Uncertainty and the Timing of Automobile Purchases*

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Abstract

Previous work by has shown that lumpy investment models well characterize individual expenditures on durables, in particular automobiles. In that class of models, a higher level of uncertainty generally implies that the household should tolerate a larger imbalance between the actual stock of the durable and the target stock before closing it by buying and/or selling. Then, if the level of uncertainty increases, aggregate expenditures should temporarily fall. This hypothesis is tested by estimating an aggregate lumpy investment model on automobile expenditure data, using stock market volatility to proxy uncertainty. The result is that expenditures fall significantly as stock market volatility increases.

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I. Introduction

It is a well-documented fact that individual expenditures on durables differ from the predictions of a standard permanent income model. In particular, purchases are lumpy and infrequent. Most of the time, households are inactive and let their stocks of durables depreciate (see, for example, Bernanke (1984)). Bar-Ilan and Blinder (1992) also show that many stochastic properties of the *aggregate* expenditure on durables are more in line with the aggregate implications of lumpy investment models than with permanent income representative agent models. An example of this is that, while *average expenditures per purchase* are well predicted by the permanent income hypothesis, the *number* of purchases is much more volatile and may have a short-run elasticity with respect to permanent income that is several times higher than unity. Recently, several successful attempts have been made to explain these features of data within a model with households facing a cost of adjusting their durable stock. Notably, Lam (1991) and Eberly (1994) estimate models where households optimally let their stock of durables deviate from a target stock within some inaction range (often called (*S,s*) band).

From the theoretical literature, it is also a well-known fact that the level of uncertainty strongly affects behavior when investments are irreversible or costly to reverse. Higher volatility of the underlying stochastic variable, for example permanent income, implies a larger "option value" of postponing investment (see for example, McDonald and Siegel, 1986, or Pindyck, 1991, 1994), which widens the individuals' inaction range (Bentolila and Bertola, 1990 and Hassler, 1996).

The purpose of this paper is to test the aggregate implication of the sensitivity of the option value to postpone durable purchases to shifts in uncertainty. More specifically, does an increase in uncertainty lead to a fall in automobile expenditures caused by simultaneous decisions to postpone purchases? To analyze this question, I construct a simple aggregate durable consumption model where households are assumed to follow lumpy investment behavior.

Individual durable stocks are adjusted infrequently and with a probability that increases smoothly with the distance between the actual stock and a stochastically moving target. Such behavior has been derived from first principles in Caballero and Engel (1999), while here, it is simply assumed. In addition, to provide a link between the level of uncertainty and expenditures, the probability of adjustment is allowed to depend on the level of uncertainty.

The implications of a concerted decision to delay durable purchases may arguably be dramatic. Romer (1990) suggests that the stock market collapse of 1929 caused a radical increase in uncertainty, which led consumers to delay their purchases of durables. The consequent fall in aggregate demand was sufficiently large to constitute a critical factor behind the Great Depression. Nevertheless, empirical evidence on the times-series relation between risk and durables consumption is scant. A notable exception is Carrol and Dunn (1997), who solve a model of house purchases where unemployment risk fluctuates over time. Although the mechanism is different from the one in Hassler (1996),[1] a key result is qualitatively similar; as uncertainty goes up, households postpone purchases by accepting a larger deviation between the current durable stock and the target.

Turning to the cross-sectional evidence, Eberly (1994) reports that households facing higher income risk choose wider inaction ranges. However, such permanent cross-section differences in risk may not be of any substantial importance for the level of aggregate expenditures, since higher income risk also means that the imbalance between the target and the actual stock moves more rapidly within the inaction range. The more rapid movement of the stock imbalance provides a positive effect on expenditures that counteracts the widening of the inaction range. In the long run, the two effects may cancel (see, Bertola and Caballero, 1990). In the short run, on the other

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[1] In Hassler (1996), the option value of postponing purchases increases in the level of uncertainty. In Carrol and Dunn (1997), on the other hand, an increase in uncertainty increases

hand, they are not likely to cancel; if the inaction range widens simultaneously for a large number of individuals, a mass of individuals who were just about to adjust their durable stock will now decide to postpone this action. The opposite will occur if the inaction range shrinks. Orchestrated shifts in the width of the inaction range, driven by variations in uncertainty, should then lead to large swings in expenditures.

An important issue in the empirical implementation of the model in this paper is how to measure the aggregate component of individual uncertainty. I have chosen to use a measure based on stock market volatility. The relevance of this measure is far from obvious and is discussed in the concluding remarks. In short, I assume the stock market to stochastically shift between two unobservable states – one with high stock market volatility and one with low. Following the method devised by Hamilton (1988, 1989), I estimate the probability of the US economy being in the high-volatility state for each month during the period 1959 - 1992. This probability is then used as a measure of uncertainty in the estimation of the consumption model. The parameters of the consumption model are estimated on monthly data on U.S. aggregate expenditures on car purchases. Non-durables purchases and relative prices are used to construct a series of aggregate target stock shocks. The estimated parameters imply a large and fairly persistent reduction in the number of individuals adjusting after a shift to the high-volatility state. When the economy shifts back to the low-volatility state, expenditures over-shoot their long run level.

The layout of the paper is as follows. In section 2, I analyze the time series variations in stock market volatility, and in Section 3, I construct and estimate the durable consumption model. Finally, I make some concluding remarks in section 4.

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the marginal value of liquid assets, functioning as buffer stocks in case of unemployment, which causes households to postpone house purchases.

II. Risk shifts

A Stochastic Risk-State Model

The purpose of this section is to construct an index of the aggregate level of uncertainty. Since the focus of the paper is on sudden discrete shifts in the probability of adjusting durable stock imbalances, it is natural to use a regime-switching model to characterize the financial market. For simplicity, I assume that the economy switches stochastically between *two* unobservable states, denoted $s_t \in \{0,1\}$, which determine the law of motion for the stock market index, denoted w_t,

$$\Delta \ln w_t = \mu_0 + (\mu_1 - \mu_0)s_t + \mu_2 \Delta s_t + (\lambda_0 + (\lambda_1 - \lambda_0)s_t)\vartheta_t, \qquad (1)$$

where Δ is the first difference operator and ϑ is a sequence of i.i.d. normal innovations.

The first two terms in (1) represent the drift of w_t in the two states and the third term implies that a state shift from 0 to 1 (1 to 0) causes w_t to shift by μ_2 ($-\mu_2$).[2] The standard deviation of innovations in the absence of state shifts is λ_0 in state 0 and λ_1 in state 1.

The state is assumed to follow a first-order Markov process with a transition matrix,

$$\begin{bmatrix} 1-\gamma_0 & \gamma_0 \\ \gamma_1 & 1-\gamma_1 \end{bmatrix}. \qquad (2)$$

If the current state is s, the probability of a state shift is γ_s. Even though the value of the current state is unobserved, the sequence $\{w_\tau\}_1^t$ provides sufficient information to estimate the parameters of the model and calculate the probabilities $P(s_t = S_t \,|\, \{W\}_1^t)$, which is done following the method described in Hamilton (1988, 1989).

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[2] Such a shift could, for example, be motivated by a change in the interest rate used to discount future income.

State Estimation Results

The parameters of the risk-state model are estimated using 396 monthly observations on the S&P 500 nominal[3] stock market index, covering the period from January 1959 to January 1992. These estimates, with estimated standard errors, are given in *Table* 1,[4] where we find clear evidence of periods of higher financial volatility. The point estimate is that the standard deviation of the S&P 500 index is increased by 1.49 percentage points from 1.81 to 3.30% per month in state 1. The relative increase in volatility exceeds 80% and is strongly significant; the z-value for a null hypothesis of equal risk in both states is 4.14.

The probability of a state shift is fairly low in both states, implying a persistent risk level. We also see that the probability of a state switch is higher in state 1, which implies that the risk due to the possibility of state shifts is higher in state 1 than in state 0. It also implies that, on average, periods of high risk are shorter than periods of low risk. The expected duration of a state is approximately $1/\gamma_0 \approx 28.3$ months in state 0 while it is $1/\gamma_1 \approx 7.4$ months in state 1. The unconditional probability of the high-risk state is 21%.

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[3] In principle, real returns should be used. On such a high frequency as monthly data, however, deflating returns appears to add, rather than reduce, the amount of noise. This could be due to miss-measurements and/or changes in taxes.

[4] The covariance matrix of the parameters is estimated as the inverse of the estimated Hessian of the likelihood function.

Table 1 State Model Parameters

	S&P 500		
	Estimated value %/month	Asymptotic St. Dev.	t-value ≠ from 0
γ_0	3.53	4.67	0.76
γ_1	13.53	1.39	9.73
μ_0	0.91	0.18	4.94
$(\mu_1-\mu_0)$	-1.91	0.71	-2.71
μ_2	-5.24	1.21	-4.35
λ_0	1.81	0.10	17.69
$(\lambda_1-\lambda_0)$	1.49	0.36	4.14

Using the estimated parameters, I calculate the series of conditional probabilities of the economy being in the high-risk state and plot these in *Figure* 1. For 105 of the 396 observations, the conditional probability of state 1 is higher than the unconditional probability, which is depicted as the horizontal line in the graph.

In Figure 1, we see that the longest periods of high probabilities of the high-risk state occur around the years 1970, 1974 and 1982. We also have periods of high probabilities of the high-risk state in 1962, 1966, 1980, 1987 and 1990; the latter two apparently due to the stock market crashes. However, the probability of the low-risk state recovered quickly after the two market crashes.

Figure 1 indicates a relationship between high-risk periods and recessions. Such a relationship is also reported in the finance literature. Schwert (1989) shows that volatility has generally been higher in months classified as recessions by NBER. Between 1859 and 1987, the standard deviation of monthly stock returns was 61 % higher during recessions and 68% higher between 1953 and 1987.

Figure 1 Probability of High Risk State, S&P 500

III. An aggregated (*S,s*)-model

The model derived in this section draws on the work by Caballero and Engel (1993) and Hassler (1996). Each individual consumer sets a target level for her durable stock, which evolves stochastically over time, driven by idiosyncratic and aggregate shocks to permanent income and by changes in the relative price of durables. The actual durable stock continuously depreciates at the rate δ. Due to adjustment costs, it is not optimal to continuously compensate for the resulting imbalance between the target and the actual stock. Instead, the individual consumer is inactive most of the time and lets her stock of durables deviate from the target without adjusting. Eventually, a discrete adjustment (a car purchase) is undertaken and the imbalance between the actual and the target stock is eliminated. These are standard assumptions for (*S,s*) models, while the following two assumptions, on the other hand, are less standard.

First, in standard (*S,s*)-models, the agent is inactive with probability one until an end-point of the inaction range is reached, when she adjusts with probability one. Following Caballero and Engel (1993), I instead assume the probability of adjustment to be increasing smoothly in the stock imbalance, defined as the square of the log difference between the actual and the target stock of the durable.[5] This feature is captured by a hazard function, generating a probability of adjustment increasing in the stock imbalance. In this paper, I postulate a simple functional form for the hazard function. Caballero and Engel (1999) instead derive an increasing function from first principles under the assumption that each agent draws an idiosyncratic and stochastic adjustment cost each period. Contingent on the realization of this adjustment cost and the stock imbalance,

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[5] The standard assumption of zero adjustment probability within the inaction range is too strong to be used in empirical implementations and may cause discontinuities in the likelihood function.

the agent decides whether to adjust or not. By specifying the distribution of the adjustment cost, the probability of adjustment, as a function of the stock imbalance, can be calculated.

Second, as discussed in the introduction, it can be shown that the optimal response to a shift in risk is to allow wider inaction bands. In the current setting, increases in the inaction band are modeled by including the current risk level, or more specifically, the probability of the high-risk state, in the hazard function, for the purpose of estimating the effect of risk on the hazard function and quantifying the implications on aggregate expenditures.

The model

The model consists of a continuum of consumers, each with a stock of durables $K_{t,i}$ with a target level $K^*_{t,i}$. The target stock at *t* is defined as the stock of durables the consumer would choose if deciding to make an adjustment at *t*. Furthermore, define the individual stock imbalance as

$$z_{t,i} = \ln \frac{K_{t,i}}{K^*_{t,i}}. \tag{3}$$

Now, let $f(z,t)$ denote the cross section density of *z* at the end of period *t.* In each period, $f(z,t)$ is affected by idiosyncratic and aggregate shocks, durable stock depreciation, and adjustments undertaken by individual households, described in the following four steps.

Step 1. Idiosyncratic Shock

The idiosyncratic shock to the log of each individual's permanent income is drawn from a log normal distribution with a standard deviation denoted σ_v. Assuming that the target stock satisfies the permanent income hypothesis, the wealth shock moves the target proportionally, which incurs a change in the distribution of stock imbalances given by

$$f^1(z,t) = \int_{-\infty}^{\infty} f(x,t-1) N(z-x,\sigma_v)\,dx\,, \tag{4}$$

where *N* is the normal density.

Step 2. Aggregate Shock

The aggregate shock, to be estimated later, is denoted ε_t, and shifts the target stock of durables proportionally for each individual, implying

$$f^2(z,t) = f^1(z+\varepsilon_t, t). \tag{5}$$

Step 3. Depreciation

The durables stock depreciates at the rate δ, causing an equivalent fall in z for everyone:

$$f^3(z,t) = f^2(z+\delta, t). \tag{6}$$

Step 4. Adjustments

Finally, individuals decide whether to adjust their stocks or not, as represented by the hazard function, thereby changing the distribution of z as follows:

$$f(z,t) = \begin{cases} (1-h(z,p_t))f^3(z,t), & \text{if } \forall z \neq 0, \\ f^3(z,t) + \int_{-\infty}^{\infty} h(x,p_t) f^3(x,t)dx, & \text{if } z = 0, \end{cases} \tag{7}$$

where p_t are the probabilities of the high-risk state calculated in Section II.[6] The hypothesis to be tested is that $h_p(z,p_t)<0$, i.e., that the adjustment probability for a given stock imbalance decreases with the probability of the economy being in the high-risk state.

By approximating $z_{t,i} \approx (K_{t,i} - K^*_{t,i})/K_{t,i}$ and using (7), we may calculate the amount of net purchases predicted by the model

$$\hat{Y}_t = \int_{-\infty}^{\infty} h(z,p_t)(-z) f^3(z,t)\overline{K}_{t,z} dz, \tag{8}$$

[6] It may be noted that f (but not f^1, f^2 and f^3) has a mass point at zero. This will be of no relevance for the empirical implementation, since z will then be discrete.

where $\overline{K}_{t,z}$ is the average durable stock of agents with a relative deviation z at time t. Assume further that $\overline{K}_{t,z}$ is (approximately) independent of z.[7] We may then write (approximately)

$$\begin{aligned} \hat{Y}_t &= \int_{-\infty}^{\infty} f^3(z,t)\overline{K}_{t,z}dz \int_{-\infty}^{\infty} h(z,p_t)(-z) f^3(z,t)dz \\ &= K_t \int_{-\infty}^{\infty} h(z,p_t) f^3(z,t)(-z)dz, \end{aligned} \tag{9}$$

where K_t is the aggregate stock of durables in the economy.

Before estimating the model, the series of aggregate shocks must be computed. For this purpose, I follow Caballero (1993) by assuming that the log of the target stock of durables (k*) is a linear function of the log of the consumption of non-durables (c) and the relative price of durables (π);

$$k^* = [1 \quad c \quad \pi]\phi, \tag{10}$$

where ϕ is a parameter vector to be estimated.

To motivate (10), consider a standard model without adjustment costs, where consumers optimally choose constant expenditure shares on non-durables and durables. The frictionless choice of the durable stock could then be written $k = \phi_1 + c - \pi$, where ϕ_1 is the log of the ratio of the two expenditure shares. Furthermore, assume that the target stock with adjustment costs is a constant ratio of the frictionless stock, which is reasonable if transaction costs are proportional to the cost of the durable.[8] Then, the specification in (10) is valid and implies, in particular, that we use the consumption of non-durables to control for changes in permanent income and precautionary savings associated with shifts in risk.[9] It should be noted that (10) is assumed to be

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[7] This amounts to assuming that knowledge of the durable stock of an individual conveys no (non-negligible) information about her position in the *(S,s)* band.

[8] If transaction costs where fixed in absolute terms, we would expect the width of the inaction ranges and the difference between the target stocks and the friction-less stocks to be inversely related to household wealth, which would invalidate the present analysis.

[9] Needless to say, this may be an imperfect control.

independent of the risk-state. The motivation for this is the finding in Hassler (1996) that the change in the target stock associated with a risk shift is small compared to the change in the width of the inaction range, unless high risk periods are expected to be (almost) permanent. In other words, I assume that the effect of a temporary increase in risk is that households postpone their purchases of durables, rather than buying cheaper ones.

Now, use the definition of the stock imbalance,

$$k_t \equiv k_t^* + z_t = [1 \quad c \quad \pi]\phi + z_t. \tag{11}$$

From the model, we know that z is a stationary variable. Under the assumption that k, c and π are integrated of order 1, (11) thus defines a cointegrating relationship.[10] I estimate ϕ by using the dynamic OLS method described by Stock and Watson (1993).[11] The aggregate shocks are then estimated as

$$\hat{\varepsilon}_t = \hat{k}_t^* - \hat{k}_{t-1}^* = (1-L)[1 \quad c_t \quad \pi_t]\hat{\phi}, \tag{12}$$

where L is the lag operator. The series k_t is constructed by integrating purchases using the depreciation rate δ.

Finally, the hazard function needs to be specified. I build on the inverted normal, used by Caballero and Engel (1999). In addition, as noted above, I allow the hazard to depend on the risk state. Thus, I set

$$h(z, p_t) = 1 - e^{-(\beta_0 - \beta_1 p_t) - (\beta_2 z)^2}. \tag{13}$$

[10] To test non-stationarity, I use the augmented Dickey-Fuller test, including lags up to the last significant at 5%. I cannot reject non-stationarity on 10% significance regardless of whether intercept and/or time trends are included.

[11] The method is to include first differences of the RHS variables at some number of leads and lags as regressors. I choose to use 4 leads and 20 lags.

As we see, β_0 captures the part of the hazard that is independent of z and p. If β_0>0, and the other parameters are zero, the model degenerates to linearity In contrast, if β_2 >0, the hazard increases in the stock imbalance. β_1 captures the effect of risk shift on the hazard. If β_1>0, an increase in risk reduces the probability of adjustment for all stock imbalances.[12] An alternative specification, where an increase in risk is allowed to affect the curvature of the hazard so as to reduce the probability of adjustment more for large stock imbalances was also tried with very similar results.[13]

Estimation

The distribution of z is discretized in 1201 equal steps between –3 and 3. At z_1 and z_{1201}, the hazard is set to unity.[14] In between, it is given by (13) with β_1 set to zero. Whenever depreciation and shocks are non-integer multiples of z_n-z_{n-1}, linear interpolations are used. Finally, I constructed the series of durables stocks by integrating purchases, taking depreciation into account. The starting value of the durables stock was set to exp(k_0^*), using relation (10). The last issue is how to obtain $f(z,0)$. Since the true ergodic distribution of the model is difficult to compute, I have instead used a risk free counterpart. To finds this, I iterated on steps 1 through 4 described in section 0, setting ε and p to their sample averages, until f(.) converged.

Due to computational resource restrictions, it has been necessary to limit the number of parameters to estimate. For the idiosyncratic risk, I used the estimate in MaCurdy (1982).[15] Using

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[12] A quadratic specification yielded very similar results.

[13] In this case the hazard was specified as $h(z,p_t)=\beta_0+((\beta_1-\beta_2 p_t)z)^2$. Results available upon request. See also the final section for a discussion on this.

[14] As we will see, the density f(.) will be sufficiently concentrated around zero to make the probability of reaching z_1 or z_{1201} negligible.

[15] The exact characteristics of this idiosyncratic uncertainty may be of importance for the results which warrants further research.

the PSID panel data set, he estimates the stochastic process for the logarithm of yearly household earnings as $\Delta y_t = \upsilon_t - 0.411\upsilon_{t-1} - 0.106\upsilon_{t-2}$ with $\sigma_\upsilon^2 = 0.054$. This implies a monthly standard deviation of permanent income equal to $(1-0.411-0.106)\sigma_\upsilon/\sqrt{12} \approx 0.0324$, which was used as the level of idiosyncratic risk in (4). The depreciation rate, δ, was set to 15% per year.

Starting from $f(z,0)$, ε_1 and k_1, steps 1 through 4 where taken, producing $\hat{Y}_1$ and $f(z,1)$. Repeating these steps until the last observation at time *T,* provided the series $\{\hat{Y}\}_1^T$.

The remaining parameters where chosen to minimize the model prediction error (net of constants). More precisely, by assuming the prediction error to be normal, we may write the negative of the concentrated log likelihood function net of constants as

$$L = \frac{T-36}{2} \ln \sum\nolimits_{37}^{T} \frac{1}{T-36} \left(\frac{Y_t - \mu_y - \left(\hat{Y}_t - \mu_{\hat{y}}\right)}{K_t} \right)^2, \tag{14}$$

where the term in brackets is the prediction error and where μ_y and $\mu_{\hat{y}}$ denote the sample averages of Y and $\hat{Y}$.[16] In order to reduce the impact of the choice of initial distribution, I excluded the first 36 observations from the calculation of L.[17]. The covariance matrix was calculated as the Hessian of L. Details of the estimation procedure are available by request.

Results

The data used in the estimation are all from Citibase. I use monthly time series on prices and on aggregate expenditures on cars and non-durables, for the period 1959:01 to 1992:01.

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[16] A much more sophisticated error structure is used in Caballero and Engel (1999).
[17] Excluding 72 observations produced very similar results.

The estimated parameters are shown in *Table* 2. We find that they are estimated with fairly good precision. In particular, the parameter associated with the risk state, β_1, is positive and significant. This implies that the adjustment probability for a given stock imbalance is lower when the risky state is more likely. The average distributions $\bar{f}(z) \equiv (T-36)^{-1}\sum_{t=37}^{T} f(z,t)$ (scaled by a factor 10) together with estimated hazards in the two risk states are shown in *Figure* 2.[18] The two U-shaped curves are the hazard functions, with the hazard in the high-risk state being the lower one. The curve with a peak at zero is the average distribution, which is heavily skewed to the left due to depreciation, implying that upgrading is much more frequent than downgrading.

An indication of the width of the inaction ranges can be obtained by calculating the mean adjustment in the two states, given by

$$\frac{\sum_{n=1}^{1201} h(z_n,p)(-z_n)\bar{f}(z_n)}{\sum_{n=1}^{1201} h(z_n,p)\bar{f}(z_n)}. \tag{15}$$

for $p = 0$ and 1. These numbers are 54.94% and 56.67%, which indicates inaction ranges of comparable magnitudes as those that where found in Eberly (1994), who estimate that households adjust their automobiles when the stock imbalance is around 50%.

[18] The spike at $\bar{f}(0)$ is outside the figures. Its value is 0.0368.

Table 2 Parameter Estimates

	parameter * 100 (t-stat)
β_0	3.67 (44.9)
β_1	0.77 (6.19)
β_2	10.81 (3.42)
$L(\cdot \mid \alpha_0, \alpha_1, \delta)$	-1907.3

The fall in expenditures associated with a shift from low to high risk depends on the current distribution of stock imbalances. To express the magnitude of the fall, I compute the amount of expenditures that would result if the distribution of stock imbalances was $\bar{f}(z)$ in the two states. The result is that expenditures fall by 15.67%. The reduction is accounted for by a reduction in the number of adjusters, which falls by 18.24%, while the average adjustment, as already noted increases slightly.

Figure 2 Average Distribution of Stock Imbalances and Hazard Functions

The fall in expenditures after a risk increase is persistent; if the economy remains in the high-risk state for one year, expenditures are 8.83% lower than they would have been in the low-risk state. On the other hand, when the economy returns to the low-risk state, expenditures overshoot their long-run level. If the return to the low-risk occurs after one year, expenditures 7.32% percent higher than if the economy had remained in the low-risk state all along. This is an example of what is sometimes phrased "pent-up demand", discussed in, for example, Carrol and Dunn (1997), and is due to the fact that a period of high risk and low adjustment hazards leads to a higher than average concentration of households with large stock imbalances (old cars). As the risk level falls, a large share of these households will adjust the imbalance (buying a car). In the long run, however, expenditures are not sensitive to the width of the inaction ranges. If the economy stays for ever in the high-risk state, expenditures are, in fact, slightly higher than in a permanent low-risk state (0.5%).[19]

IV. Concluding remarks

The results in the previous section support the hypothesis that variations in aggregate uncertainty may be of importance for the volatility of expenditures on durables, and that this can be interpreted as shifts in the inaction range of households in a model with adjustment costs. The sensitivity of expenditures to the level of uncertainty was found to be large in the short and medium run but approximately zero in the long run. In line with the evidence in Bar-Ilan and Blinder (1992), the volatility is to a large extent due to variations in the number of agents who adjust their automobile holdings.

Many questions are left unanswered in this paper. It is certainly not clear that shocks to individual target stocks are measured appropriately by using non-durables consumption and relative prices. Since stock market volatility is counter-cyclical, a shift to higher volatility is likely to coincide with a negative revision of permanent income and a fall in the target stock of durables. The resulting fall in expenditures could, in the model presented in this paper mistakenly be attributed to a shift in uncertainty, if target stock shift is inappropriately calculated. Temporary fluctuations in the relative price of durables could also create a "speculative" motive for purchases, which might also be correlated with financial volatility. Similarly, non-separability between the demand for durables and non-durables might be of importance.

Accepting that shifts in uncertainty affect expenditures on durables does nevertheless not mean that such shifts could be detected at the financial markets. The typical household does not own

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[19] Note, however, that behavior depends on the expected duration of risk shifts (Hassler, 1996).

much public stock and a large portion of its wealth consists of expected future labor income.[20] Is there then any reason to believe that shifts in financial volatility can capture shifts in uncertainty as perceived by the household? This is certainly an open issue, but it does not seem implausible that shifts in the volatility of the stock market are sufficiently good indicators of shifts in household risk. Fluctuations in risk may be due to variations in the volatility of a stochastic trend common both to firm values and household wealth, for example technology shocks. In this case, the variances of household wealth and the stock market, as well as their levels, are positively correlated. There is also evidence of a positive relationship between financial and macroeconomic volatility. Schwert (1989) reports that financial volatility was a significant factor for the prediction of future volatility in industrial production during the period 1891-1987.

A positive correlation between the stock market index and household wealth is, however, not necessary for their volatilities to be positively correlated. Another potential source of volatility is variations in the labor share of total income. Such variations would tend to give negative correlations between the value of firms and human capital. Nevertheless, increased volatility in the labor share will increase the volatility of the stock market as well as of human capital. In any case, attempts to use other measures of uncertainty, for example, unemployment, as in Carrol and Dunn (1997), are certainly warranted.

These and other issues provide a solid motivation for further research on the empirical relevance of the lumpy investment model for expenditures on durables. An important issue is whether the reduction in expenditures associated with an increase in risk is due to a uniform reduction in the probability of adjustment for all stock imbalances (as assumed in this paper) or if the adjustment probability falls more for large stock imbalances than for small. In the former case, aggregate demand falls due to a reduction in the number of adjustments, while in the latter, also average

[20] See Roll (1977) for an early discussion on the implications of this.

adjustment sizes fall when risk increases. In a working paper version of this paper (Hassler, 2000), I estimated a specification of the model in line with the latter hypothesis. That specification yielded results very similar to the ones presented above, except that the fall in purchases at risk shifts was largely due to reductions in average adjustments rather than the number of adjusters. Although the evidence reported in Bar-Ilan and Blinder (1992) seems to point in the direction of a specification where it is the number of adjustments that varies over time, it would be of interest to test the competing specification directly, i.e., on data containing the aggregate number of adjusters in addition to aggregate expenditures. Turning instead to micro-models, it would be of interest to extend a model like the one in Eberly (1994) to allow stochastic fluctuations in the level of uncertainty, provided that high frequency data on individual levels of uncertainty becomes available.

Despite all unanswered questions, a line of research taking the aggregate implications of microeconomic lumpy investment behavior seriously seems feasible and of potential importance for understanding the particular relationships between variations in risk and purchases of durables.

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Figure 1

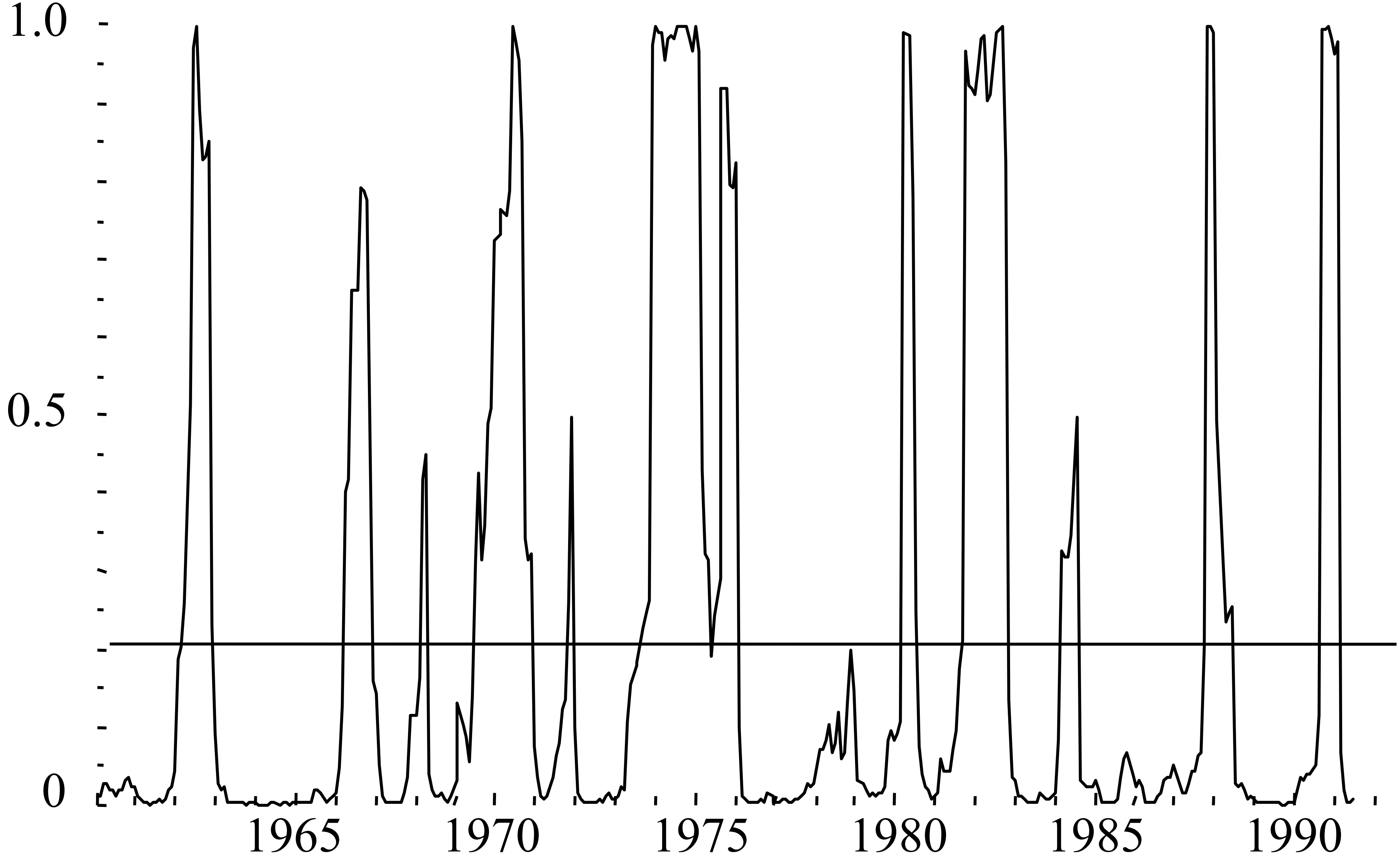

Figure 2