model in equation (1) is then modified to allow for the possibility of individuals' participation decisions responding to the unemployment rate differently depending on whether the unemployment rate is sufficiently higher or lower than it was a year ago. The specification allows the response to vary according to the relative size of the unemployment rate change since it is possible that for some range of unemployment rate differences the response is not asymmetric. The modified specification is:[6]

$$LFP_i = \phi\left(\beta + \mathrm{B}' X_i + \gamma_0 UR_i^0 + \gamma_1 UR_i^+ + \gamma_2 UR_i^-\right) + \varepsilon_i \tag{2}$$

where

$$\begin{aligned}
UR_i^0 &= \begin{Bmatrix} UR_t \text{ if } UR_{t-1} - \delta \le UR_t < UR_{t-1} + \delta \\ 0 \text{ otherwise} \end{Bmatrix} \\
UR_i^+ &= \begin{Bmatrix} UR_t \text{ if } UR_t \ge UR_{t-1} + \delta \\ 0 \text{ otherwise} \end{Bmatrix} \\
UR_i^- &= \begin{Bmatrix} UR_t \text{ if } UR_t < UR_{t-1} - \delta \\ 0 \text{ otherwise} \end{Bmatrix}
\end{aligned} \tag{3}$$

and $\delta > 0$. This modified specification measures the extent to which individuals respond asymmetrically to changes in the unemployment rate. The three parameters on the unemployment rate regressors in equation (2) measure how the individual's probability of labor force participation responds to the local unemployment rate when it is within δ units of what it

[6] This specification is similar to that applied by Mocan and Bali (2005) to investigate the effect of movements in the unemployment rate on criminal activity. Another application of a similar specification can be found in Koop and Potter (1999).

was a year ago (γ_0), when it is δ units higher than it was last year (γ_1), and when it is δ units lower than it was last year (γ_2).[7]

The symmetry threshold parameter, δ, is the amount by which the current unemployment rate has to differ from the unemployment rate last year before individuals respond differently according to the direction of the change in the unemployment rate. Equation (2) is estimated for different values of δ, incremented by 0.1 percentage points. The model parameter estimates are those which result at the value of δ which yields the largest likelihood function value. Separate models are estimated for different gender and education groups.

The model specification in equation (2) allows a direct statistical test of asymmetric behavior. The null hypothesis is that labor force participation decisions respond the same to changes in the unemployment rate regardless of whether it is higher or lower than it was a year ago:

$$H_0: \gamma_0 = \gamma_1 = \gamma_2 \tag{4}$$

In addition to the testable hypothesis depicted in equation (4), the estimate of δ will provide an indication of the practical significance of any statistically significant asymmetric behavior. For example, even if the null hypothesis of equation (4) is rejected, the value of δ may be so large as to preclude any useful expectation of differential behavior when the unemployment rate rises or falls.

For the most part, previous studies of the inverse relationship between the unemployment rate and labor force participation decisions have made use of aggregate data and have assumed

[7] Various model specifications were estimates with no appreciable difference in any of the conclusions presented here. Specifically, a model with a double-symmetry threshold parameter, a model with a continuous unemployment rate difference regressor, and a model with a simple unemployment rate movement (up or down) indicator variable were all explored. These models were determined to be less complete or to offer no additional insight to the results obtained from estimating the model described by equation (2).

that the relationship is symmetrical (for example, see Darby et al. 2001, Gay and Wascher 1989, and Lenten 2000). Exceptions include Blau (1978), who allows for a differential impact of the unemployment rate on entry and exit decisions of married women, and Blank and Shierholz (2005) who investigate how individual labor force decisions respond to labor market conditions across gender and education levels. The analysis in this paper improves upon the investigation by Blau by using multiple years of data and by allowing a threshold effect across gender and education groups. By allowing for asymmetric labor force responses, the present analysis will also expand upon the work by Blank and Shierholz.

B. Data

Data on the outgoing rotation groups from the March Current Population Survey (CPS) is used to evaluate determinants of labor force participation behavior among men and women in the U.S. between the ages of 25 and 54.[8] The historical aggregate unemployment rate for this group is presented in Figure 2, and displays similar characteristics to the unemployment rate for all individuals over 16 shown in Figure 1.

[Figure 2 here]

The data used in the regression analysis cover the years 1994 through 2005; a major survey re-design in 1994 makes comparisons of labor force participation before and after 1994 (especially for women) problematic (see Polivka 1996). The CPS is used for two primary reasons. First, these are the data from which the Bureau of Labor Statistics estimates and reports

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[8] The CPS is a monthly survey of about 50,000 households conducted by the United States Bureau of the Census for the Bureau of Labor Statistics. The CPS is the primary source of information on the labor force characteristics of the U.S. population. The sample is selected to represent the civilian noninstitutional population, and respondents are interviewed to obtain information about the employment status of each member of the household 15 years of age and older.

the labor force participation rate. Second, it provides a consistent, long-running, and large sample on which to investigate systematic determinants of observed behavior. All analyses are performed using the March supplement weight, since this is the only weight that is valid since 2002 and since some of the regressors come from the supplemental part of the survey.

The usual demographic and human capital regressors are included in the specification. These include age; age squared; number of children under six years; number of children between six and 18 years; non-labor income; and amount of disability income, if any; and dummy variables for education (of course these are omitted when the sample is stratified by education); race; marital status; geographic region; and year in the sample. All dollar variables are in 2004 values. The unemployment rate regressors are defined as in equation (3), where UR_t corresponds to the respondent's state-level unemployment rate for February in year *t* and UR_{t-1} is the respondent's state-level unemployment rate for February in the previous year.[9] While the sample time period includes only one national recession, within each year there is considerable variation across state-level unemployment rates with some respondents facing weaker and some facing stronger labor market conditions than in the previous year.

Sample means for the subgroups on which the model is estimated are presented in Table 1. The differences in the averages across the samples are typical. For example, women are less likely to be in the labor force than men, women receive less disability income than men, and women are less likely to have less than a high school education. In addition, college educated women are slightly younger and are more likely to have young (rather than older) children, than

[9] Ideally, π would be tailored specifically to reflect each individual's employment prospects. This would require a measure of the unemployment rate specific to each person's demographics (such as race to account for the potential impact of discrimination on employment opportunities), each person's human capital (such as education, industry, and occupation), and each person's geographic location. In the absence of a more precise measure, we opt to use the state-level unemployment rate. Geographic factors are likely to be important to an individual's specific employment prospects, and race and gender unemployment rates are available only at the national level.

women with less than a college degree. Both college-educated men and women are also more likely to married than their less-educated counterparts.

[Table 1 here]

IV. Results

There are several dimensions to the results of the analysis described above. First, conditional on the estimate of δ, a statistical test is performed to determine if individual responses are significantly different when the unemployment rate is higher, the same, or lower than last year. The second dimension of results is how behavior differs across gender and educational groups. Do the labor force participation decisions of men and women and those with different education levels respond differently to a given change in the unemployment rate? Lastly, there is an issue of practical significance of any identified asymmetrical behavior. Even if the specification in equation (3) is preferred statistically to the specification in equation (1), the estimated value of δ may imply that behavior is asymmetric for only extremely large changes in the unemployment rate.

Table 2 summarizes the results across all three dimensions. The value of δ that maximizes the likelihood function for each subgroup is reported in column 1. Column (1) is the range of unemployment rate changes for which the response is symmetric. Columns (2)-(4) give the marginal sensitivity of the labor force participation rate of group *j* when the unemployment rate is, respectively, more than δ_j higher, more than δ_j lower, or within δ_j of the rate in the preceding year. The Wald test statistic corresponding to the null hypothesis in equation (4) is reported in column 5. The ML parameter estimates at each sub-group's optimal symmetry threshold (δ) are reported in Appendix A.

[Table 2 here]

A. The Estimate of the Symmetry Threshold Parameter

The estimate of δ_j indicates the range of unemployment rate values within which labor force responses are symmetric for group j. This range is narrower for women and, within gender, more narrow among the less educated. Specifically, the labor force participation of women with less than a college education responds asymmetrically when the local area unemployment rate is more than 0.6 percentage points different than the unemployment rate of the previous year. The least asymmetric behavior is exhibited by college-educated men, whose labor force response differs only when the unemployment rate is more than 2.1 percentage points higher or lower than the previous year.

The smaller symmetry thresholds for women and the less-educated means that it takes smaller movements in the unemployment rate to elicit asymmetric behavior from these demographic groups. This implies that the aggregate unemployment rate should exhibit greater asymmetry among women and the less-educated over time.

Some casual evidence of this prediction can be found by comparing the length of time it takes the aggregate unemployment rate to go from peak to trough and from trough to peak around recessionary episodes. Table 3 lists these average lengths of times (in quarters) for men, women, those with less than a high school degree, and those with a college degree or more. As expected, the average number of quarters it takes the unemployment rate to go from peak to trough is longer for each group than the average number of quarters it takes to go from trough to peak (this is the asymmetry seen in Figure 2). The larger difference between average peak-to-trough quarters and trough-to-peak quarters for women and the less-educated provides some corroborating evidence of the greater asymmetry in the labor supply response of these groups.

[Table 3 here]

B. Marginal Impact of the Unemployment Rate on Labor Force Participation

The results in columns 2-4 in Table 2 yield several predictable results. First of all, labor force participation decisions of women and the less educated are more responsive to changes in the unemployment rate than those of men and the more educated, respectively. This can be seen by the larger negative marginal effects. For a 0.5 percentage point increase in the unemployment rate (a change smaller than any group's symmetry threshold), the expected labor force participation of a college-educated woman decreases by 0.18 percentage points and for a less-educated woman by 0.87 percentage points. By contrast, for the same increase in the unemployment rate, the expected labor force participation of a college-educated man will decrease by 0.09 percentage points and of a less-educated man by 0.48 percentage points. Men are half as sensitive to changes in labor market conditions as their educationally equivalent female counterparts.

These results are to be expected given the weaker labor force attachment of women and the less educated to the labor market.[10] Weaker attachment means that the value of time out of the labor market (the person's reservation wage) is higher. As a result, for any given decrease in chances of finding a job (π), the expected wage will be more likely to fall below the reservation wage for women and the less educated than it is for men or the more educated. In addition, when prospects improve (π increases), women and the less educated are more likely to be out of the

[10] Evidence of weaker labor market attachment of women and the less-educated can be found in Erosa et al. (2005) and Antecol and Bedard (2004).

labor market to begin with and be feeling the stronger pressures of the positive substitution effect pulling them into the labor market.

The implication of this greater sensitivity to changing labor market conditions is that for whatever asymmetric behavior exists, and for a given change in labor demand, women and the less-educated enter and exit the labor force more quickly in response to changing labor market conditions and, thus, the amplitude of the unemployment rate cycles, ceteris paribus, will be smaller for women and the less educated. In other words, when more workers exit the labor force as jobs are lost, the unemployment rate doesn't rise as high, and when more workers enter the labor force when jobs are created, the unemployment rate doesn't fall as far. Since labor *demand* is quite different for workers with different education levels, it would be difficult to confirm the smaller amplitude implied by changes in labor supply for less-educated workers by simply comparing unemployment rates cycles across education. However, Figure 3 suggests that the implication of smaller amplitude of aggregate unemployment rate cycles for women is borne out when comparing aggregate unemployment rate cycles of men and women, at least since the 1980s.

[Figure 3 here]

The second result of note from columns 2-4 in Table 2 is the uniformly larger impact of a change in the unemployment rate on labor force participation decisions when the unemployment rate has declined. In other words, the signal that local labor market conditions are improving increases the probability of participating in the labor market by a larger amount across both gender and education groups than the probability declines when the unemployment rate has risen. For example, when the unemployment rate is more than 0.6 percentage points higher than a year earlier, a one percentage point rise in the unemployment rate lowers the expected participation rate of a college-educated woman by 0.37 percentage points. But when the unemployment rate is more than 0.6 percentage points lower than a year earlier, a one percentage point decline in the unemployment rate raises the participation probability by 0.60 percentage points (almost twice the impact of an unemployment rate *increase* of the same absolute magnitude).

The finding of a larger labor force participation response to improvements in local labor market conditions relative to declines is consistent with the behavioral explanation offered for observing asymmetric movement of the unemployment rate across the business cycle. The conflicting income and substitution effect dampens the exiting of the labor market as the economy weakens, but the entrance of non-participants as the economy improves is spurred by the absence of an income effect.

C. Statistical and Practical Significance of Asymmetric Behavior

Column 5 of Table 2 provides a test of how significant the statistical difference is between assuming symmetric labor force response to changes in the economy and allowing that behavior to respond asymmetrically. The null hypothesis in equation (4) is rejected for all sub-groups except college-educated men. Even for those groups for whom the null hypothesis is rejected, there is also an issue of practical significance that must be addressed. For men (of both education levels) the estimates of δ are especially large. In fact, for men with less than a college education the response to the level of the unemployment rate is symmetric for 94.2 percent of the sample, and symmetric for 99.0 percent of the sample of college educated men (see Table 4). So for almost all unemployment comparisons, the asymmetry does not influence male participation decisions, although the level of the unemployment rate does. The asymmetry is more relevant for females, and especially for less-educated women. For women with less than a college education the response to the level of the unemployment rate is symmetric for 62.4 percent of the sample, and symmetric for 78.4 percent of the sample of college educated women.

[Table 4 here]

D. Implications of an Aging Population

A practical application of the analysis presented in this paper is to explore behavioral labor supply responses to changes in labor market conditions across a variety of demographic characteristics. The reason for doing this would be to anticipate the impact of changes in those characteristics on movement in the aggregate unemployment rate. One important change that will be taking place in the U.S. over the next twenty years is the aging of the population. According to U.S. Census population projections, the fastest growing age group in the U.S. between 2010 and 2030 are those between 65 and 85 years of age.[11] Between 2000 and 2010, the fastest growing age group will be those 45 to 64. A natural question is what sort of implication this demographic shift might have on the behavior of the unemployment rate. In this regard, the analysis described above is repeated for different age groups of men and women. For three age groups, Table 5 contains the estimates of the symmetry threshold parameter, marginal effects of a one percentage point change in the unemployment rate, and the Wald test statistic for the null hypothesis of symmetric behavior. Of course, extrapolating these results into the future requires strong assumptions about the constancy of preferences and worker demand.

[Table 5 here]

[11] U.S. Census Bureau, "U.S. Interim Projections by Age, Sex, Race, and Hispanic Origin," http://www.census.gov/ipc/www/usinterimproj/ (accessed 12 May 2006).

The attractiveness of alternative activities for the younger (e.g., schooling) and the older (e.g., retirement) groups, means that they will naturally be more marginally attached to the labor market, making their responses to changes in local labor market conditions stronger. For example, for a one percentage point increase in the unemployment rate, the expected labor force participation for women progresses from -1.64 percentage points for 18-24 year olds, to -1.12 percentage points for 25-54 year olds, to -1.27 for 55-74 year olds. For men, the responses are -1.35 for 18-24 year olds, -0.73 for 25-54 year olds, and -1.56 for 55-74 year olds.

The pattern seen earlier of greater labor market sensitivity of women aged 25-54, relative to men, is also seen among the younger age group. A one percentage point increase in the unemployment rate reduces women's expected labor force participation by 1.64 percentage points but only reduces men's by 1.35 percentage points. The difference across gender is even more dramatic when local labor market conditions are improving, because at any given time women are more likely to be out of the labor market, feeling the pull of the substitution effect as conditions improve. The relative sensitivity across gender is much more similar for the older age group. For a 0.7 percentage point or less increase in the local unemployment rate, the expected labor force participation among men declines by 1.20 percentage points and among women by 1.27 percentage points. In addition, the labor supply response is much more symmetric for older women than it is at earlier ages or than it is for men. It takes an unemployment rate change of 1.8 percentage points or more for older women to respond differently to weakening or strengthening labor market conditions.

As a whole, however, the labor supply decisions of older workers are generally more responsive to changes in local labor market conditions than mid-aged workers, suggesting that the aggregate unemployment rate (all else equal) will exhibit less variation over time as the population ages. In addition, while the symmetry threshold declines with age among men, it increases for women, and given that women are still (and will probably continue to be) the marginal worker between the two, overall asymmetry should decrease, again, ceteris paribus.

Interestingly, the direction of the asymmetry reverses for older men, compared with all other age and gender groups. The results in Table 5 suggest that the labor supply decisions of older men respond more dramatically to rising unemployment rates than declining unemployment rates. This is not consistent with the theoretical predictions presented earlier. However, since men have typically accumulated greater wealth by retirement age, because of their more extensive labor market experience, labor market exits may be more feasible at age 55 and beyond for men than for women. It may also be the case that older men have deteriorating skills or physical abilities that make continued labor market attachment less attractive at older ages. This may be less true for women as they age, given that skill or physical atrophy are typically not as critical in traditional female occupations.

V. Conclusions

Individual decisions about labor force participation (which are sensitive to the strength of the labor market) are found to respond differently to local labor market conditions, depending on whether the labor market is getting stronger, increasing employment opportunities, or whether the labor market is getting weaker, decreasing employment opportunities. This asymmetric individual labor supply response to changes in local labor market conditions is probably responsible for at least some of the asymmetry observed in the aggregate movements of the U.S. unemployment rate, although it doesn't rule out other potential contributors, such as fixed costs to labor market entry or sticky wages.

It was determined that for those between the ages of 25 and 54, behavior among women and the less-educated exhibits the greatest degree of asymmetry, whereas college-educated men respond the same to changes in labor market conditions regardless of whether conditions are improving or weakening. It was also found that the labor force participation decisions of women and the less-educated are more sensitive overall, which, ceteris paribus, likely contributes to flatter unemployment rate series for these groups. Given the results presented here, one might expect that as women continue to become more attached to the labor market, their behavior will more closely emulate that of men, with the result being greater symmetry and greater variation in the U.S. aggregate unemployment rate series. In addition, the same tendencies will occur as the percent of the population with a college degree continues to increase.

In consideration of the rapidly aging population in the U.S., the analysis was repeated for younger (18-24 year olds) and older (55-74 year olds) age groups. The results suggest that as the population ages, other things equal, the aggregate unemployment rate will likely becoming less variable and more symmetric.

This type of analysis could easily be repeated to determine how other demographic changes (e.g., race, marital status) might affect the nature of aggregate data series. Also, while the quantitative results are applicable only to the U.S. experience, the conceptual and empirical framework could be applied to individual labor supply responses in other countries as well.

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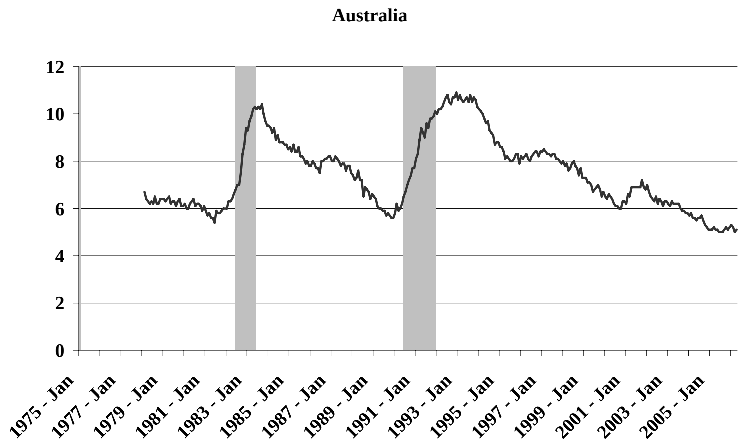
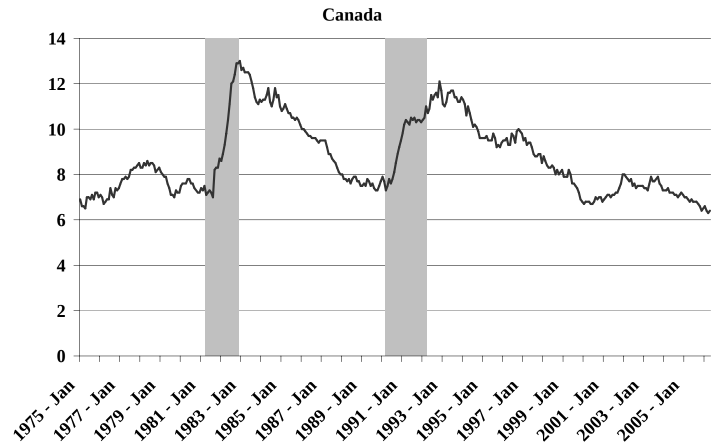
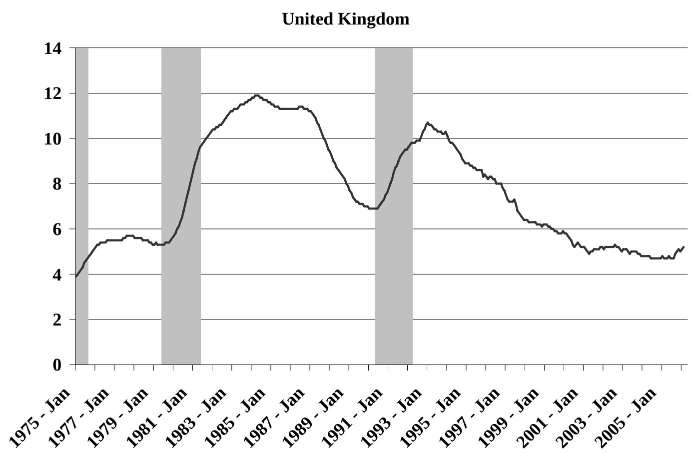
Figure 1. The Unemployment Rate 1975-2005: Australia, Canada, United Kingdom, and United States



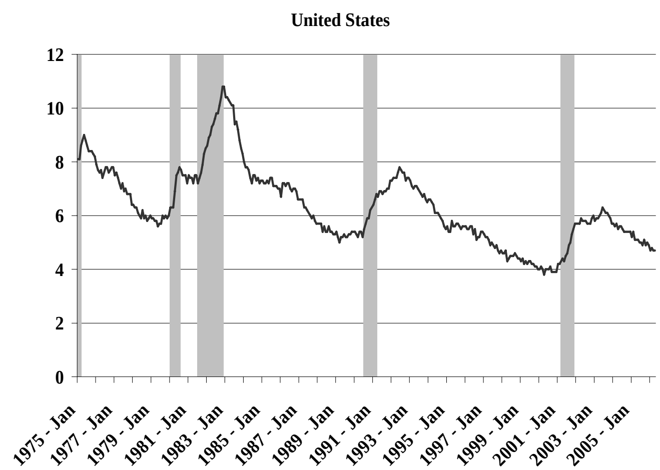
Source: Australian Bureau of Statistics/Haver Analytics



Source: Statistics Canada\Haver Analytics

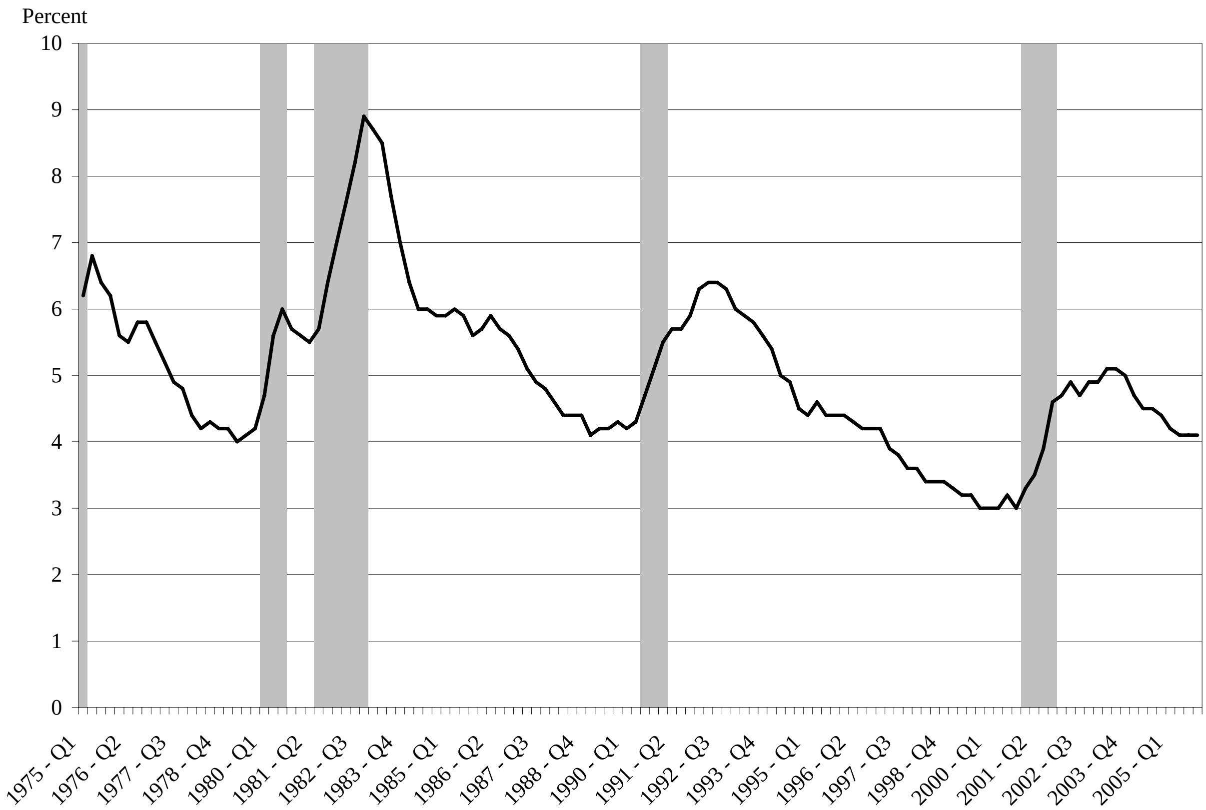


Source: Office for National Statistics\Haver



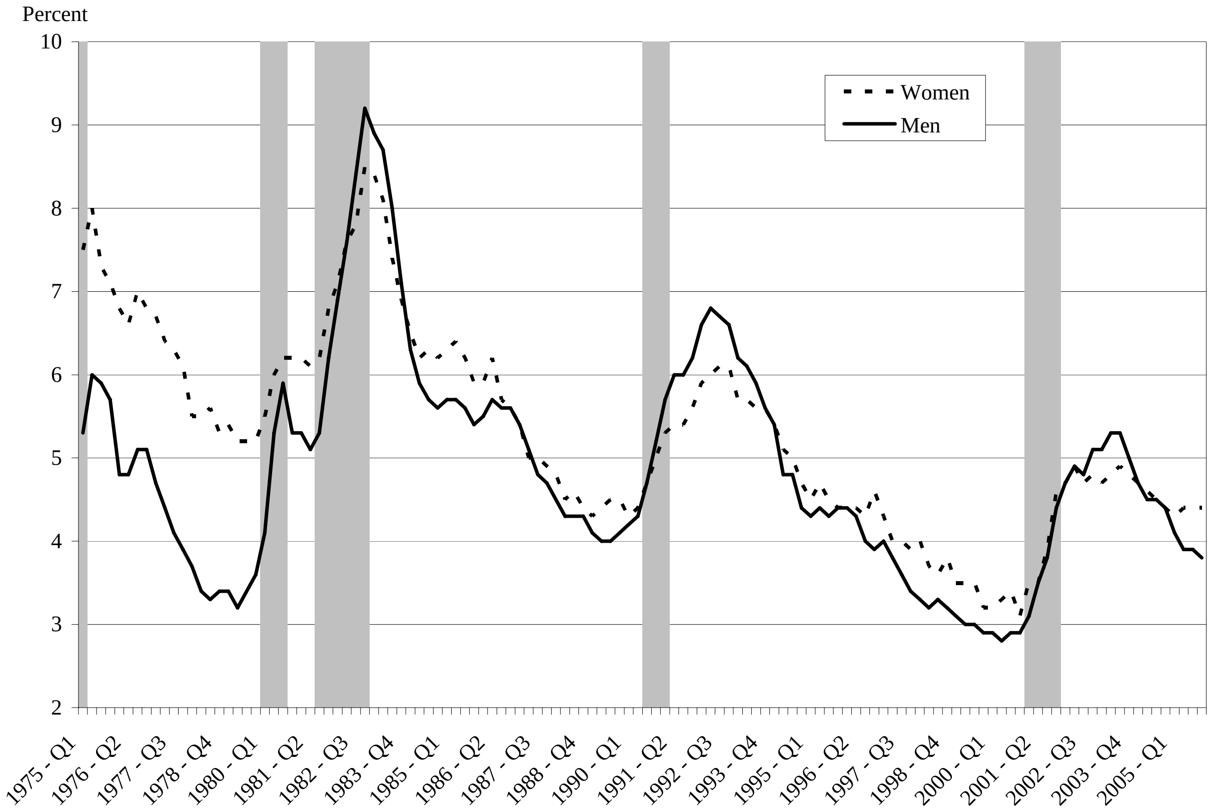
Source: Bureau of Labor Statistics/Haver

Figure 2. The U.S. Unemployment Rate 1975-2005, ages 25-54.



Source: Bureau of Labor Statistics, Current Population Survey (http://www.cps.gov).

Figure 3. The U.S. Unemployment Rate 1975-2005, men and women separately, ages 25-54.



Source: Bureau of Labor Statistics, Current Population Survey (http://www.cps.gov).

Table 1. Sample means.

	Men		Women	
Variable	Less than College	College or More	Less than College	College or More
Labor Force Participant = 1	0.890	0.959	0.738	0.844
Age	38.920	39.874	39.358	39.012
No. of Children LT 6	0.262	0.316	0.288	0.324
No. of Children 6-18	0.582	0.587	0.783	0.585
Married, spouse present = 1	0.588	0.686	0.618	0.671
Less than high school degree	0.182	0	0.154	0
High school degree	0.818	0	0.846	0
College degree or more	0	1	0	1
Non-labor income	22.044	31.214	36.229	58.808
Black = 1	0.138	0.069	0.158	0.093
Disability income	114.824	69.561	63.324	62.525
Northeast = 1	0.181	0.221	0.186	0.227
Midwest = 1	0.239	0.232	0.236	0.231
South = 1	0.364	0.327	0.370	0.338
West = 1	0.215	0.219	0.208	0.203
No. of Observations	372,494	268,156	406,250	297,112

Note: All dollar values are 2004 values. Sample is from the outgoing rotation groups of the March Current Population Survey and includes men and women 25-54 years of age.

Table 2. Estimation results, by gender and education, ages 25-54; the marginal impact on labor force participation of a one percentage point change in the local unemployment rate.

	$\hat{\delta}$ (1)	$\frac{\partial P[LFP=1]}{\partial UR^{+}}$ (2)	$\frac{\partial P[LFP=1]}{\partial UR^{0}}$ (3)	$\frac{\partial P[LFP=1]}{\partial UR^{-}}$ (4)	Wald Test $H_0 : \gamma_0 = \gamma_1 = \gamma_2$ (5)
Men					
LT College	1.8	-0.81	-0.97	-1.37	21.98 (0.00)
College or more	2.1	-0.01	-0.19	-0.51	3.50 (0.17)
Women					
LT College	0.6	-1.46	-1.74	-1.97	45.85 (0.00)
College or more	0.9	-0.37	-0.37	-0.60	8.36 (0.02)

Notes: The marginal effects are calculated for each person, then averaged across the sample. Parameter estimates from a maximum likelihood estimation of a probit model are contained in Appendix A. Column 1 is the range of unemployment rate changes (since last year) for which the response is symmetric. Columns 2-4 give the marginal sensitivity of the labor force participation decision for group *j* when the unemployment rate is, respectively, more than δ_j higher, more than δ_j lower, or within δ_j of last year. Column 5 reports the Wald test statistic, which is distributed as a chi-squared random variable with two degrees of freedom under the null hypothesis that labor force participation decisions are made symmetrically with regard to changes in the unemployment rate. The number in parentheses are the associated p-values.

Table 3. Average Number of Quarters from Peak to Trough and from Trough to Peak, U.S. Quarterly Unemployment Rate 1978-2005.

	Average Number of Quarters		
	Peak to Trough	Trough to Peak	Difference (P→T)-(T→P)
Men	20.7	10.0	10.7
Women	20.7	9.3	11.4
College or more	32.0	8.0	23
Less than High School	33.0	9.0	25

Source: Bureau of Labor Statistics, Current Population Survey (www.bls.gov). The unemployment rate movements for men and women correspond to those 25-54 years of age. Movements in the unemployment rate by education level correspond to those 25 years and older.

Table 4. Distribution of Sample.

	$\hat{\delta}$ (1)	N (2)	$UR_t < UR_{t-1} - \hat{\delta}$ (3)	$UR_{t-1} - \hat{\delta} \leq UR_t < UR_{t-1} + \hat{\delta}$ (4)	$UR_t \geq UR_{t-1} + \hat{\delta}$ (5)
Men					
Less than college degree	1.8	372,494	1.5%	94.2%	4.3%
College degree or more	2.1	268,156	0.4%	99.0%	0.6%
Women					
Less than college degree	0.6	406,250	23.5%	62.4%	14.1%
College degree or more	0.9	297,112	10.6%	78.4%	11.0%

Notes: This table presents the percent of the sample that faces a state unemployment rate that is more than d lower than last year's unemployment rate (column 3), that is within d of last year's rate (column 4), and that is greater than d higher than last year's rate (column 5).

Table 5. Estimation results, by gender and age; the marginal impact on labor force participation of a one percentage point change in the local unemployment rate.

	$\hat{\delta}$ (1)	$\frac{\partial P[LFP=1]}{\partial UR^{+}}$ (2)	$\frac{\partial P[LFP=1]}{\partial UR^{0}}$ (3)	$\frac{\partial P[LFP=1]}{\partial UR^{-}}$ (4)	Wald Test $H_0 : \gamma_0 = \gamma_1 = \gamma_2$ (5)
Men					
Ages 18-24	0.6	-1.35	-1.50	-1.74	9.39 (0.01)
Ages 25-54	1.8	-0.62	-0.73	-1.06	22.94 (0.00)
Ages 55-74	0.7	-1.56	-1.20	-1.30	6.79 (0.03)
Women					
Ages 18-24	0.2	-1.64	-1.49	-2.01	31.02 (0.00)
Ages 25-54	0.6	-1.12	-1.36	-1.56	52.61 (0.00)
Ages 55-74	1.8	-1.20	-1.27	-2.25	26.39 (0.00)

Notes: See notes to table 2. Parameter estimates from a maximum likelihood estimation of the probit model are contained in Table A2.

Table A1. Maximum likelihood probit estimates of labor force participation (equation 2), by gender and education, ages 25-54.

	Men		Women	
	Less than College	College or More	Less than College	College or More
Constant	1.350 (0.107) *	-0.256 (0.226)	-0.226 (0.078) *	0.546 (0.158) *
Age	0.010 (0.005) ^	0.110 (0.011) *	0.063 (0.004) *	0.067 (0.008) *
Age Squared	-0.000 (0.000) *	-0.001 (0.000) *	-0.001 (0.000) *	-0.001 (0.000) *
No. of Children LT 6	0.026 (0.009) *	0.091 (0.020) *	-0.346 (0.005) *	-0.434 (0.009) *
No. of Children 6-18	0.045 (0.005) *	0.108 (0.013)*	-0.064 (0.003) *	-0.136 (0.006) *
Married, spouse present = 1	0.578 (0.010) *	0.470 (0.023) *	-0.057 (0.007) *	-0.101 (0.015) *
High school degree	0.483 (0.010) *	--	0.669 (0.008) *	--
Non-labor income	-0.004 (0.000) *	-0.002 (0.000) *	-0.002 (0.000) *	-0.003 (0.000) *
Black = 1	-0.365 (0.012) *	-0.253 (0.031) *	-0.014 (0.009)	0.171 (0.023) *
Disability income	-0.000 (0.000) *	-0.000 (0.000) *	-0.000 (0.000) *	-0.000 (0.000) *
Midwest = 1	0.070 (0.013) *	0.093 (0.026) *	0.101 (0.009) *	0.099 (0.016) *
South = 1	0.012 (0.012)	-0.000 (0.024)	-0.029 (0.008) *	-0.046 (0.015) *
West = 1	0.094 (0.013) *	-0.019 (0.026)	0.040 (0.009) *	-0.067 (0.017) *
UR_i^+	-0.048 (0.006) *	-0.029 (0.015) ^	-0.048 (0.003) *	-0.017 (0.007) +
UR_i^0	-0.058 (0.004) *	-0.022 (0.009)+	-0.058 (0.003) *	-0.017 (0.006) *
UR_i^-	-0.081 (0.007) *	-0.062 (0.024) *	-0.065 (0.003) *	-0.028 (0.007) *
No. of Observations	268,156	104,338	297,112	109,138
$\hat{\delta}$	1.8	2.1	0.6	0.9
Log-likelihood	-82,605.15	-16,414.43	-159,379.70	-42,432.96

Note: All dollar values are 2004 values. All estimations include a set of year fixed-effects. * indicates significance at the one percent level, + indicates significance at the five percent level and ^ indicates significance at the ten percent level.

Table A2. Maximum likelihood probit estimates of the labor force participation (equation 2) by gender and age.

	Men			Women		
	Ages 18-24	Ages 25-54	Ages 55-74	Ages 18-24	Ages 25-54	Ages 55-74
Constant	-3.543 (0.799)*	0.875 (0.096)*	14.580 (0.673)*	-0.326 (0.722)	-0.133 (0.069)^	7.873 (0.625)*
Age	0.309 (0.077)*	0.029 (0.005)*	-0.351 (0.021)*	0.016 (0.069)	0.056 (0.003)*	-0.150 (0.020)*
Age Squared	-0.004 (0.002)+	-0.001 (0.000)*	0.002 (0.000)*	0.002 (0.002)	-0.001 (0.000)*	0.000 (0.000)+
No. of Children LT 6	0.061 (0.019)*	0.046 (0.008)*	0.060 (0.039)	-0.245 (0.009)*	-0.374 (0.004)*	-0.104 (0.035)*
No. of Children 6-18	-0.029 (0.008)*	0.058 (0.005)*	0.125 (0.013)*	-0.011 (0.008)	-0.074 (0.003)*	-0.054 (0.016)*
Married, spouse present = 1	0.522 (0.030)*	0.556 (0.009)*	0.324 (0.012)*	-0.197 (0.016)*	-0.060 (0.006)*	-0.237 (0.009)*
High school degree	0.119 (0.015)*	0.480 (0.010)*	0.299 (0.012)*	0.394 (0.014)*	0.675 (0.008)*	0.470 (0.011)*
GE College	0.175 (0.033)*	0.865 (0.012)*	0.679 (0.014)*	0.768 (0.028)*	1.035 (0.009)*	0.743 (0.015)*
Non-labor income	-0.003 (0.000)*	-0.003 (0.000)*	-0.003 (0.000)*	-0.002 (0.000)*	-0.003 (0.000)*	-0.001 (0.000)*
Black=1	-0.385 (0.018)*	-0.352 (0.011)*	-0.179 (0.016)*	-0.187 (0.016)*	0.009 (0.008)	-0.056 (0.014)*
Disability income	-0.000 (0.000)*	-0.000 (0.000)*	-0.000 (0.000)*	-0.000 (0.000)^	-0.000 (0.000)*	-0.000 (0.000)*
Midwest = 1	0.251 (0.018)*	0.073 (0.011)*	-0.007 (0.014)	0.215 (0.017)*	0.097 (0.008)*	0.059 (0.012)*
South = 1	0.128 (0.017)*	0.011 (0.010)	-0.065 (0.012)*	0.059 (0.016)*	-0.035 (0.007)*	-0.074 (0.011)*
West = 1	0.235 (0.019)*	0.075 (0.012)*	-0.026 (0.014)^	0.125 (0.017)*	0.020 (0.008)+	-0.038 (0.013)*
URP	-0.047 (0.007)*	-0.043 (0.005)*	-0.050 (0.005)*	-0.049 (0.006)*	-0.040 (0.003)*	-0.040 (0.006)*
URM	-0.060 (0.007)*	-0.074 (0.007)*	-0.039 (0.005)*	-0.061 (0.006)*	-0.056 (0.003)*	-0.074 (0.008)*
UR0	-0.052 (0.006)*	-0.051 (0.004)*	-0.042 (0.005)*	-0.045 (0.006)*	-0.049 (0.003)*	-0.042 (0.004)*
No. of Observations	76499	372494	123080	80551	406250	141449
$\hat{\delta}$	0.6	1.8	0.7	0.2	0.6	1.8
Log-likelihood	-39190.88	-99448.72	-67078.066	-46957.42	-202029.07	-75607.28

Note: All dollar values are 2004 values. All estimations include a set of year fixed-effects. * indicates significance at the one percent level, + indicates significance at the five percent level and ^ indicates significance at the ten percent level.