

Asset Pricing Program Review: Liquidity, Trading and Asset Prices

John H. Cochrane*

1 Introduction

NBER Asset Pricing Program members write 90 working papers in a typical year, and 18 papers per year are presented in the program meetings and summer institute. These papers are spread over an astonishing range of topic areas. Naming the papers written in the four and a half years since the last program report, let alone providing any sort of intelligible summary of their contents, would quickly fill the available space and exhaust the most dedicated reader's patience. Therefore, I'll describe in depth one area that seems to me to be particularly interesting and potentially novel to likely readers of this report. I proceed with an apology to all the authors whose papers are thus omitted. In addition, I confine myself to papers in the NBER working paper series or presented at asset pricing program meetings in the last four and a half years. I apologize in advance to non-NBER authors and authors of older papers whose work should be discussed in a comprehensive literature review.

The area on which I focus goes by a variety of names, including liquidity, trading, volume, market frictions, short-sales constraints, and limits to arbitrage. For a long time, there has been an implicit separation of effort in asset pricing. Researchers operating in the frictionless macroeconomics-based tradition study the broad level of prices, while researchers in the market microstructure tradition, filled with non-Walrasian trading, asymmetric information, and so on, were pretty much regarded as studying small (but interesting) refinements, where prices fall in the bid-ask spread rather than where the spread is in the first place.

Recently, this separation has begun to erode. At one level, this erosion is the beginning of a long-expected understanding of trading and volume. The classic theory of finance has no volume at all: Prices adjust until investors are happy to continue doing what they were doing all along, holding the market portfolio. Simple modifications such as lifecycle and rebalancing motives don't come near to explaining observed volume. Put bluntly, the classic theory of

*Graduate School of Business, University of Chicago and NBER. 5807 S. Woodlawn Ave., Chicago IL 60637. <http://gsbwww.uchicago.edu/fac/john.cochrane/research/Papers/>

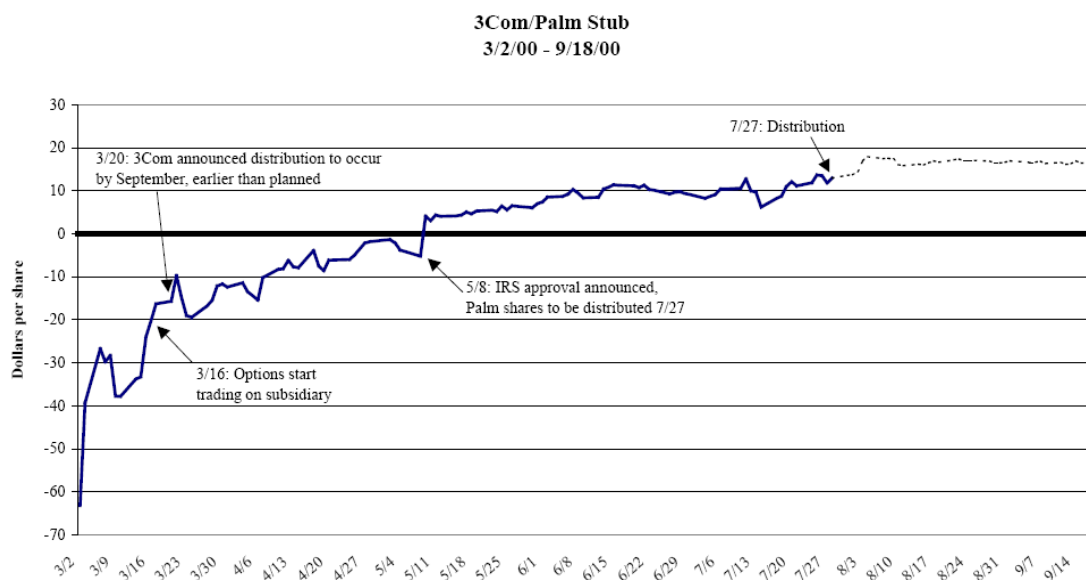
finance predicts that the NYSE and NASDAQ do not exist. Lifecycle stock trading could be handled at a retail level, like (say) life insurance. These markets *exist* to support high frequency trading. They are at bottom markets of *information*, (or, some might say, opinion) not really markets for stocks and bonds.

Now, perhaps prices *are* set as if volume is zero, and then volume and the attendant microstructure issues *can* be studied separately. But perhaps not; perhaps volume, trading, liquidity and market structure effects spill over to affect the level of prices. This is the issue I focus on. I start with empirical work, and follow with economic modeling that tries to understand the emerging set of facts.

2 Empirical work

2.1 3Com, Palm and convenience yield

The paper that most vividly brought this constellation of ideas to my attention is Owen A. Lamont and Richard H. Thaler’s “Can the Market Add and Subtract? Mispricing in Tech Stock Carve-Outs” (NBER WP 8302 and *Journal of Political Economy* 111: 227-268). Lamont and Thaler start with the case of 3Com and Palm. On March 2nd 2000, 3Com sold a fraction of Palm in an initial public offering. 3Com retained about 95 percent of the shares, and announced that it would distribute those shares to 3Com shareholders by the end of the year at about 1.5 shares per 1 3Com share. Thus, one could obtain 150 Palm share in two ways 1) buy 150 Palm shares directly 2) buy 100 3Com shares, and end up in six months with 150 Palm as well as 100 3Com.



Surely the latter strategy should cost more. But in fact, the latter strategy was cheaper. Palm prices exploded, 3Com prices fell, and at the end of the first day of trading the “stub value” of 3Com shares (the value of 3Com less the embedded Palm shares) was *negative* \$63! This violation of the law of one price lasted quite a while, as shown in Lamont and Thaler’s Figure 3, reproduced here. The event was not unique. Lamont and Thaler study six additional cases of negative stub values in a carve-out followed by spin-off.

Lamont and Thaler carefully document that these events did *not* present exploitable arbitrage opportunities. Most simply, a trader might want to short Palm and buy 3Com. But the costs of shorting were so high as to make this unprofitable or impossible. Rationed out of the short market, a trader might try to buy put options. But this did not work either. The option market became delinked from the stock market; there were wide violations of put-call parity, precisely because arbitraging between stocks and options required shorting stocks.

The absence of an exploitable arbitrage is a little bit comforting, but it does not address the basic question: why were the prices so out of line in the first place? Lamont and Thaler’s view is simply that there were a large number of “irrational” traders, who just did not see the chance to buy Palm embedded in 3Com, and for whom buying Palm rather than 3Com (and similar cases) was therefore “simply a mistake.”

Intrigued by this paper, I wrote “Stocks as Money: Convenience Yield and the Tech-Stock Bubble” (NBER WP 8987 and in William C. Hunter, George G. Kaufman and Michael Pomerleano, Eds., *Asset Price Bubbles* Cambridge: MIT Press 2003).

3Com and Palm reminds me of money and bonds. As 3Com and Palm are both claims to Palm shares in six months, so money and a six month treasury bill are both claims to a dollar in six months. Yet the bill is cheaper and the dollar “overpriced.”

You might object that nobody holds money for six months. The whole point of money is that you hold it only for a short time, in order to make transactions. But few people held Palm for six months either. Lamont and Thaler document that 19% of available Palm shares traded hands *every day* in the first 20 days after the IPO, and several of their other cases have even larger volume. Furthermore, Palm had a 7% standard deviation of *daily* returns, or a 15% standard deviation of 5-day returns—as much as the S&P500 moves in a year. If you can predict any of this movement, the 2/10 percent per day expected loss due to “overpricing” is trivial; it’s less than the commissions and bid-ask spread facing these active traders.

You might object that money is “special” because you need to hold it to make transactions. Palm stock was special too. To bet on information about Palm, you had to hold Palm stock. Even to short Palm, you must first find a lender, borrow Palm shares and then sell them. . Options trading or trading in 3Com stock (3Com still held 95% of Palm shares) are poor substitutes, as both markets became delinked from high frequency movements in Palm stock market in this period.

Palm and money behave similarly in many other ways. Money is *more* overpriced – the interest rate is higher – when velocity is higher. The same is true for 3Com and Palm: the “overpricing” was highly correlated with Palm volume.

The monetary overpricing (interest rate) is lower when the money supply is larger. The same is true for 3Com and Palm. Palm started with only 5% of total shares available, and less than that available for trading since those receiving IPO allocations are strongly discouraged from flipping (selling) or lending their shares. Short-selling provides an extra “supply” of shares, just as checking accounts provide extra money for transactions. Short selling in Palm built up quickly after the IPO. Palm peaked at 146% short interest – the average share had been lent out to short more than once – more than doubling the supply. As this supply increased, the overpricing fell.

3Com *fell* during the Palm IPO, even as the latter was exploding in value and even though 3Com still held 95% of Palm shares. With no horrible news about the rest of 3Com, this fall only makes sense if the Palm-information traders all coordinate on trading Palm shares, so “convenience yield” for trading in Palm prospects suddenly moves to Palm and away from 3Com.

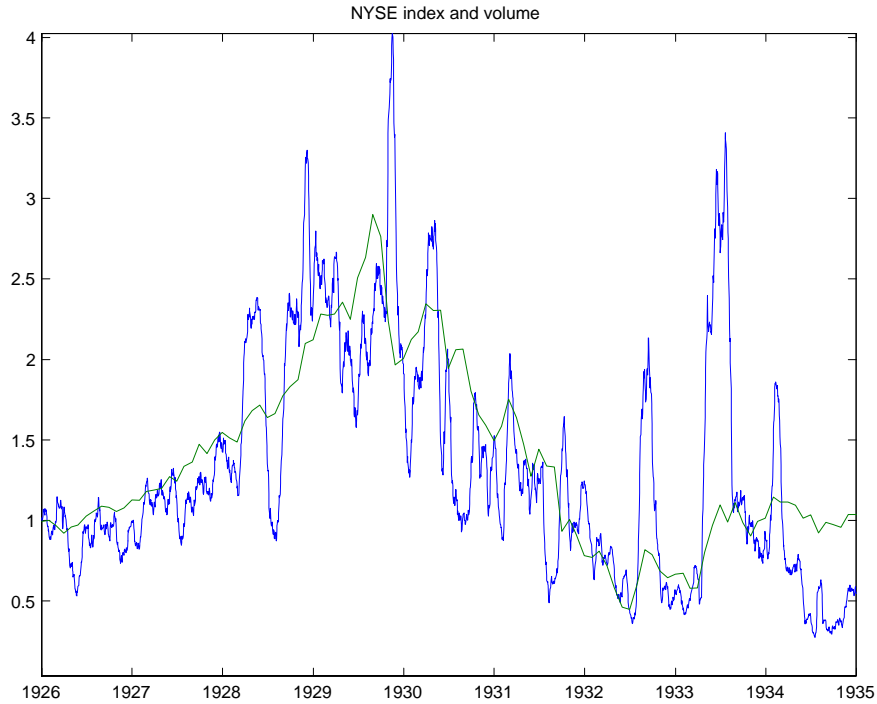
In sum, these observations suggest to me that trading generated a “convenience yield” for Palm shares, just as physical trading generates a convenience yield for money. People wanted to trade on information or opinions about the fortunes of Palm’s invention, the PDA. To do this, they had to hold Palm shares, but Palm shares were in short supply. This “convenience yield” nicely links a large number of phenomena: 1) “Overpricing” of seemingly identical securities; 2) “Overpricing” is higher when volume is higher; 3) “Overpricing” is higher when share supply is lower; 4) “Overpricing” is higher when there are fewer substitutes for trading (options, correlated stocks) 5) “Overpricing” is higher when there is more price volatility (a sign of more information flow); 6) 3Com stock *fell* at the Palm IPO.

Most stories for 3Com-Palm are at best silent on 2-6. In particular, “irrational investors” or “rational bubbles” do not link “overpricing” with volatility and volume, whereas *all* of the famous “bubbles” have featured tremendous turnover and volatility. If something about the psychology of evaluating risks makes traders irrationally attracted to Palm, why do 20% change their minds and resell their Palm shares on any given day?

You might object, how could convenience yields or liquidity premia be that large? First, recall that monetary “overpricing” can be quite large as well. In a 100% per year hyperinflation, currency trades at twice the value of six month bills, and probably still with less than 20% daily turnover. Second, recall the Gordon growth formula $P/D = 1/(r - g)$. If a stock has a P/D ratio of 50, $r-g = 0.02$ so a one percentage point change in expected return can double the price if it’s persistent. Liquidity premia up of one percent or so are observed in the bond market, so one might not be surprised by substantial liquidity premia in stock prices.

Is a substantial “convenience yield” for trading an important part of stock valuation in general? Some simple facts in “Stocks as money” suggest the possibility. In particular, “high

price” stocks trade frequently, both in the cross section and in the time series. For example, I reproduce here a graph of the NYSE index and volume through the great crash of 1929. The correlation is impressive. With different labels, a monetary economist might happily point to velocity (volume) stably tracking interest rates (price of money/price of bonds).



Share volume (20 day moving average) and NYSE index in the great crash. Volume is the more volatile series. NYSE index from CRSP; volume from NYSE. Both series normalized to 1 in 1926.

This well-known correlation is usually interpreted that price declines cause volume to dry up (for unknown reasons). For example John M. Griffin Federico Nardari Rene M. Stulz “Stock Market Trading and Market Conditions” W10719 show that volume is bigger after good returns, and markets “dry up” after bad returns, and interpret it this way. But perhaps some of the opposite is true as well: perhaps a decrease in the desire to trade (a decrease in information flow) or ability to trade makes shares less valuable.

These patterns are not unique to Palm-3Com. Eli Ofek and Matthew Richardson “Dot-Com Mania: The Rise and Fall of Internet Stock Prices” (NBER WP8630 and *Journal of Finance* 58 (2003) 1113-1137) document that many of these features hold for the period of remarkably high price, volatility and trading volume in the technology sector of the Nasdaq as a whole. One of their most interesting observations is that returns are negative around the expiration of many IPO’s lockup period. (For some time after an IPO, insiders are typically forbidden to sell their shares. When the lockup expires, a large number of shares are released

for trading or lending to shorts). Furthermore, the price decline of the overall Nasdaq tech sector in March 2000 coincided with a large release of shares from lockup (see their Figure 2).

2.2 Short sales constraints

A central part of all “overpricing” stories is that there are limits to the ability of arbitrageurs to establish long-term short positions. If short sales are expensive, and the shorts are the “marginal investor” setting prices, we ought to see that stocks with higher short costs have lower subsequent returns. Alas, data on short costs are hard to come by. Charles Jones and Owen Lamont “Short Sale Constraints and Stock Returns” (NBER WP 8494 and *Journal of Financial Economics*, (2002), 66:2–3, 207–39) exploit the interesting fact that the short market was in some ways more developed in the 1920s than it is now. In particular, rebate rates were tabulated and published. (When you borrow a stock to short, you must deposit collateral. In theory you should receive interest on the collateral – the rebate – but often you get a sub-market rate, no interest at all, and sometimes you must pay for the privilege of shorting.) They find that indeed stocks with higher shorting costs earn lower returns after the fact. However, to the extent that it can be measured, the returns do not decline one-for-one with the short cost.

Though it’s a common idea to relate short interest (the fraction of shares that are shorted) to “overpricing,” this idea has a fundamental conceptual flaw. *Unmet* demand for shorting should correlated with lower subsequent returns. A large *met* demand only means a wide dispersion in opinion that markets are able to respond to, not a situation in which shorts are unable to express that opinion.

Short interest can be used however. Owen A. Lamont and Jeremy C. Stein “Aggregate Short Interest and Market Valuations”(NBER WP 10218 and *American Economic Review* (May 2004) 94:2, 29-32) show that overall short interest actually *declined* as the Nasdaq reached its peak in 2000. This surprising fact suggests another path by which the ability to short is limited: the shorts can be wiped out on the way up. Lamont and Stein point in particular to the effect that open-end funds have on the shorting process. Since investors can demand their money at any point, short funds are forced to liquidate at a loss if the market goes up further (making the short position even more desirable) before an eventual decline. Of course *why* investors in short funds should get nervous is a nagging question – the string of losses are a “sunk cost” that only means the gain will be larger when it comes.

Owen Lamont “Go Down Fighting: Short Sellers vs. Firms” (NBER WP 10659 presented at Spring 2003 AP program meeting) uses another clever approach. Companies can use a variety of devices to discourage short sales, including legal threats, investigations, lawsuits, and various technical actions, such as persuading share holders to demand certificates which then cannot be lent out to shorts. (Apparently companies and regulators believe firmly that demand curves slope down.) Lamont finds that a sample of companies taking such actions

had subsequent returns of minus 2 percent per month.

One nagging question is, “if you can’t short stocks, why not buy put options?” In the 3Com/Palm case, Lamont and Thaler document well that options and stocks became delinked – there were massive violations of put-call parity. But is this an isolated, extreme case? Eli Ofek, Matthew Richardson, Robert F. Whitelaw “Limited Arbitrage and Short Sales Restrictions: Evidence from the Options Markets” (NBER WP 9423 presented at Fall 2002 AP program meeting, Forthcoming *Journal of Financial Economics*) claim otherwise. They find in fact frequent violations in put-call parity, that are strongly related to the cost of shorting. Their violations forecast subsequent low returns on stocks. (Battilio, Robert, and Paul Schultz 2004, “Options and the Bubble” Manuscript, University of Notre Dame, have recently questioned Ofek and Richardson’s finding of put-call parity violations, claiming that the use of intraday options data rather than closing quotes resolves most of them. They do not address Ofek and Richardson’s finding of negative expected returns however.)

2.3 Liquidity premia

Financial economists have long suspected that less liquid securities might have to offer an expected return higher than that justified by the covariance of the security’s return with the market or other factors, and thus the security might have a lower price level. (See Maureen O’Hara 2003, “Presidential Address: Liquidity and Price Discovery,” *Journal of Finance* 58, 1335-1354 for a review.) The motivation has traditionally focused more on the price discount that an “illiquid” security might have relative to a frictionless market rather than “convenience yield,” or a price premium a security might enjoy for its special usefulness in allowing information trading, but the issues are closely related.

Bonds

It’s easier to see liquidity premia in bonds than in stocks, since the payoffs are known. Liquidity premia are clear in US treasuries, for example, in the spread between on-the-run (just issued) and off-the-run issues. Seeing them in other, potentially much more illiquid bonds is harder, since a spread may be due to default as well as liquidity.

Francis A. Longstaff “The Flight-to-Liquidity Premium in U.S. Treasury Bond Prices” (NBER WP 9312) separates default from liquidity premia by comparing US Treasury with Refcorp bonds. Most agency bonds (Fannie Mae, Freddie Mac, etc.) carry some small default risk, but Refcorp bonds do not: Their principal is fully collateralized by Treasury bonds, and the Treasury guarantees full payment of coupons. Thus, they are identical to Treasury bonds in all aspects but liquidity (and, perhaps, obscurity). Longstaff finds that their average premia range from about 10 to 16 basis points of yield (0.10 to 0.16 percent). The premia vary significantly over time. The maximum range from 90 basis points for the three-month premium to about 35 basis points for the seven-year premium. These apparently small yield spreads can imply big price spreads for long-maturity bonds, up to 15% in Longstaff’s data.

Francis A. Longstaff, Sanjay Mithal, and Eric Neis, “Corporate Yield Spreads: Default Risk or Liquidity? New Evidence From the Credit-Default Swap market” (NBER WP 10418) use the swap market to obtain market-price-based estimates of the default premium, and hence measure the residual liquidity premium. (One can now buy “default insurance” on particular bonds, and the premium for this insurance can be used to measure the default premium in a bond yield.) Most previous calculations suggested that corporate bond yields were much larger than default alone could account for, but Longstaff, Mithal and Neis find otherwise: 51 percent of the yield spread of AAA/AA- bonds, 56 percent for A-, 71 percent for BBB and 83 percent for BB- are accounted for by default premia measured in the credit-default swap market. However, a substantial residual remains, between 20 to 100 basis points. This component is strongly related to measures of illiquidity such as the size of the bid/ask spread and principal amount outstanding.

Stocks

Lubos Pastor and Robert F. Stambaugh “Liquidity Risk and Expected Stock Returns” (NBER WP 8462 and *Journal of Political Economy* 111, 642-685) find that stocks whose prices decline when the market gets more illiquid receive a compensation in expected returns. Dividing stocks into 10 portfolios based on liquidity betas (regression coefficients of stock returns on market liquidity, with other factors as controls), the portfolio of high-beta stocks earned 9% more than the portfolio of low beta stocks, *after* accounting for market, size, and value-growth effects with the Fama-French 3 factor model. Almost all of this premium is accounted for by spread in liquidity betas and a factor risk premium estimated across 10 portfolios. (The canonical asset pricing model is $E(R^i) = \beta_i \lambda$. Thus, a spread in average returns $E(R^i)$ across portfolios i is explained if they are linearly related to the betas β_i . A test whether $\hat{\lambda} = 0$ is often performed to assess the significance of the model.)

Viral V. Acharya, Lasse H. Pedersen 2004 “Asset Pricing with Liquidity Risk” (NBER WP10814) perform a similar but more general investigation. They examine all four channels for a liquidity premium. A the security might have to pay a premium simply to compensate for its particular illiquidity or transactions cost, but this is the least interesting (and, as we will see in the theory discussion, least likely) effect. Second, a security might have to pay a premium because it becomes more *illiquid in bad times*, i.e. when the market goes down. If you have to sell it, (and sellers are the marginal investor) this tendency amounts to a larger beta than would be measured by the midpoint of a bid-asked spread. Third, the security’s price (the midpoint) might decline when markets as a whole become less liquid. If “market liquidity” is a state variable, an event that drives up the marginal utility of a marginal investor, then this tendency will also result in a return premium. This is the mechanism that Pastor and Stambaugh investigated. Fourth, the security could become more illiquid when the market becomes more illiquid. Of course these characteristics are correlated in the data, which makes sorting out their relative importance more difficult.

Acharya and Pedersen form 25 portfolios sorted on the basis of previous year’s liquidity (the liquidity of the individual stocks, this time, not Pastor and Stambaugh’s regression coefficient of return on market liquidity). They find average returns range from 0.48% to 1.10

% per month as the illiquidity of the portfolios rises. However, their measure of illiquidity is (intentionally) highly correlated with size, and the size ranges from 12.5 to 0.02 billion dollars in the 25 portfolios. Then, they examine whether the four sources of covariation described above explain the variation in average returns. The illiquidity covariances are significant in some specifications. Interestingly their most important effect (the largest premium λ in $E(R^i) = \beta_i \lambda$) is the covariance of liquidity with market return – the chance the stock may get more *illiquid* if the market goes down.

While both papers find that liquidity betas do correlate with average returns, and they account with some success for the expected returns of portfolios sorted on liquidity measures, neither paper claims that “liquidity betas” are a complete description of stock returns. Neither model explains the average returns of portfolios sorted on book to market, size or past returns by liquidity betas alone. This is not a failing; in fact it is predicted by Acharya and Petersen’s model, in which liquidity premia operate above and beyond the usual CAPM. It just means that we will have to understand liquidity as an additional feature above and beyond the usual picture of returns driven by the macroeconomic state variables familiar from the frictionless view.

Looking a little more deeply into the making of this sausage will show some of the achievement of these papers, and some of the challenges that remain. The biggest challenge is “how do you measure liquidity?” (and to some extent, how do you *define* liquidity) both at the individual-stock level and at the market level. Larger bid-ask spreads and transactions costs are indicative of course, but a larger sense of liquidity really matters: how much is for sale at the bid-ask points (“depth”), and most of all how bad will the “price impact” of a trade be?

Pastor and Stambaugh’s basic idea is that stocks are “illiquid” if there is a large price-impact of orders. They define liquidity for stock i in month t as the OLS estimate of $\gamma_{i,t}$ in a regression taken over the days of the month,

$$r_{i,d+1,t}^e = \theta_{i,t} + \phi_{i,t} r_{i,d,t} + \gamma_{i,t} \text{sign}(r_{i,d,t}^e) \cdot v_{i,d,t} + \varepsilon_{i,d+1,t}$$

where r = return, r^e = return in excess of market return, and v = dollar volume. The idea is that a big “buy order” in an illiquid stock at date d will result in large volume and negative return. If it really was price impact, and not news, we should see an unusually large return the next day (correcting for any typical serial correlation with the ϕ term – whatever that means), as the price bounces back. Thus a large negative γ_{it} indicates an illiquid stock.

Pastor and Stambaugh want innovations in market liquidity, which they construct as follows. (The paper is about risk as measured by regressions of individual returns on market liquidity.) First they find changes in the average liquidity of individual stocks, scaled by the

growing size of the market, and then they find innovations to those changes.

$$\begin{aligned}\Delta\hat{\gamma}_t &= \left(\frac{m_t}{m_1}\right) \frac{1}{N_t} \sum_{i=1}^N (\hat{\gamma}_{i,t} - \hat{\gamma}_{i,t-1}) \\ \Delta\hat{\gamma}_t &= a + b\hat{\gamma}_{t-1} + c\left(\frac{m_{t-1}}{m_t}\right) + u_t\end{aligned}$$

Their “market liquidity” is $L_t = u_t/100$.

Acharya and Pedersen define the liquidity of stock i in month t as the average absolute return divided by dollar volume.

$$\begin{aligned}ILLIQ_t^i &= \text{liquidity of stock } i \text{ for month } t = \frac{1}{\#Days} \sum_{d=1}^{\#days} \frac{\|R_{t,d}^i\|}{V_{t,d}^i} \\ c_t^i &= \min(0.25 + 0.30 \times ILLIQ_t^i \times P_{t-1}^M, 30)\end{aligned}$$

where R is daily return, V is dollar volume and P_{t-1}^M is an index of the capitalization of the total market portfolio. The idea of the first equation is that a stock is illiquid if small volume is associated with large price changes. This is a fundamentally different measure: Acharya and Pedersen look for price changes at date d , where Pastor and Stambaugh look for a bounce-back, predictable price changes in the return from t to $t+1$. The first equation leaves a size effect though – as inflation increases dollar volumes, illiquidity apparently decreases. The second equation normalizes by market values to remove this effect through time, and caps the measure to remove outliers. However, the cross-sectional scaling with size remains: smaller stocks who have smaller *dollar* volume for the same *turnover* (fraction of outstanding shares that trade) are automatically more illiquid.

Having seen the details, it’s clear that these authors are grappling with deep conceptual problems in very sophisticated ways – but that a cleaner definition and measurement of “liquidity,” though obviously a difficult objective, will be a valuable one.

2.4 Order flow, price impact, and downward sloping demand curves

One indication of “illiquidity” or “convenience yield” is “price impact” or a “downward sloping demand curve” for stocks. A non-financial economist, quite used to downward-sloping demand curves, might be puzzled why we even worry about this question. After all, if you show up with a truckful of tomatoes in Harvard Square at 2:00 AM determined to sell them in the next half hour, you’re not going to get a very good price. There are arbitrageurs hanging around financial markets, of course, but even they have limited capacity to bear risk.

However, if the sale is *announced*, or so regular that it becomes expected, then arbitrageurs should know to show up, so the presumption leans much more to a flat “demand”

(in quotes because half the time it's “supply”) curve. For this reason, we should be more surprised to see “price impact” of regular or expected sales or purchases in a frictionless market.

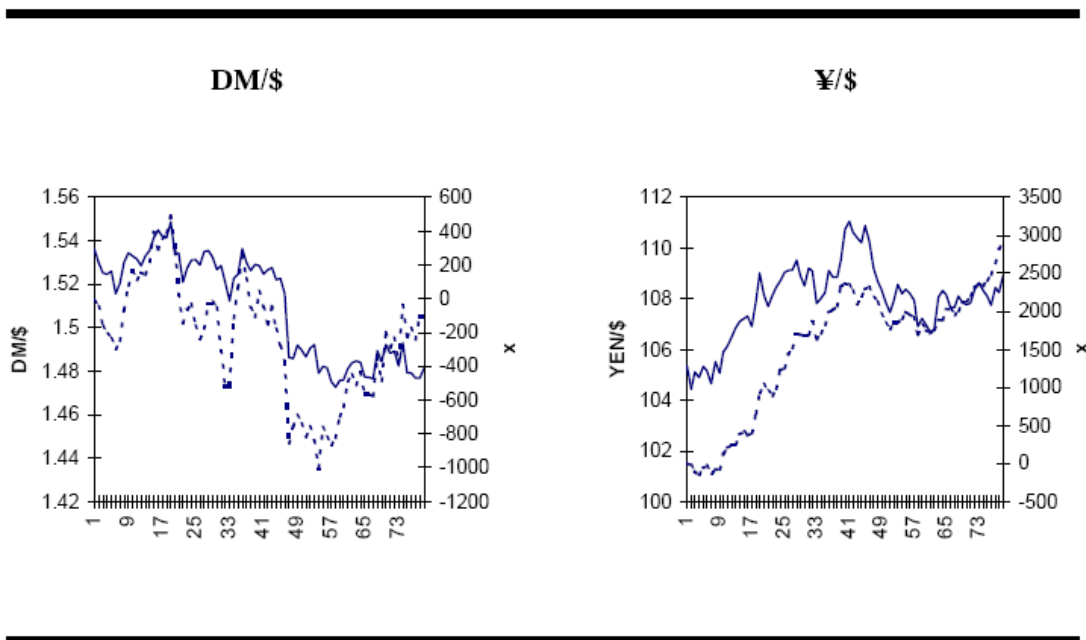
Market microstructure models have an additional story for price-impact: asymmetric information. If you offer to sell a lot of stock unexpectedly, this might mean you know something the traders don't, and they will therefore only offer a lower price. Thus, we are more surprised to see price-impact of regular, expected or otherwise information-free trading.

Martin D.D. Evans and Richard K. Lyons “Order Flow and Exchange Rate Dynamics” (NBER WP7317, *Journal of Political Economy*, 110: 170-180) show exchange rate movements are highly correlated with order flow. I reproduce Figure 1 from their paper here. The solid lines are the spot rates of the DM and Yen against the Dollar. The dashed lines are order flow. The correlation is impressive.

Figure 1

Four Months of Exchange Rates (solid) and Order Flow (dashed)

May 1-August 31, 1996



A difficulty in most studies of this sort is that you typically do not know if a trade is a “buy” or a “sell”, and in fact we routinely make fun of journalists who report a wave of

“buying” since every “buy” must correspond to a “sell.” Evans and Lyons’ data set does record which side initiated the transaction, so “order flow” can be measured and does make some sense. (Many studies rely on whether the trade takes place above or below the midpoint of the bid-ask spread to identify the sign of the trade, but direct measurement is obviously much cleaner.)

Evans and Lyons interpret the correlation as causal, that order flow *causes* the exchange rate to move. In this paper and in “A New Micro Model of Exchange Rate Dynamics” (NBER WP10379 presented at 2004 Summer Institute) they provide rich theoretical models that produces this sort of effect. The latter model combines standard general equilibrium models (productivity shocks, consumption, investment, capital formation) with microstructure in the exchange market, in particular that agents know more about their home shocks than foreigners.

Michael W. Brandt and Kenneth A. Kavajecz “Price Discovery in the U.S. Treasury Market: The Impact of Orderflow and Liquidity on the Yield Curve” (NBER WP 9529 and forthcoming *Journal of Finance* 2004 December) perform a similar and much more detailed analysis in the market for US Treasury bonds. Brandt and Kavajecz have trade-by-trade data in government bonds from the GovPX system on which the bonds are traded. They also know who initiated the trade – whether is it a “buy” or a “sell.” With all quotes at a given time, they can measure bid-ask spread and depth; how much is for sale at what price.

Brandt and Kavajecz aggregate bonds into maturity bins and on-the-run, just off- the-run and off- the-run status. (Newly issued bonds are said to be “on the run.” They are most actively traded, since they make their way from the government to long-term holders such as pension funds. Trading in off-the-run bonds can be quite thin as many US treasury investors are passive.) They run regressions in daily data of yields in these classes on lagged yield curve factors (level, slope and curvature, linear combinations of lagged yields) and order flows.

$$y_{t+1}^i = \alpha^i + \beta_l (l'y_t) + \beta_s (s'y_t) + \beta_c (c'y_t) + \beta_1 of_{t+1}^1 + \beta_2 of_{t+1}^2 + \dots + \beta_N of_{t+1}^N + \varepsilon_{t+1}$$

where y_t denotes the vector of all yields at time t , $l'y_t$ is the “level” factor, $s'y_t$ is the “slope” factor, $c'y_t$ is the “curvature” factor and of_{t+1}^j is the order flow of class j between day t and day $t + 1$. In each case, yields at $t+1$ are significantly related to order flow between date t and date $t+1$, with R^2 nearing 30%. For yields of class i , orderflow of that class is the most important right hand variable. Interestingly, other orderflows enter as well. Order flow in the 2-5 year maturity is the most important other class in each case. A single common factor in order flows ($\beta(1'of_{t+1})$ where of denotes the vector of all order flows) across all yields also compactly captures the cross-effects.

To examine how orderflow affects the overall shape of the yield curve rather than individual bond yields, they regress factor portfolios (the average of all yields = level, and other linear combinations for slope and curvature) on order flows of different classes of bonds.

$$l'y_{t+1} = \alpha^i + \beta_l (l'y_t) + \beta_s (s'y_t) + \beta_c (c'y_t) + \beta_1 of_{t+1}^1 + \beta_2 of_{t+1}^2 + \dots + \beta_N of_{t+1}^N + \varepsilon_{t+1}$$

and similarly with $s'y_{t+1}$ and $c'y_{t+1}$ on the left hand side. They find that the “level” factor is most influenced by order flow. Order flows across all maturities forecast changes in the level of interest rates, and a common “level” factor in order flow moves the common “level” factor in yields with nearly the same R^2 as the multiple regression using order flows on all maturities. Other factors are much less related to order flow at all, let alone factors in order flow. For example, there does *not* seem to be a “slope” factor in order flow (buy short, sell long) that induces changes in the slope of the yield curve. Interestingly, the effects are stronger for liquid on-the-run rather than less liquid off-the-run bonds.

Brandt and Kavajecz interpret their findings as evidence for “price discovery” rather than “illiquidity” or “price impact.” In a market of symmetric information, that information raises prices without any trading. In a market with asymmetrically informed agents, those with the information will trade on that information as prices rise, so that price rises and buy orders will be correlated as we see. “Price discovery” makes sense of the fact that orderflow of *other* classes helps to forecast yield changes in class i . This would not happen if traders were simply pushing on class-specific demand and supply curves. In addition, “price discovery” makes sense of the fact that order flow in the *liquid* on-the-run bonds is the important one for forecasting returns.

Kenneth A. Froot and Tarun Ramadorai “Currency Returns, Institutional Investor Flows, and Exchange Rate Fundamentals” (NBER WP 9101) correlate exchange rates with flows between institutional investors. Again, they exploit a data set that shows all purchases and sales, so they know in which direction the “flow” is. They find that daily flows exhibit a correlation with daily excess returns of about 30%.

They undertake a dynamic analysis and uncover “trend-following” by managers: a 1% surprise appreciation results in a 0.37 standard deviation inflow over 30 trading days, for the major currencies in the sample. Consistent with this finding, the flow/return correlation rises strongly with horizon, peaking at about 45% at horizons of about a month. The flow/return correlation then declines rapidly with horizon. In long horizons, they find that fundamentals, not flows drive exchange rates.

In sum, we have a striking fact, that order flow is highly correlated with price changes. We also have three interpretations of this correlation. 1) Perhaps order flow *causes* the price change, simply running in to the illiquidity, “downward sloping demand” or “limited ability to bear risk” of market-makers. 2) Perhaps “price discovery” causes the correlation; informed investors come in and bid up prices to where they will go once the information becomes public, and do a bit of trading on the way. 3) Perhaps causality runs backwards: perhaps prices change, and then “trend-following” and “momentum” traders pile volume in that direction. The cross-asset correlations and dynamics suggest the second and third interpretations, but I look forward to detailed cross-sectional and time-series analysis to add evidence that will sort these out. The second and third interpretations at least argue that we need to understand where order flow comes from before arguing that it causes price changes.

Nicholas Barberis Andrei Shleifer and Jeffrey Wurgler’s “Comovement” (NBER WP

8895 Forthcoming *Journal of Financial Economics*) extends a long line of research on S&P500 inclusion effects suggesting “downward sloping demand curves.” They find that stocks start to comove more with the S&P500 index as soon as they are included in that index. In single regressions, daily betas (regression coefficients of stock return on S&P500 index return) increase by 0.15 and weekly betas increase by 0.110 on inclusion (i.e. a typical regression coefficient increases from 1.0 to 1.15). Considerations such as non-trading and lagged betas weaken the magnitudes and statistics a bit, but do not eliminate the effect. In a nice refinement, they run regressions of individual stocks on both S&P500 and non-S&P500 stocks. The coefficients on S&P500 rise more, up to 0.3, and those on non-S&P500 decline on inclusion, though the standard errors are somewhat wider as the right hand variables are highly correlated. Monthly betas do not increase, with the natural interpretation that short run demand curves slope down but long-run curves do not. There is a natural source of volume that occurs on S&P500 inclusion: index arbitrage of individual stocks vs. the index and S&P500 options, and demand from S&P500 index funds. But since these are a predictable source of trading, it is surprising that they run in to an illiquidity.

3 Economic models

So far I have written as if we had good economic models of trading, liquidity, convenience yield, and so on. Of course nothing of the sort is true. Solid economic understanding of all these issues, and even clean definitions or verbal stories, remain a challenge.

Two fundamental stumbling blocks stand in the way. First of all, why is there so much trading? It’s no mystery to the layman; people are trading on information and opinion. But economic models of information-based trading quickly stumble on the “no-trade theorem.” Paul Milgrom and Nancy Stokey (“Information, Trade and Common Knowledge ” *Journal of Economic Theory*, 26 (1982), 17-27) show that rational traders should act like Groucho Marx, who famously didn’t want to belong to any club who would have him. Anyone who wants to sell to you knows something you don’t know. Not everyone can be smarter or better informed than the average.

Second, models of illiquidity premia stem fundamentally from transactions costs. But agents solving typical portfolio problem can easily avoid transactions costs by refusing to trade very often, a point made most famously by George M. Constantinides, “Capital Market Equilibrium with Transaction Costs.” (*Journal of Political Economy* 94 (1986), 842–62.) As a result, large transactions costs typically have small price effects. The two points are related. The classic theory of finance doesn’t give much of a reason to trade, so it naturally does not assign much of a penalty for assets that are hard to trade.

As I review theory papers designed to understand volume and liquidity premia, you will see a variety of unpalatable devices used to avoid these two fundamental barriers. For example, no-trade theorems are often broken by sprinkling in some “noise traders” who buy or sell for unspecified reasons unrelated to information. You will see models with “opti-

mists” and “pessimists” who have different priors, or who irrationally overweight their own information. You will see models that crank up lifecycle or hedging motives for trade to unreasonable levels in order to generate some volume. For example, one writes a model with agents that last two months, so each must buy and sell his entire portfolio in two months. Another posits that investors exogenously withdraw funds from managers after poor returns. Another introduces random preference shifts.

How one interprets these ingredients is a matter of philosophy. Some people see them as proof that finance needs to abandon economics for its behavioral foundations, and thus the assumptions are worth advertising or fussing about, depending on one’s views on that question. I tend to see them as sensible shortcuts, quick modeling tricks where starting from “deep microfoundations” would waste too much time and space on the way to the phenomenon we want to capture, and thus not worth making much of a fuss about either way. I find it hard to swallow the proposition that there can never be *any* model built on economics in which the NYSE and NASDAQ exist, but I don’t want to wait for its construction to start thinking about the economics of liquidity. In a similar way, macroeconomists write models with cash-in-advance constraints, money in the utility function, sticky prices and so on, not because they believe literally in these specifications but as a convenient shortcut to a money demand curve on the way to studying something else, without waiting for the endless “microfoundations of money” project to be finished. Buttressing this view that not much essential is at stake, it seems pretty clear in most cases that assumptions could easily be substituted with no effect on the basic results. Most models just need *some, any* reason for trade. Similarly, the liquidity models just postulate transactions costs rather than derive a bid-ask spread from asymmetric information, and happily go on.

Of course, this means that the answers are not fully satisfactory until the microfoundations of trade really are understood. You never know for sure that a shortcut leads to the right road unless you have a full map, and deeper models will be an ongoing project. At any rate, a look at the current crop of models will give the reader a better sense of where these devices fit in, how to interpret them, and what a really satisfactory model of volume, information trading, and liquidity might look like.

3.1 Convenience yield, short sales and search

Darrell Duffie, Nicolae Gârleanu and Lasse Heje Pedersen “Securities Lending, Shorting, and Pricing” (*Journal of Financial Economics* 66 (2002), 307-339 presented at the Spring 2001 program meeting) is a model that captures many of the 3Com - Palm and short-sales constraint phenomena. This is model of pure shorting. Relatively optimistic agents hold the security only to search for a relatively pessimistic agent who will borrow it, and then sell it to a relatively optimistic agent again.

A security has an unknown value at some random date in the future. Some agents are “optimists” and some are “pessimists.” They simply have different prior views on this value.

Shares are traded by a Walrasian auctioneer in a centralized market at each moment. To sell short, however, a pessimist must first locate another agent from whom to borrow the shares. The search proceeds by random matching. When a pessimist meets an optimist, they engage in a Nash bargaining over the borrowing fee or rebate rate. The model starts, as after an IPO, with no short interest.

At any time, optimists are willing to pay more than even they think the stock is worth, because they can earn fees from lending shares out to shorts. (This is the heart of Jones and Lamont's findings above.) In fact, it is rational for them to buy shares at "too high prices" and then hold them for some time as they search for a short to whom to lend the shares. Thus, in this market *everyone* thinks shares are overvalued at current prices, but they hold them nonetheless, waiting to find someone to lend them to for short sales. As one might expect, price and volume decrease over time, and short interest increases, just the pattern we see in 3Com-Palm.

Lending fees are larger if the difference of opinions is larger, and the price and lending fee are higher if the float is smaller. The overpricing is more drawn out if one has to wait 3 days for settlement before lending out a share again, as well as search for new borrowers. The model does not generate volatility and much volume however; the only volume is the expanding lending, selling short, and lending again.

Darrell Duffie, Nicolae Garleanu and Lasse Heje Pedersen's "Over-the-Counter Markets" (NBER Working Paper 10816, previously "Valuation in Dynamic Bargaining Markets") presents a related matching and search model. The focus of this paper is on bid-ask spreads, and the point is to develop a theory of these spread completely different from the standard one. In the standard theory, dealers hold an inventory of the asset, and manage the bid-ask spread to control this inventory and to control asymmetric information, i.e. the chance that an "informed" trader will take advantage of the dealer. This model has no inventory and no asymmetric information.

The setup corresponds to the many assets that are at least partially traded over the counter. Agents randomly switch between low and high discount rates, motivating trade of a single claim to future consumption. (When you get more impatient, you sell to consume now). In addition, there are market-makers who can instantly unload their positions on the inter-dealer market. Agents meet randomly. The bid-ask spread reflects the dealer's bargaining power vs. the investors' other options – how easily he can find another investor to trade with, or another dealer. For example, spreads charged by dealers will be lower the easier it is for investors to find other investors in the over-the-counter market.

Wei Xiong, Harrison Hong and José Scheinkman's "Asset Float and Speculative Bubbles" (presented at the Fall 2003 AP program meeting) is another model aimed at the curious features of the late 90's Nasdaq, and Ofek and Richardson's finding that prices decline at the end of lockup periods in particular. They study a mechanism by which small float and short sales constraints lead to 'overpriced' securities, a 'bubble' in prices, defined for them as a situation in which agents rationally buying stocks they know to be overpriced on the

expectation of further price rises, high turnover, and high volatility. All these features decline when float increases, even when it is known in advance that float will increase.

There are three periods, 0, 1 and 2. An asset has a random payoff in period 2. Two investors are each endowed with half of the shares and they have identical mean-variance utility functions over terminal wealth. They may trade at period 0 or 1, but are subject to short sales constraints. At period 1 they each receive a signal about the asset payoff. The signals are public, but each investor is “overconfident” about “his” signal, thinking it more correlated with the true payoff than it really is. As a result, the (ex-post) “optimist” will buy from the “pessimist” in period 1. Since they face short-sales constraints, there will be regions in which one agent holds everything, and the period 1 valuation depends entirely on his signal. Working back, Xiong et al. show that the price at time 0 will be larger than *both* agents’ expectations of fundamental value at time 0. They are both willing to pay for the “resale option” that an “overconfident” agent comes along and bids the price up even further. To the authors, this captures the essence of a ‘bubble’.

As the share size increases, the overall price in periods 0 and 1 decreases. This is the only asset, so each agent has to bear more risk. It also becomes less likely then that in period 1, after information is revealed, that one or the other agent hits his short sale constraint. If nobody hits the short sale constraint, the “resale option” disappears. Conversely, with a very small share size, it becomes almost certain that one or the other agent will hit his short-sale constraint and therefore the asset will be ‘overpriced’ in period 1. (Here quadratic utility is important. Were it log utility, nobody would ever want to be short.) Thus, ‘overpricing’ is greater when share supply is lower, as Lamont and Thaler find for 3Com-Palm and as Ofek and Richardson find around lockup expiration in the Nasdaq.

Furthermore, as the share supply gets smaller it becomes more and more certain that one agent will sell all of his shares to the other. Thus proportional turnover (not dollar turnover) is larger when share supplies are smaller. Similarly, price volatility is higher.

Xiong Hong and Scheinkman go on to show that the model continues to work in a multiperiod setting in which the agents know that a lockup expiration will add shares to the market. Thus, a *predictable* fall in price when shares *predictably* increase, a “downward sloping demand” of the puzzling sort, emerges.

3.2 Liquidity and quality premia

Viral V. Acharya and Lasse H. Pedersen (NBER WP 10814) present a model along with the empirical work I surveyed above, and the model captures the four variants of a liquidity premium: In addition to the standard market beta, expected returns are higher for stocks that are illiquid on average, for stocks whose illiquidity gets worse when the market goes down, for stocks whose price goes down when the market gets more illiquid, and for stocks which become more illiquid when the market gets more illiquid.

The model consists of overlapping generations. Agents live two periods, earn income in

the first period and consume in both periods. Thus they buy securities when young and sell them when old. Agents in a generation also have different risk aversion. “Illiquidity” is simply a random per-share cost C^i of selling each security – sellers receive $P^i - C^i$ per share. “Market illiquidity” is then just the value-weighted average of these costs. Securities are claims to dividend streams, and both dividends and the costs follow AR(1) processes.

The theory is then quite simple: since every agent liquidates his portfolio in the second period of his life, the CAPM holds exactly using returns *after* transactions costs. Simply expanding the standard expression of the CAPM that expected (return - cost) is proportional to the regression beta of (return - cost) on the (market return - cost), we obtain that expected returns rise with the expected cost of the individual security and the four “betas” listed above. Furthermore, since liquidity (transactions cost) is persistent, the model generates time-varying expected returns predictable on the basis of liquidity variables. (This is an important point. Many of the most popular trading strategies used by hedge funds and similar traders exploit return predictions based on the intersection of past returns and volume data.)

Dimitri Vayanos, “Flight to Quality, Flight to Liquidity, and the Pricing of Risk” (NBER WP 10327) is motivated by another striking recent event, the “flight to quality” or “flight to liquidity” following the Russian bond default in 1998. This event seems to provide a paradigm of liquidity issues. For example, the on-the-run vs. off-the-run 30 year US treasury spread widened from 4 basis points (0.04%) to 28 bp. The spread between AA-rated corporate bonds and government bonds increased from 80bp to 150bp. At the same time, prices became much more volatile. For example, the implied volatility of the S&P500 index increased from 23% to 43%.

Naturally, “spread traders” who were typically short liquid securities (e.g. on-the-run 30 year bonds) and long the illiquid ones (e.g. off-the-run 29 year bonds) suffered huge losses. Withdrawals by investors as well as margin calls forced liquidations at unfavorable prices. The losses were made worse by seemingly uncorrelated assets becoming more correlated, revealing a common “liquidity factor” in returns. LTCM was the most famous casualty. Certainly these traders would have given up a lot of utility for a dollar delivered in that date and state, motivating a “risk premium” for assets that do not do so.

Vayanos presents a very sophisticated (in the sense that lots of things are endogenous) model that shows how *illiquidity* is linked to *volatility*, and captures the larger betas and correlations of assets in times of high volatility and illiquidity.

Investors in this model are all fund managers, and they earn a fixed fraction of assets under management. They face fixed asset-specific transactions costs. They also face the danger of a total withdrawal of funds. The chance of such a withdrawal is a linear function of the probability of achieving a return below a certain threshold, and is thus an increasing function of the fund’s volatility. After withdrawal, the manager gets to start a new fund of the same size as the old one right away. Thus the “withdrawal” simply means that the manager may have to pay the transactions costs (liquidation value - net asset value) and

the model is formally equivalent to one with representative consumer-investors who face random liquidation events (more likely with higher volatility) in which they have to pay the transactions costs and then reinvest. The model is completed with the dividend processes of n risky assets that mean-revert, and have stochastic volatility (square root processes). The dividends are driven by a common shock, a volatility shock and an idiosyncratic shock.

One result is an expected return model with liquidity and volatility effects. The expected return of each asset depends, first, on covariances with the market return (CAPM), but with a time-varying risk premium that is higher in times of volatility. Second, expected returns depend on the covariance of the asset with the volatility of dividend growth, again with a time-varying risk premium. Finally, the expected return of each asset rises if the transactions cost of that asset are higher, but again with a coefficient that is larger when volatility is larger. In each case, higher (exogenous) volatility of dividends, and hence of returns, increases the chance of withdrawals; the fund managers then require higher returns.

The model also predicts that conditional market betas vary through time, and their spread across assets is larger when volatility is higher. It also predicts that the correlation between assets typically increases in times of higher volatility. These properties flow from the assumption that the probability of withdrawals depends linearly on poor performance – the left tail of the return distribution. The chance of a left-tail event is a nonlinear function of volatility. When volatility is low, the chance is low and slowly increasing in volatility. When volatility is high, the chance of poor performance runs in to the steeply sloping part of the conditional density, and so has a large effect.

The model suggests a theory for a “liquidity pricing factor” such as found by Pastor and Stambaugh. While the transactions costs (bid-ask spread) in the model are constant for each asset, in a time of higher volatility small generalizations of the model suggest higher “price impact”, which forms the basis of Pastor and Stambaugh’s aggregate liquidity factor.

Bryan R. Routledge Stanley E. Zin “Model Uncertainty and Liquidity” (NBER WP 8683) offer a different and frictionless interpretation. Many “flights to quality” have come after extreme market movements, movements that put to the test sophisticated traders’ hedging models, and found them failing. In their frictionless view, bid-ask spreads widen when agents become more uncertain about the validity of their models.

Francis A. Longstaff “Financial Claustrophobia: Asset Pricing in Illiquid Markets” W10411 and presented at 2004 SI is another model of liquidity and flight to quality. The model has two “Lucas Trees.” There also are two agents, one more impatient than the other. They can trade at time zero, but then they cannot trade for T periods. The length of this “blackout” period is the concept of illiquidity in the model. Longstaff solves for the resulting prices of the two trees.

In this model, the portfolio allocations can be quite different under illiquidity, even if that illiquidity is arbitrarily short-lived. The reason is that a log-utility investor can never have a short position in an asset for a finite time interval, as he then faces a probability of negative wealth. The impatient consumer cannot therefore borrow. Rather than hold the

market portfolio of the two trees, agents now hold very polarized portfolios. The change in demand also has large effects on the prices of the two assets.

Anthony Lynch and Sinan Tan, “Explaining the Magnitude of Liquidity Premia: The Roles of Return Predictability, Wealth Shocks and State-Dependent Transaction Costs” (Presented at Spring 2004 AP meeting) tackle the low-volume problem and the Constantinides puzzle head-on. They consider a standard portfolio problem. They add predictable returns, another reason for individual or heterogenous investors to trade. They add a stochastic labor income process, calibrated to PSID data, and wealth shocks to give a dynamic hedging motive. Finally, they introduce transactions costs to distinguish liquid and illiquid assets. Some calibrations of the model give liquidity premia in the ballpark found by Pastor and Stambaugh and Acharya and Pedersen. Of course, being partial equilibrium, we’re not sure who is on the other side of all this trading, or why things like predictable returns persist.

3.3 Volume and liquidity

Andrew W. Lo, Harry Mamaysky and Jiang Wang “Asset Prices and Trading Volume Under Fixed Transactions Costs” (NBER WP 8311 and *Journal of Political Economy* v112, 5 (October 2004): 1054-90) construct a model of volume and liquidity. At heart they study how transactions costs reduce volume and induce a price discount.

As always, we first need some reason for agents to trade in the first place. (The puzzle is that there is too *much* volume, not too little.) Lo, Mamaysky and Wang achieve this by giving agents a nontradeable risky asset – a business, a job, etc. The outside income is correlated with the stock market, so the agents want to hedge it. As the outside income increases or declines in value, the optimal hedge changes, giving the agents a reason to trade continuously. Adding transactions costs, the agents trade less frequently, in discontinuous lumps. As a result, the agents bear more risk, and so demand less of the risky asset. Then, the risky asset has a price (“illiquidity”) discount. This discount is approximately proportional to the square root of the transactions cost, so it is large for small costs.

Specifically, Lo, Mamaysky and Wang model two agents in continuous time. The only assets are a stock – a claim to a random walk dividend – and a riskless bond. The “outside income” is a claim to the same dividend process, but the size of this claim also varies as a random walk. There is one kind of tree in the valley, so all trees bear the same amount of fruit. Some trees live in the orchard, and agents trade claims to those trees. Some trees are constantly uprooted from one agent’s yard and planted in the other’s yard. The lucky guy who got the tree will then want to sell some stock (claims to the orchard) to the unlucky guy who lost the tree. He keeps his increased wealth, but the right risk exposure gets reestablished in this way. The (substantial) technical achievement of the model is to solve for the agents’ trading policies (a band of inaction) and the equilibrium asset price when there is in addition a fixed (per trade, not per share) transactions cost.

The perfect correlation of “outside income” with the stock seems artificial, but compo-

nents of outside income uncorrelated with stocks generate no hedging demand. Therefore, this is a useful simplification, so long as one’s quantitative evaluation of the model recognizes that this is the component of income correlated with stocks and not the whole thing.

Andrew W. Lo and Jiang Wang “Trading Volume: Implications of An Intertemporal Capital Asset Pricing Model” W8565, continue an exploration of volume motivated by dynamic hedging. They write a model with investors who vary in risk aversion, and in sensitivity to a second, non-market state variable. (For example, older investors may care less than younger investors about a decline in short term interest rates, which lowers prospective returns to investment.) As a result, investors continuously trade both the market portfolio and a hedge portfolio for this state variable. Then Lo and Wang identify the composition of the hedge portfolio by looking for factor structure in *volume*.

I think the best way to think of these papers, as the rest of this literature, is to regard the outside income and hedging as a useful shortcut to generate some trading, and then focus on the effects of liquidity on this market. It is a model of how transactions costs *reduce* trading and induce price discounts, not a model of trading in the first place. The idea that the massive turnover on the NYSE is all due to agents changing dynamic hedges for their outside income just doesn’t pass my sniff test. Whatever caused 20% of outstanding Palm shares to change hands every day, it surely was not hedging demands, either hedging outside incomes or state variables that forecast future returns.

Perhaps in response to this sort of doubt, Guillermo Llorente, Roni Michaely, Gideon Saar and Jiang Wang “Dynamic Volume-Return Relation of Individual Stocks” (NBER WP 8312 forthcoming *Review of Financial Studies*) examine the dynamic relation between volume and returns to try to separate volume into “hedging” and “speculative” components. They run regressions of the form

$$R_{it+1} = C0_i + C1_i R_{it} + C2_i V_{it} R_{it} + error_{it+1}$$

for each stock i where V = volume in daily data. They argue that $C2 > 0$ indicates “speculative trade”: informed investors know that R_{it+1} is large, they buy on that knowledge sending R_{it} up a bit. By contrast, $C2 < 0$ represents “hedging trade”; agents selling in to a market without information will push the price down temporarily, so R_{it+1} will reverse sign, as with Pastor and Stambaugh’s liquidity measure. (Again, controlling for “regular” serial correlation in $C1$ in this study gives me pause.) The main finding is straightforward. Stocks with higher bid/ask spreads and smaller size – proxies for larger “information asymmetry” have large positive values of C_2 . Large stocks with small bid/ask spreads have negative values of C_2 suggesting more “hedging” motive.

4 Concluding comments

Exchanges exist to *trade* stocks and bonds, and most of that trade occurs on information. For a long time, we have presumed that this trading activity has at best a second-order effect

on the *level* of asset prices. Now both empirical work and theory are pointing to the exiting possibility that it is not; that a substantial portion of level and variation of asset prices, both over time and across assets, may reflect how those assets are used in trading. This study is in its infancy. You can see empiricists struggling with definitions of liquidity and how to see its effects, and you can see theorists struggling in formalizing this intuition with the classic theorems that rule out information trading, and that give transactions costs second order effects. But it is a time of great progress on both fronts.