Is liquidity endogenously determined?*

Robert Kieschnick
School of Management
University of Texas at Dallas
Richardson, TX 75080
rkiesch@utdallas.edu

Douglas O. Cook
Culverhouse College of Management
University of Alabama
Tuscaloosa, AL 35487
dcook@cba.ua.edu

Onur Arugaslan
Department of Finance and Commercial Law
Haworth College of Business
Western Michigan University
Kalamazoo, MI 49008-5420
onur.arugaslan@wmich.edu

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ABSTRACT

Is liquidity a priced risk factor, or is it endogenously determined by other risk factors that extant studies exclude? Using a large sample of U.S. stocks from 1970 through 2006, we find evidence that different measures of liquidity, both at the security level and at the aggregate level, are endogenous, not exogenous variables. Then, using a unique sample of U.S. firms with two classes of traded stock between 1980 and 2004, we find that the unconditional mean returns of stocks that differ in their liquidity or illiquidity are not significantly different and that exposures to either aggregate liquidity or innovations in aggregate liquidity are not significant determinants of their conditional returns. Consequently, our evidence is consistent with the arguments in Huang and Wang (2007), Johnson (2006, 2008), Novy-Marx (2006), and Rahi and Zigrand (2007) that liquidity is endogenously determined, and not a priced risk factor. Nevertheless, consistent with Novy-Marx (2006), our study also suggests why liquidity measures are good proxies for excluded risk factors.

Keywords: stock returns, liquidity, idiosyncratic risk

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1. Introduction

Is the liquidity of a security and/or its sensitivity to aggregate liquidity shocks exogenous determinants of its required returns as implied by regressions of some measure or measures of such variables on security returns? Or, alternatively, is liquidity endogenously determined with security returns by many of the same factors that explain these returns? There are theoretical arguments for either of these positions.

Some argue that liquidity is a priced risk factor.[1] Within this group of proponents, liquidity is perceived to influence required returns in three different ways. First, there are those who argue that less liquid securities should yield higher expected returns (e.g., Amihud and Mendelson (1986)). Next, some maintain that securities that are more sensitive to aggregate liquidity shocks should promise higher returns (e.g., Pastor and Stambaugh (2003)). Finally, there are those who claim that securities that are either less liquid or more sensitive to aggregate liquidity shocks should yield higher expected returns (e.g., Acharya and Pedersen (2005)).[2]

In contrast, others maintain that liquidity is not a priced risk factor, but rather endogenously determined by the same factors that influence required returns. Johnson (2006) considers how market liquidity might be related to underlying sources of uncertainty and suggests that even if liquidity is not a priced risk factor, it may appear to be due to omitted factors. Johnson demonstrates through simulations that because of the correlation of aggregate liquidity shocks with priced risk factors, one might observe the kind of evidence reported in Pastor and Stambaugh (2003), for example, even when these

[1] We will use "priced risk factor" to signify a factor that determines a security's required return.
[2] We will not discuss this literature in detail as Amihud, Mendelson, and Pedersen (2005) provide a good summary of it.

shocks are not priced risk factors. Similarly, Novy-Marx (2006) argues that since measures of illiquidity are driven by the price elasticity of demand, illiquidity will proxy for any unobserved risk factor.

Focusing on a different aspect, Huang and Wang (2007) develop a model in which investors face idiosyncratic shocks and participation costs, but where required returns are determined outside the model. They show within this framework that the demand for liquidity is endogenously driven by idiosyncratic shocks that force investors to re-balance their portfolios. While these idiosyncratic shocks affect prices: causing return distributions to be negatively skewed and fat-tailed, they do not determine required returns. While Johnson (2008) takes a different approach from Huang and Wang, his modeling of the random arrival and exit of traders also leads to demand shocks determining changes in liquidity. Finally, Rahi and Zigrand (2007) argue that the variety of liquidity measures in existence define liquidity in terms of its attributes, not its function. Consequently, they define liquidity in terms of the gains from trade realized in equilibrium. Given this definition, liquidity, just like prices, is endogenously determined.

To date, there has been no study that has taken these endogeneity arguments seriously and empirically examined their implications. Further, we know of no study that purports to find evidence that some measure of liquidity is priced that also tests whether its evidence is subject to an omitted variables bias. There are, however, a plethora of empirical studies that regress some measure of liquidity on a set of explanatory variables and find that liquidity is influenced by some firm characteristic (like advertising expenditures, institutional ownership, governance, or firm size). These studies demonstrate that the liquidity of a stock is correlated with various firm features. Such correlations are consistent with the criticism that studies that claim to find evidence that liquidity is priced have failed to adequately control for other priced risk factors; e.g., the price elasticity of demand for a stock, with which liquidity is potentially correlated.

This study focuses on testing the above endogeneity arguments. There are two ways to test these arguments given that these models also suggest that priced risk factors are time varying. One approach uses a Hausman test, employing instrumental variables to test different liquidity measures for exogeneity. The second approach involves research design, similar to those used in twin studies in biology, to test whether different liquidity measures are significant because of omitted priced risk factors.

We do both. First, using a large sample of U.S. firms whose shares of common stock traded between 1970 and 2006, we test whether different liquidity measures, both at the individual and aggregate levels, are endogenous variables in regressions on excess returns. Next, we use a unique research design to address the implied omitted variables problem and test additional implications of this class of models. Specifically, we examine the returns and liquidity of two classes of traded common stock issued by the same U.S. corporations from 1980 through 2004. Our study design is analogous to the aforementioned twin studies in biology that attempt to tease out the effects of "nature versus nurture." This design allows us to control for omitted risk factors that are correlated with issuer characteristics.

To conduct this examination, we organize the remainder of the paper as follows. Section 2 briefly discusses why prior evidence suggesting that liquidity is priced is not adequate to establish that conclusion. Section 3 uses an instrumental variables approach to provide large sample evidence on whether different liquidity measures are exogenous or endogenous variables in regressions on excess returns. Using a research design incorporating dual class stock, Section 4 examines the omitted variables arguments in more detail. Section 5 concludes with a summary of our findings and suggestions for further research.

We find evidence for the following conclusions. First, different measures of liquidity, either at the individual security level or at the aggregate level, are endogenous variables based on Hausman tests. Second, although the liquidity or illiquidity of our sample of two classes of dual class stocks is significantly different, the mean (median) returns of the two daily return distributions are not significantly different. Third, the differences in illiquidity and differences in unconditional variances are significantly correlated. Fourth, the factor loadings on Amihud's lagged aggregate illiquidity measure, Amihud's aggregate illiquidity innovation measure, and Pastor and Stambaugh's liquidity innovation measure as well as the factor loadings that *predict* idiosyncratic risk or aggregate volatility innovations are statistically insignificant. However, the idiosyncratic shocks experienced by these two classes of stock are significantly different while the differences in illiquidity and differences in *contemporaneous* idiosyncratic shocks are highly correlated.

Altogether, our results are consistent with arguments that the liquidity of a security and/or its sensitivity to aggregate liquidity shocks are endogenously determined by priced risk factors that are excluded from existing research. Consequently our evidence, as Novy-Marx (2006) suggests, also provides a rationale for why liquidity measures are good proxies for excluded priced risk factors.

2. Why prior evidence on the pricing of liquidity is inadequate to establish this conclusion.

We will not discuss the empirical literature on the pricing of liquidity in detail as Amihud, Mendelson, and Pedersen (2005) provide a good summary of this literature. Instead, we will point out several important reasons why prior studies have not been adequate to show that liquidity is a priced risk factor.

Many studies that purport to find that liquidity, in some form, is a priced risk factor regress some measure of liquidity or illiquidity, either at the security level or the aggregate level, on security returns or security excess returns (security returns less a proxy for the risk free rate of return). All such studies profiled in Amihud, Mendelson, and Pedersen's review suffer from two critical problems. First, they assume that their liquidity measure or measures are exogenous determinants of security returns but do not test this assumption. Second, they assume that they have included all the priced risk factors. Given the lack of consensus in the asset pricing literature on what are priced risk factors, this second assumption is a problem for any asset pricing study. Violation of either of these assumptions undermines the interpretation of their statistical evidence.

Other studies that purport to find evidence that liquidity is priced examine the relative prices of two similar securities, one of which is more "liquid." All the studies of restricted stock discussed in Amihud, Mendelson, and Pedersen's review are examples of this type of study. The essential problem with these studies, as discussed below in more detail, is their failure to recognize that the prices of these two types of securities may differ because of differences in expected cash flows and not because of differences in required returns. Restricted stock studies are especially prone to this problem as Silber's (1991) study illustrates.

Silber examines the relative prices of restricted and unrestricted stock for 69 firms on one day between 1981 and 1988. While he reports a mean discount of 34% for restricted stock relative to unrestricted stock, he also reports that some of the restricted shares trade at a premium, which is totally inconsistent with his assumption that price differences are simply driven by differences in their liquidities but suggests instead that other factors are involved. The relative prices of restricted to unrestricted stock are likely to be influenced by a variety of factors that this and similar studies ignore such as the vesting period, the nature and length of the restrictions, the transferability of the restricted securities, the financial strength of the firm, and additional rights attached to restricted shares. Since all of these factors influence expectations about future cash flows associated with owning either the restricted or unrestricted stock, they can account for the average discount without assuming that liquidity is priced. Further, by its nature, restricted stock influences the timing of expected cash flows and thereby its price.[3]

Regardless of whether one identifies such additional factors or not, the key point is that there is no logical reason why differences in "liquidities" are not associated with differences in expected cash flows rather than with differences in required returns. The mere fact that one might observe the price of a less "liquid" asset to be lower than a similar more "liquid" asset does not establish that its required returns are different. Many measures of liquidity or illiquidity are price impact measures and so might just as logically be related to an investor's expected cash flows (i.e., expected prices) as they are to required returns.

[3] A similar example involves the relative pricing of restricted and unrestricted stock options, which are similar to European call versus American call options. If the issuing firm pays dividends then one should expect the relative prices to be different and the restricted stock option to trade at a discount to the unrestricted stock option although this discount has nothing to do with relative liquidities.

3. Is Liquidity Endogenous? – An instrumental variables approach

Posing the following question illustrates the logic of several of the endogeneity arguments we consider: What is the liquidity of an asset for which there is no demand? This question is pertinent since the liquidity of any asset is correlated with its demand and so liquidity or illiquidity will always appear to be priced if we exclude some determinant of the demand for an asset.

To address Johnson's (2006) and Novy-Marx's (2006) omitted variable arguments, we first analyze whether different measures of liquidity or illiquidity are exogenous variables in excess return regressions. The standard econometric method for examining this issue is to use a Hausman (1978) type test to compare the estimates from instrumental variable estimation to that of an estimation that assumes variable exogeneity. Consequently, we follow this methodology.

We use monthly CRSP data from 1970 through 2006 to estimate two regression models of the following form:

$$R_{i,t} - R_{f,t} = \alpha_i + \beta_{i,mkt} * \; R_{mkt,t} - R_{f,t} \; + \beta_{i,smb} * SMB_t + \beta_{i,hml} * HML_t + \beta_i * LM_i + \varepsilon_{i,t} \qquad (1)$$

In each of the regression models, we add different liquidity measures (LM_t) to the Fama and French (1993) three-factor model, which serves as our base model. We obtain the Fama and French factor data from WRDS. For our first model, we obtain Pastor and Stambaugh's (2003) monthly liquidity innovation factor, an aggregate liquidity measure, from WRDS and use it as our priced liquidity measure. For our second model, we use monthly CRSP data to calculate Amihud's (2002) illiquidity measure (ILLIQ), which is security specific, and use it as our priced liquidity measure.

We then estimate a series of panel regression models using the GMM method with correction for autocorrelation and heteroskedasticity.[4] There are two reasons for using individual stock data rather than portfolio data. First, Ang, Liu, and Schwarz (2008) provide evidence that using individual stocks leads to more efficient tests of factor models. Second, it would be extremely difficult to implement an instrumental variables approach to exogeneity testing using portfolios.

For Pastor and Stambaugh's (2003) liquidity innovation factor, we find the logarithm of the number of shares issued and outstanding and a dummy variable representing whether a stock was in the S&P index to be acceptable instruments. These instruments make sense because the logarithm of the number of shares issued and outstanding represents a key feature of the supply function for a stock at any given time. Therefore, this variable can be used to capture changes in a stock's supply curve. Support for the S&P 500 index is provided by the fact that prior research (e.g., Shleifer (1986), Kaul, Mehrotra, Morck (2000), etc.) on the demand elasticity of stock uses this index to identify such elasticity. As an additional instrument, we examine whether a stock is in the S&P small cap index or not as such membership tends to vary more over time than the S&P 500 and is, therefore, more likely to capture exogenous shocks to demand for a stock.

For our first regression model using Pastor and Stambaugh's liquidity innovation factor, we find the logarithm of the number of shares issued and outstanding as well as membership in the S&P index to be relevant instruments according to the Kleibergen-Paap rk LM Statistic of 29.876 and a corresponding p value less than 1%. These

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[4] We use Stata code provided by Braum, Schaffer, and Stillman (2007).

instruments also pass the Hansen J test with a J statistic of 0.004 and a corresponding p value greater than 95%. Thus, our instruments appear to be valid instruments. For this liquidity measure, the Durbin-Wu-Hausman exogeneity test statistic of 322.675 is significant at less than the 1% level and so rejects the exogeneity of Pastor and Stambaugh's (2003) liquidity innovation factor.

If we add membership in the S&P small cap index as an additional instrument, the Kleibergen-Paap rk LM Statistic increases to 31.97 with a p value less than 1%. These three instruments also pass the Hansen J test with a J statistic of 0.009 and a corresponding p value greater than 99%. Again, our instruments appear to be valid instruments. For this regression model, we obtain a Durbin-Wu-Hausman exogeneity test statistic of 348.923, which is significant at less than the 1% level. Consequently, both regression models reject the exogeneity of Pastor and Stambaugh's (2003) liquidity innovation factor, and so are consistent with the different endogeneity arguments.[5]

Turning to a security level measure of liquidity, we use Amihud's (2002) illiquidity measure, which we compute for each of our sample stocks using monthly CRSP data. One of the difficulties in testing this measure of liquidity is that a stock's return factors into its definition. Consequently, it is more difficult to find instruments correlated with it and yet uncorrelated with the residual of the excess return regression. After considering several potential instruments, we find that dummy variables signifying whether a stock is in S&P's mid-cap index and whether a stock is in S&P's small-cap index are acceptable instruments. For this regression model, the instruments are relevant

[5] It is worth noting that Sohn (2008) reports evidence that Pastor and Stambaugh's factor portfolio, constructed by sorting on their liquidity innovation factor, appears to be driven by innovations in volatility – which is consistent with our evidence and with the models of Johnson (2006) and Huang and Wang (2007).

according to the Kleibergen-Paap rk LM Statistic of 4726.58 and a corresponding p-value less than 1%. These instruments marginally pass the Hansen J test with a statistic of 3.5663 and a corresponding p value greater than 6%. For this liquidity measure, the Durbin-Wu-Hausman exogeneity test statistic of 38.181 is significant at less than the 1% level and so rejects the exogeneity of Amihud's illiquidity measure.[6]

Altogether, our evidence implies that both of these liquidity measures, at the individual security level and at the aggregate level, are endogenous variables in regressions on excess returns, and so our evidence is consistent with the different endogeneity arguments.[7]

4. Is Liquidity Endogenous? – A research design approach

Since one may dispute the above evidence by questioning the validity of our instruments, we also address our research question using a design approach. This approach also allows us to address other issues raised by the endogeneity arguments that are not easily addressed using standard methods since we are controlling for a variety of firm characteristics.

Clarke (2005) recommends the design approach since adding more control variables does not necessarily mitigate the problem. However, before discussing the design approach, we should note that Spiegel and Wang (2006) report evidence that adding a measure of idiosyncratic risk eliminates the significance of liquidity in excess return regressions. In addition, Ho and Hung (2008) report evidence that adding

[6] Consistent with this conclusion, Linnainmaa and Rosu (2008) use Finnish data and find evidence that bid-ask spreads are endogenously determined.

[7] We should note that we also tested other liquidity measures (e.g., Pastor and Stambaugh's level factor, Amihud's aggregate illiquidity measure, etc.) and derive the same conclusions.

measures of investor sentiment also eliminates the significance of liquidity in excess return regressions. Consequently, both of these studies are consistent with the argument that liquidity is observed to be a priced risk factor due to excluded risk factors.

While suggestive, the above evidence is not conclusive since it could be argued that their included variables are not priced risk factors. Thus, we approach the issue differently, focusing on research design as Hanushek and Jackson (1977), Clarke (2005), and others point out that this approach is an effective way to address omitted variable problems. To illustrate the logic of the appropriate research design, we use Hanushek and Jackson's illustration.

Suppose that the true model is:

$$Y_t = \beta_1 + \beta_2 X_{2t} + \beta_3 X_{3t} + \beta_4 X_{4t} + \varepsilon_t \,, \tag{4}$$

but we estimate instead:

$$Y_t = \beta_1 + \beta_2 X_{2t} + \beta_3 X_{3t} + \varepsilon_t \,. \tag{5}$$

In this case, the estimates of β_2 and β_3 will be biased by their correlation with X_4. For example, we can write:

$$E\ \beta_2 \ = \beta_2 + \beta_4 b_{42t}, where\, b_{42t} = \frac{r_{42} - r_{32} r_{24}}{1 - r_{32}^2} \sqrt{\frac{V_4}{V_2}} \tag{6}$$

Now, by research design, we can create a situation where the variance of X_4 is zero and so eliminate the bias introduced by excluding X_4. This design is exactly what twin studies in biology accomplish since they examine samples in which there is no variance in the genetic endowment of the paired subjects. For our study, the analogous research design would be to pair traded securities issued by the same firm, and so control for firm characteristics that determine its securities' sensitivities to excluded risk factors. We argue that firms with dual class stock where both classes of shares are traded fit this requirement.

4.1. A Selective Review of the Literature on Dual Class Stock

Before turning to a description of our dual class sample, we provide a selective review of the literature on dual class stock. While a number of aspects of the use of dual class stock have been studied, we are primarily interested in how that literature has used such stock to measure the value of voting rights since it brings up the core issues under study.

There are several different methods for valuing the voting rights associated with common stock. One method is to calculate the ratio of the price of common stock with superior voting rights to that of stock with inferior voting rights (e.g., Lease, McConnell, and Mikkelson (1983)). Another method is to compute the voting premium as the price differential between voting and non-voting stocks divided by the price of non-voting stocks. For example, Zingales (1994) defines the voting premium as:

$$VP_t^i = \left(P_{vt}^i - P_{nvt}^i\right) \Big/ P_{nvt}^i \ , \qquad (1)$$

where P_{vt}^i, and P_{nvt}^i represent the price of common stock with voting rights and the price of common stock without voting rights, respectively.[8] Both measures depend upon the

[8] Zingales also adjusts this expression for any extra dividends paid to non-voting common stock as follows: $VP_t^i = \left(P_{vt}^i - P_{nvt}^i\right) \Big/ \left(P_{nvt}^i - \varepsilon^i \Big/ \rho^i P_{nvt}^i\right)$, where ε^i, ρ^i represent the additional dividends attributed to non-voting stock and an "appropriate" discount factor, respectively. Zingales does not discuss what this discount factor should be or how he measured it.

difference between the price of stock with superior voting rights and the price of stock with inferior voting rights.

Note that this premium is not equivalent to a stock return, or more importantly, a required return. In fact, the implicit assumption of most, if not all, of this research is that the required rates of return for the two stock classes are equivalent. To see this, we can use the basic discounted cash flow model of stock valuation to calculate the price difference:

$$P_{svr} - P_{ivr} = \sum_{t=1}^{\infty} \frac{E\ \ NCF_{svr}}{1 + r_{svr}} - \sum_{t=1}^{\infty} \frac{E\ \ NCF_{ivr}}{1 + r_{ivr}} \qquad (2)$$

where svr represents superior voting rights and ivr represents inferior voting rights. Now, if $r_{svr} \neq r_{ivr}$, then the price differential no longer reflects just the value of voting rights as assumed by this literature.

Consistent with the implicit assumption that the required rates of return across the two stock classes are the same, Amoako-Adu, Smith, and Schnabel (1990) find no significant difference between the betas of Canadian common stock with superior and inferior voting rights. Further, and more significantly, Foerster and Porter (1993) examine the daily returns of 36 dual class Canadian firms from 1980 through 1987 with both classes of stock trading with equal dividend rights and equal liquidation rights. They find the average daily returns of the two classes to be equal. Since their results do not depend on a particular asset-pricing model, this represents stronger evidence that the required rates of return for the two stock classes are equal.

Interestingly, Foerster and Porter point out that the class with superior voting rights tends to be less liquid than the class with inferior voting rights. DeAngelo and

DeAngelo (1985), Megginson (1990), and Pagano and Roell (1990) also provide evidence that the liquidity of the two classes of stock is typically different. Consequently, these two streams of literature raise questions about how liquidity does affect the pricing of dual class stock.

Zingales (1995) touches upon this issue when he reports finding that the voting premium is not related to the relative trading volume of the two classes of stock: one with inferior and one with superior voting rights. In contrast, Neumann (2003) finds that the voting premium is negatively correlated with either the ratio of the bid-ask spread of the two classes or an implied liquidity measure that he constructs. Neumann's interpretation is that liquidity influences the pricing of the two classes of stock. However, as equation (1) demonstrates, it is not clear if variation in the relative voting premium that Neumann examines is due to his liquidity measure affecting $E(NCF_{svr})$ and $E(NCF_{ivr})$ or affecting r_{svr} and r_{ivr}. The return decomposition literature (e.g., Vuolteenaho (2002)) demonstrates that this is a non-trivial question. If one accepts the results of Amoako-Adu, Smith, and Schnabel (1990) and Foerster and Porter (1993), then Neumann's results are driven by how $E(NCF_{svr})$ and $E(NCF_{ivr})$ influence the demand for these securities and, thereby, their liquidity.

This discussion is particularly relevant to prior analyses (e.g., Amihud (2002)) that suggest liquidity risk, measured in a number of ways, is a priced risk factor. To our knowledge, none of these studies has controlled for $E(NCF_t)$ sufficiently to be certain that their results are not driven by the correlation between their liquidity measure and the demand for a security caused by changes in its E(NCF)s.[9] This concern is just another

[9] The recent sub-prime "crisis" is a perfect illustration of the correlation between $E(NCF_t)$s, the demand for a security, and measures of its liquidity.

way of framing Novy-Marx's (2006) criticism of these studies.

4.2 Sample and Sample Data

As noted above, we implement the research design approach to the omitted variables problem by identifying dual class stocks with both classes traded. To do this, we begin by attempting to identify all U.S. public corporations with two classes of stock that traded during the time period 1980 through 2004. We do not include firms with tracking stock because tracking stock is a claim on a separate portion of the firm and does not contain the same operating assets as other equity claims on the firm. We require that both claims be on the same operating assets, or firm, and so share the same firm characteristics, including news events. This requirement is important since it controls, to the extent possible, for firm-specific characteristics and news, while allowing for the possibility that the different claims will have different liquidity.

With this in mind, we identify three potential sources of sample firms: 15 firms with dual class stock at the beginning of 1980, 370 firms that went public with dual class stock, and 178 firms that recapitalized from single to dual class stock during our time period. We then eliminate potential sample firms when both classes of their common stock do not trade concurrently or when there is no CRSP data available. Our remaining sample of 112 firms becomes the focus of this study.

For each of these firms, we collect the following from CRSP: price, closing bid/ask spread, and trading volume data for each trading day over a one-year period. We establish that the one-year period is free of change in control contests to avoid the contamination that such contests would present to our analyses. For the three respective groups, the data are primarily during 1980, during the one-year period following their going public, and over the one-year period after their conversion to dual class stock. Note that by construction, each pair of stocks shares the same exposure to industry and macroeconomic influences on their daily security returns.

4.3 Analysis of Sample Data

4.3.1 Analysis of differences in liquidity

Hasbrouck's (2005) review suggests that there are several different measures for the liquidity or illiquidity of a security. Since TAQ data are not available prior to 1993, we use daily measures that can be constructed with daily CRSP data rather than measures based on bid/ask (TAQ) data, as the latter would severely restrict our sample. Specifically, we use the Amihud illiquidity measure (Amihud (2002)) since Hasbrouck's (2005) evidence suggests that this measure is highly correlated with the alternative measures.[10]

For each day, we compute the difference in illiquidity between the two classes of stock and test for each firm whether the mean or median is equal to zero. It is important to note that this method of analysis is analogous to what has been done in Monte Carlo studies as each firm/pair effectively represents an independent sample. Also, recall that our empirical design controls for a number of influences, like firm specific news as well as macroeconomic news, since these impact both classes of stock for a given firm. Therefore, the critical issue becomes whether the number of rejections of the null

[10] We also examine the Amivest (Cooper, Groth, and Avera (1985)) measure of liquidity and find similar evidence to that reported for Amihud's illiquidity measure.

hypothesis exceeds the expected number given the marginal significance level of the test statistic.[11]

In Panel A of Table 1, we report the number of significantly different means or medians across the two classes of stock, at the 1%, 5%, and 10% marginal significance levels. This reported evidence clearly suggests that there are significant differences in illiquidity between the two classes of stock, a result consistent with the evidence reported in DeAngelo and DeAngelo (1985), Megginson (1990), Pagano and Roell (1990), and Neumann (2003).

A potential problem with using the CRSP return series is that returns are based on bid-ask averages when the stock class does not trade, resulting in inaccurate realizable returns. In addition, since CRSP does not report market closing prices for the NASDAQ Small Cap Market prior to June 15, 1992, this portion of the return series is based completely on bid-ask averages. Therefore, for our sample stocks, we construct daily returns based on a price and dividend series that includes only trading days during their respective sample periods. Using these returns, we re-compute the Amihud illiquidity measure and report the results in Panel B of Table 1. As with Panel A, we observe that the two classes of stock are equally illiquid too infrequently to conclude that they have the same illiquidity. Thus, we again conclude that the illiquidity or liquidity of the two classes of stock differs.

Altogether, this evidence is consistent with the evidence in DeAngelo and DeAngelo (1985), Megginson (1990), and Pagano and Roell (1990) that the liquidities of stocks with superior and inferior voting rights are different.

[11] Note that this test procedure is not subject to the multiple comparison criticism since the draws are independent and we are comparing the number of rejections to the predicted number under different probabilities of rejection.

4.3.2 Analysis of differences in daily returns

Given the above results, if the liquidity of a security is a priced risk factor then we should expect the means of the daily return distributions for the two classes of stock to be significantly different. Note that these expectations should hold under any asset-pricing model in which liquidity is a priced risk factor. In contrast, if the endogeneity arguments are correct, then it is unlikely that we will observe any significant differences in the means of the distributions of daily returns for these two classes of stock since we have controlled for a number of their common features.

To test this hypothesis and its alternative, we compute daily the difference in returns between the two stock classes and test for each firm whether the mean or median is equal to zero. Again, it is important to note that this method of analysis is analogous to what is done in Monte Carlo studies as each firm effectively represents an independent sample. So, the critical issue becomes whether the number of rejections of the null hypothesis exceeds the expected number given the marginal significance level of the test statistic.

Table 2 shows that there is no firm/share combination for which we can reject the mean or median of their daily return differences to be significantly different from zero.[12] Altogether, our results are consistent with Foerster and Porter's (1993) evidence for Canadian firms. However, unlike Foerster and Porter (1993), we do not require that the sample firms' dual class stock have the same dividend rights and liquidation rights. Thus, our return evidence is even stronger than their evidence. These results along with

[12] We find similar results when we construct returns from price and dividend data and exclude non-trading days.

the prior illiquidity evidence are consistent with models that suggest that a security's liquidity is endogenously determined by the same factors that determine its demand. This same evidence, however, is not consistent with models that imply that a security's liquidity or illiquidity is a priced risk factor since these models imply that the mean returns should be significantly different if their liquidities are significantly different.

4.3.3 Analysis of return variances

The models of Johnson (2006), Johnson (2008) as well as Huang and Wang (2007) suggest that measures of a stock's liquidity or illiquidity should be correlated with its return volatility. To test this hypothesis, we begin by using Levene's (1960) test to determine whether the matched pairs of traded dual class stocks have equal variances.

More specifically, we use Brown and Forsythe's (1974) mean and median variations of Levene's test as they allow for a wider variety of non-normal distributions. Table 3 shows that for these two tests we reject the equality of variances using the mean (median) measure for 20 (21), 28 (28), and 32 (32) cases at the 1 percent, 5 percent, and 10 percent levels of significance. Since these rejection rates are higher than the number of 1%, 5%, and 10% rejections that would be expected under the null hypothesis of equality, we conclude that the variances of these two distributions are different.[13]

The evidence that the liquidity and unconditional variances of the two securities issued by the same firm differ while the unconditional means are equivalent is consistent with both Johnson (2006) and Huang and Wang (2007). These models predict that we should observe a correlation between such unconditional variances and measures of

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[13] We find similar results when we construct returns from price and dividend data and exclude non-trading days.

liquidity, since the latter is driven by idiosyncratic shocks. To test this conjecture more directly, we compute the difference in the mean Amihud illiquidity measure and the difference in the variance of daily returns for the two classes of stock for each firm. We then compute the correlation of these differences across firms and test for significance. We observe a correlation of 0.47, which is significant at the 1% marginal significance level. Thus, we do observe a substantial positive relationship between the variance of a security's returns and its illiquidity that is consistent with Johnson (2006), Johnson (2008), and Huang and Wang (2007).[14]

4.3.4 Regression analysis of daily returns and daily illiquidity measures

Because our prior analyses differ from typical empirical procedures, we now employ regression analysis to check the robustness of our conclusions concerning the differences in liquidity and lack of differences in returns for our two classes of stock.

Specifically, we create a pooled cross-section and regress daily stock returns on a dummy variable that takes on the value 1 if the stock has superior voting rights. We report these results in Table 4 Panel A. Similarly, we regress Amihud's illiquidity measure on a dummy variable that takes on the value 1 for the stock with superior voting rights and report the results in Table 4 Panel B. In both regressions, we use sandwich estimators of the standard errors adjusted for clustering at the firm level.[15]

Consistent with our prior evidence, we find a significant difference in the average liquidities but no significant difference in the average returns for these two classes of

[14] See, for example, equation 3 in Johnson (2008). Note that our methodology implicitly controls for other firm characteristics by focusing on the differences for a given firm, and so reflects the implications of these models.
[15] It is worth pointing out that we also estimate random effects models and derive the same conclusions. However, we cannot estimate fixed effects models since the dual class dummy is a fixed effect.

stock. This analysis is particularly interesting since it is equivalent to comparing two equally weighted portfolios: one of stock with superior voting rights and one of stock with inferior voting rights. According to the criteria set out in Acharya and Pedersen (2005, page 392), our results imply that the liquidity of stocks is not a priced risk factor.

4.3.5 Analysis of Conditional Excess Returns

Thus far, we have found evidence that when we control for firm characteristics, the first moment of a security's return distribution is *not* related to its liquidity, while its second moment is. Such results are consistent with Johnson (2006), Johnson (2008), and Huang and Wang (2007). This evidence, however, does not rule out the possibility that sensitivities to aggregate liquidity shocks are priced risk factors. Given the equivalence of the mean or median daily stock returns for the two classes of stock, if aggregate liquidity shocks are priced risk factors, then the liquidity betas of these classes of stock should be the same, or counter-balanced by the loading on other shared risk factors.

To explore these possibilities, we regress different risk factors and various explanatory variables on daily excess stock returns (daily holding period stock returns less Treasury rates) over matching 12 month periods (i.e., the same periods used in the above analyses). In each of these regressions, we use the Fama and French (1993) three-factor model as our control model, and include a dummy variable (VD_i) that indicates whether the security has superior voting rights. Specifically, our base model is:

$$R_{i,t} - R_{f,t} = \alpha_i + \beta_i * VD_i + \beta_{i,mkt} * \ R_{mkt,t} - R_{f,t} \ + \beta_{i,smb} * SMB_t + \beta_{i,hml} * HML_t + \varepsilon_{i,t} \qquad (7)$$

To this base model, we add different measures of aggregate liquidity innovations to determine if such innovations are priced risk factors. Specifically, we first compute

Amihud's (2002) illiquidity measure, lnAILLIQ, as the logarithm of the average across stocks of their daily absolute stock return divided by their daily dollar volume for each day from January 2, 1980 through December 31, 2004. We then compute his aggregate innovations (residual) measure, lnALLIQ^{U} and his lagged measure lnAILLIQ_{t-1}. The aggregate residual measure, lnALLIQ^{U}, should capture the innovations in aggregate liquidity in a manner similar to Pastor and Stambaugh's (2003) aggregate liquidity innovations measure. Since we use these data to form panels, we follow Petersen (2006) and use Rogers' estimators of the standard error adjusted for clustering at the firm level.[16]

In Table 5 Column 2, we report the result of regressing the daily excess returns of our paired stocks over matching one-year periods on our control model and Amihud's illiquidity innovations measure. The insignificance of the dummy variable for the stock with superior voting rights suggests that the conditional means are equivalent and so provide complimentary evidence to that in Table 4 for the mean returns. More importantly, we do not find the coefficient on Amihud's illiquidity innovation measure to be significant, which implies that it is not a priced risk factor.[17] Such a result, however, is consistent with Johnson's (2006) argument that aggregate liquidity shocks may be correlated with excluded priced risk factors, and so may appear to be priced.

To explore this conclusion further, we follow Amihud (2002) and expand the regression model to include his lagged aggregate illiquidity measure, and report results in Table 5 Column 3. These results suggest that neither the aggregate illiquidity innovation

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[16] Adjusting the standard errors for two way clustering (i.e., by firm and time), or adjusting the standard errors for clustering at just the security level does not change our basic conclusions. We also tried to employ the Fama and Macbeth (1973) procedure using Peterson's Stata program (FM) but it failed to produce usable results.

[17] Some may attribute this lack of significance to our sample size. This conjecture, however, is inconsistent with the fact that our statistical tests were sufficiently powerful to reject the null hypothesis that the Fama/French three-factor model does not explain excess returns.

measure nor the aggregate illiquidity measure is a priced risk factor. These results are also consistent with our unconditional mean return results.

Finally, to see whether compensating factor loadings might account for the equivalency of the unconditional daily mean returns, we expand the previous regression model to include interaction terms between the dummy variable for superior voting rights class and each of the conjectured risk factors, and report results in Table 5 Column 4. We find no evidence that compensating factor loadings explain the equivalence of the unconditional means.

Thus, the above analysis is consistent with several conclusions. First, this evidence is consistent with the argument that prior findings that aggregate liquidity/illiquidity measures are significant determinants of excess stock returns suffers from a significant omitted variables problem. Second, these results are consistent with the arguments in Johnson (2006), and others, that such measures will appear to be priced risk factors even when they are not because such measures are correlated with excluded priced risk factors. And third, the fact that we continue to observe statistically significant loadings on the Fama-French factors suggests that their significance is not driven by excluded priced risk factors.

To explore the robustness of these results to alternative specifications, we consider the inclusion of the momentum factor and the substitution of an alternative aggregate liquidity innovation factor. We include the momentum factor because Sagi and Seasholes (2007) provide evidence that momentum is driven by firm-specific attributes. Consequently, if our research design adequately controls for excluded firm characteristics then we should not observe this factor to be significant if they are correct. We substitute a different aggregate liquidity innovation factor because one might argue that our mis-measurement of this factor has led to our failure to find it significant.

To do this we compute monthly excess returns for our sample stocks so as to be able to use the monthly momentum factor and the Pastor and Stambaugh (2003) liquidity innovation factor available on WRDS. Like the prior analysis, we form a panel data set and estimate standard errors using Rogers' estimators with adjustment for clustering at the firm level. In Column 2 of Table 6, we report the results from regressing excess returns on Pastor and Stambaugh's (2003) liquidity innovation factor and our control model. We do not find the Pastor and Stambaugh liquidity factor to have a significant loading, which is inconsistent with it being a priced risk factor. Such results, however, are consistent with our earlier Durbin-Wu-Hausman exogeneity test results.

In Table 6 Column 3, we extend this regression model by adding the momentum factor. The results not only reject the momentum factor as a priced risk factor, but also re-affirm our failure to observe significant differences in the conditional returns of the two classes of stock. As suggested above, the fact that we reject the momentum factor suggests that our research design does an adequate job of controlling for excluded firm characteristics since Sagi and Seasholes (2007) provide evidence that momentum is driven by firm-specific attributes.

Finally, in Column 4 of Table 6, we extend the Column 3 regression by adding interaction terms between our superior voting rights dummy variable and each of the five risk factors. These results mirror the results for the daily excess returns reported in Column 4 of Table 5. Consequently, we do not find any evidence that differences in factor loadings account for our results.

Altogether, our evidence is consistent with the arguments of Johnson (2006) and Novy-Marx (2006) that measures of aggregate liquidity or liquidity innovation may appear to be priced because they are correlated with either excluded risk factors or the price elasticity of demand since our research design controls for firm-specific attributes to the greatest extent possible. However, these arguments have some additional implications.

For example, as mentioned earlier, Johnson's (2006) model implies that liquidity and volatility or idiosyncratic risk should be highly correlated as both are driven by excluded priced risk factors. Similarly, Huang and Wang (2007) argue that liquidity should be correlated with idiosyncratic volatility. Consistent with this implication, Spiegel and Wang (2006) report that the statistical significance of liquidity in explaining the cross-section of stock returns disappears when the analysis accounts for firm idiosyncratic risk. Consequently, if we are controlling for excluded firm attributes that determine the sensitivity of a stock to such factor(s), then idiosyncratic risk should not be a priced risk factor. We test this conjecture by following Spiegel and Wang, but using daily data, and estimating a daily idiosyncratic risk measure using the EGARCH model that they estimate using monthly data. Specifically,

$$
\begin{aligned}
&R_{i,t} - R_{f,t} = \alpha_i + \beta_{i,mkt} * \ \ R_{mkt,t} - R_{f,t} \ \ + \beta_{i,smb} * SMB_t + \beta_{i,hml} * HML_t + \varepsilon_{i,t} \\
&\varepsilon_{i,t} = \sqrt{h_{i,t}} \times v_t \\
&\ln h_{i,t} = \bar{w}_i + \sum_{m=1}^{p} \delta_{i,,m} \ln h_{i,t-m} + \sum_{m=1}^{q} \eta_{i,n} \ \ |v_{t-n}| - E|v_{t-n}| + \Psi_i v_{t-n}
\end{aligned} \tag{8}
$$

We use the previous day's EGARCH estimate of the conditional volatility ($h_{i,t-1}$) as the estimate for today's conditional idiosyncratic risk measure. To test whether this potential risk factor is priced, we regress daily excess returns on this predicted conditional idiosyncratic risk measure and the Fama/French three factors, and report the results in Table 7 Column 2.[18] While the sign of the coefficient on this factor is the same as in Spiegel and Wang, we do not find it to be statistically significant. Consequently, this evidence is consistent with the notion that idiosyncratic risk appears to be priced because it is correlated with excluded priced risk factors controlled for by our research design.

Taking a different tack, we note that using daily return data Ang, Hodrick, Xing, and Zhang (2006) show that innovation in aggregate volatility is a priced risk factor. Within either Johnson's (2006) or Huang and Wang's (2007) model, shocks to demand that force portfolio rebalancing can create a correlation between measures of illiquidity and aggregate volatility. Consequently, we should not observe innovations in aggregate volatility to be a priced risk factor if its effects are really working through either excluded risk factors or the elasticity of demand over which our research design offers some control.

To test this conjecture, we follow Ang, Hodrick, Xing, and Zhang (2006) and use daily innovations in the VIX index.[19] We report the results of incorporating this factor into the basic Fama and French three-factor model in Table 7 Column 3. While we find the loadings on the three factors in Fama and French's (1993) regression to be statistically significant, we do not find the coefficient on this innovation in aggregate volatility to be significant – even though its sign is consistent with Ang, Hodrick, Xing, and Zhang's results. Consequently, this evidence is also consistent with the conjecture

[18] We do not include the voting rights dummy in these regressions, as it was not significant in our previous daily excess return regressions.
[19] Like Ang, Hodrick, Xing, and Zhang, we use the index based on the S&P 100, rather than on the S&P 500, because of the availability of these data over a longer time horizon.

that innovations in aggregate volatility appear to be priced risk factors because of their correlation with excluded priced risk factors.

4.3.6 Analysis of idiosyncratic shocks

Thus far, our evidence is consistent with the models developed in Johnson (2006), Johnson (2008), and Huang and Wang (2007). However, the key point of these models, and particularly the Huang and Wang model, is that demand shocks, and particularly idiosyncratic demand shocks, give the appearance that liquidity is a priced risk factor. While the above evidence using EGARCH idiosyncratic risk estimates might appear to be inconsistent with these arguments, it is not. Within the above models, it is idiosyncratic shocks *within* a period that influence measures of liquidity within the *same* period, and not *anticipated* idiosyncratic shocks. Thus, if these arguments are correct, we should observe a significantly positive correlation between differences in the idiosyncratic shocks experienced by the two classes of stock and differences in their measured liquidity/illiquidity, when there are differences in the idiosyncratic shocks received.

To test these conjectures, we first test whether the distribution of daily idiosyncratic risks for the two classes of stock are equivalent. Specifically, the standard approach to measuring idiosyncratic risk is to use the residuals from a regression of stock returns on identified risk factors. We compute squared residuals using the Fama-French three-factor model, the Fama-French three-factor model with different aggregate liquidity measures, and the Fama-French three-factor model with the momentum factor added. However, we only report results for the first idiosyncratic risk measure because the results are effectively the same across models and because we doubt whether these additional measured residuals are the appropriate ones to use since we did not observe evidence earlier that these additional factors were priced risk factors.

We report an analysis of the differences in the squared residuals, between the two classes of stock for each sample firm in Table 8.[20] Both the mean and median tests suggest that there are more significant differences between these two classes of stock than would be expected under the null hypothesis of no difference. Thus, we conclude that these two classes of stock do experience different idiosyncratic shocks. Interestingly, this evidence is consistent with the notion that the value of voting rights are driven by the private benefits of control – which might be expected to be subject to more idiosyncratic shocks.

Given this evidence, we now examine the correlation between the difference in idiosyncratic risk and the difference in illiquidity of the two securities. Based on either Johnson (2006) or Huang and Wang (2007), we should expect a significantly positive correlation. Consistent with this expectation, we observe a Pearson correlation of 0.837, which is significant at the 0.001 level, and a Spearman rank correlation of 0.734, which is also significant at the 0.001 level. Interestingly, the fact that these correlations are much higher than those reported between the unconditional variance and the measure of illiquidity is consistent with the notion that the earlier results were driven by the effect of idiosyncratic shocks on the liquidity of a stock and on its unconditional variance. Consequently, we observe strong evidence that the liquidity of a security is correlated with its *contemporaneous* idiosyncratic shocks.[21]

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[20] In our reported tests, we compute the square of the difference in residuals. However, we reach similar conclusions if we calculate the difference in the squared residuals.
[21] It is relevant to note that Tetlock (2007) provides evidence that is consistent with that in our paper. He studies trading in digital options and finds that increases in liquidity are correlated with noise trading,

5. Summary and Conclusions

Is the liquidity of a security and/or its sensitivity to aggregate liquidity shocks an exogenous determinant of its required return as implied by regressions of some measure or measures of such on security returns? Or, alternatively, is liquidity endogenously determined with security returns by many of the same factors that explain these returns? These questions have evoked a substantial amount of discussion and varied arguments, but to date, there has been no empirical study which has focused on the argument that liquidity is endogenously determined.

With respect to this argument, Johnson (2006), Novy-Marx (2006), and Huang and Wang (2007) develop models that imply liquidity will appear priced because it is correlated with excluded priced risk factors. There are two ways to address this type of argument: an instrumental variables approach and a research design approach. We pursue both approaches in this study.

To implement the instrumental variables approach, we examine the excess returns of U.S. stocks from 1970 through 2006 using the Fama and French (1993) three-factor model as our base model along with different measures of liquidity (e.g., Amihud's (2002) illiquidity measure as a security specific liquidity measure, and Pastor and Stambaugh's (2003) liquidity innovation factor as an aggregate liquidity measure). The Durbin-Wu-Hausman's test of exogeneity rejects these liquidity measures as exogeneous variables, and so suggests that they are endogenous variables.

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which is equivalent to the trading induced by idiosyncratic shocks to demand in either Johnson's model or Huang and Wang's model.

To implement the research design approach, we focus on the return, liquidity, and risk of two classes of traded common stock issued by the same U.S. corporations over the time period, 1980 through 2004. We focus on these securities because they share the same firm characteristics, and so our study is analogous to the use of twin studies in biology to study "nature versus nurture" arguments. Based on our analysis of these securities, we find evidence for the following.

While the liquidity (or illiquidity) and unconditional variances of daily stock returns of the two types of shares are significantly different, the mean returns of the two daily return distributions are not significantly different. We also find that these differences in illiquidity and differences in unconditional variances are significantly correlated. We discover that the factor loadings on Amihud's lagged aggregate illiquidity measure, Amihud's aggregate illiquidity innovation measure, and Pastor and Stambaugh liquidity innovation measure are unable to explain excess returns. In addition, we find that the factor loadings that *predict* idiosyncratic risk or aggregate volatility innovations are also statistically insignificant in explaining excess returns. However, we find that the idiosyncratic shocks experienced by these two classes of stock are significantly different and the differences in illiquidity and the differences in *contemporaneous* idiosyncratic shocks are highly correlated.

These findings lead us to the following conclusions. First, the lack of significant differences in mean returns of the two classes of stock despite their significant differences in liquidity is consistent with models that imply liquidity is not a priced risk factor but endogenously determined by the same risk factors that determine price. Second, the lack of significance of the aggregate liquidity measures once firm characteristics are adequately controlled for is again consistent with models that imply liquidity is not a priced risk factor but endogenously determined by the same risk factors that determine price. Third, the lack of significance of *predicted* idiosyncratic risk and innovations in aggregate market volatility once firm characteristics are adequately controlled for is consistent with arguments that these factors likely influence security returns through excluded risk factors that are correlated with firm characteristics. Fourth, our evidence is consistent with the argument that liquidity is correlated with *contemporaneous* idiosyncratic volatility.

Altogether our evidence is consistent with the arguments in Huang and Wang (2007), Johnson (2006, 2008), Novy-Marx (2006), and Rahi and Zigrand (2007) that different measures of liquidity are endogenous variables in security return regressions. No doubt there will be those who argue that liquidity is a priced risk factor, but it should now be incumbent on them to provide evidence that their particular liquidity measure is an exogenous determinant of security returns.

Nevertheless, as Novy-Marx (2006) points out, our evidence also implies that different measures of liquidity are likely to be good proxies for excluded risk factors. Consequently, it makes sense that studies like Eckbo and Norli (2005) or Butler and Wan (2009) find that liquidity explains different stock return “anomalies.”

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Table 1
Liquidity Analysis

These tables report differences in Amihud's illiquidity measure (2002) for 112 firms across two classes of stock that traded during 1980-2004. We analyze daily CRSP returns during 1980 for firms with traded dual class stock as of 1980, during the year after going public with dual class stock, or for the year after recapitalizing as traded dual class stock. In Panel A, we use CRSP return data. In Panel B, we construct daily returns based on a price and dividend series that includes only trading days over the above periods for the three respective groups. We use a matched pair t- (Mann-Whitney) test to determine whether the illiquidity means (medians) differ from each other. In the panels below, we list the number of cases out of 112 that reject the null hypothesis pertaining to a probability level that the null hypothesis of equal means (medians) is violated.

Panel A: Amihud's illiquidity measure using CRSP return data

Test / Number of Different Cases	1% level	5% level	10% level
Mean	66	67	70
Median	68	68	72

Panel B: Amihud's illiquidity measure using returns constructed from CRSP price and dividend data

Test / Number of Different Cases	1% level	5% level	10% level
Mean	59	61	68
Median	67	66	73

Table 2
Analysis of Mean Daily Returns

This table reports differences in returns for 112 firms with two class of traded stock between 1980 and 2004. We analyze daily CRSP returns during 1980 for firms with traded dual class stock as of 1980, during the year after going public with dual class stock, or for the year after recapitalizing as traded dual class stock. We use a matched pair t- (Mann-Whitney) test to determine whether the return means (medians) differ from each other. In the table below, we list the number of cases pertaining to a probability level that the null hypothesis of equal means (medians) is violated.

Test / Number of Cases	1% level	5% level	10% level
Mean	0	0	0
Median	0	0	0

Table 3
Test of Variance Equivalence

This table reports differences in variance for restructuring firms with identifiably two classes of voting rights. We analyze daily CRSP returns during 1980 for firms with traded dual class stock as of 1980, during the year after going public with dual class stock, or for the year after recapitalizing as traded dual class stock. We use the Levene test to determine whether the variances differ from each other. In the table below, we list the number of cases pertaining to a probability level that the null hypothesis of equal variance is violated.

Test	Number of Cases Rejecting the Null at the:		
	1% level	5% level	10% level
Levene – mean test	20	28	32
Levene – median test	21	28	32

Table 4
Regression analysis of Daily Returns and Illiquidity Measures

We create a pooled crossed section by identifying firms with traded dual class stock during 1980, firms that went public with traded dual class stock during 1980-2004, and firms that recapitalized from single to dual class stock during the 1980-2004 period. We analyze daily CRSP returns during 1980 for firms with traded dual class stock as of 1980, during the year after going public with dual class stock, or for the year after recapitalizing as traded dual class stock. We regress daily stock returns of a pooled on a dummy variable that takes on the value 1 if the stock has superior voting rights and report these results in Table 4 Panel A. Similarly, we regress Amihud's illiquidity measure on a dummy variable that takes on the value 1 for the stock with superior voting rights and report the results in Table 4 Panel B. Both regressions use Huber-White estimators for the standard deviations adjusted for clustering on the firm. We report p-values associated with the hypothesis that the coefficient equals zero within parentheses.

Panel A: Regression of daily returns on voting rights dummy

	Daily Return	P value
Constant	0.00066	0.00
Dummy (1 if superior voting rights)	-0.00015	0.69
F test	0.15	0.69

Panel B: Regression of Amihud's illiquidity measure on voting rights dummy

	Amihud's illiquidity measure	P value
Constant	0.0000157	0.00
Dummy (1 if superior voting rights)	0.00000586	0.00
F test	23.92	0.00

Table 5
Regression analysis of Daily Excess Returns

We create a pooled cross-section of stocks by identifying firms with traded dual class stock during 1980, firms that went public with traded dual class stock during 1980-2004, and firms that recapitalized from single to dual class stock during the 1980-2004 period. We analyze daily CRSP excess returns during 1980 for firms with traded dual class stock as of 1980, during the year after going public with dual class stock, or for the year after recapitalizing as traded dual class stock. We obtain the Fama-French (1993) daily factors (HML, SMB, MKTRF) from the Wharton Research Data System (WRDS). We compute Amihud's (2002) aggregate market illiquidity measure, lnAILLIQ, as the logarithm of the average across stocks of their daily absolute stock return divided by their daily dollar volume for each day from January 2, 1980 through December 31, 2004. We also compute Amihud's aggregate residual measure, $lnALLIQ^U$ and his lagged measure $lnAILLIQ_{t-1}$, as he did. Vote represents a dummy variable that takes on the value 1 if the stock has superior voting rights. All regressions use Rogers' estimators for the standard deviations adjusted for clustering on the firm. We report p-values associated with the hypothesis that the coefficient equals zero within parentheses.

	$E(R_i) - R_f$	$E(R_i) - R_f$	$E(R_i) - R_f$
Constant	0.0003 (0.06)	-0.003 (0.55)	-0.002 (0.69)
HML	0.4014 (0.00)	0.401 (0.00)	0.454 (0.00)
SMB	0.6125 (0.00)	0.6117 (0.00)	0.623 (0.00)
MKTRF	0.8886 (0.00)	0.8887 (0.00)	0.948 (0.00)
$lnALLIQ^U$	0.0005 (0.49)	0.0004 (0.53)	0.001 (0.23)
$lnAILLIQ_{t-1}$		-0.0003 (0.51)	-0.0002 (0.65)
Vote	-0.00005 (0.65)	-0.00005 (0.65)	-0.001 (0.12)
Vote*HML			-0.107 (0.80)
Vote*SMB			-0.024 (0.80)
Vote*MKTRF			-0.119 (0.02)
Vote*$lnALLIQ^U$			-0.001 (0.24)
Vote*$lnAILLIQ_{t-1}$			-0.0001 (0.52)
Observations	55782	55782	55782
R^2	0.028	0.028	0.028

Table 6
Regression analysis of Monthly Excess Returns

We create a pooled cross-section of stocks by identifying firms with traded dual class stock during 1980, firms that went public with traded dual class stock during 1980-2004, and firms that recapitalized from single to dual class stock during the 1980-2004 period. We examine the monthly excess returns of these stocks over the 12 months during 1980 for firms with traded dual class stock during 1980, the 12-month period after going public with dual class stock, or the 12-month period after recapitalizing as traded dual class stock. We obtain the Fama-French (1993) factors (HML, SMB, MKTRF), the momentum factor (Momentum), and the Pastor and Stambaugh (2003) liquidity innovations factor (PS Liquidity) from the Wharton Research Data System (WRDS). Vote represents a dummy variable that takes on the value 1 if the stock has superior voting rights. All regressions use Rogers' estimators for the standard deviations adjusted for clustering on the firm. We report p-values associated with the hypothesis that the coefficient equals zero within parentheses.

	$E(R_i) - R_f$	$E(R_i) - R_f$	$E(R_i) - R_f$
Constant	-0.002 (0.55)	-0.001 (0.69)	-0.002 (0.59)
HML	0.582 (0.00)	0.568 (0.00)	0.634 (0.00)
SMB	0.601 (0.00)	0.607 (0.00)	0.587 (0.00)
MKTRF	1.119 (0.00)	1.120 (0.00)	1.211 (0.00)
PS Liquidity	0.080 (0.37)	0.083 (0.38)	0.071 (0.48)
Momentum		-0.058 (0.57)	-0.087 (0.40)
Vote	0.0003 (0.77)	0.0003 (0.77)	0.001 (0.29)
Vote*HML			-0.130 (0.12)
Vote*SMB			0.045 (0.53)
Vote*MKTRF			-0.182 (0.01)
Vote*PS Liquidity			0.022 (0.67)
Vote*Momentum			0.060 (0.19)
Observations	2727	2727	2727
R^2	0.136	0.124	0.124

Table 7
Regression analysis of Daily Excess Returns

We create a pooled cross-section of stocks over a one-year period by identifying firms with traded dual class stock during 1980, firms that went public with traded dual class stock during 1980-2004, and firms that recapitalized from single to dual class stock during the 1980-2004 period. We analyze daily CRSP excess returns during 1980 for firms with traded dual class stock as of 1980, during the year after going public with dual class stock, or for the year after recapitalizing as traded dual class stock. We obtain the Fama-French (1993) daily factors (HML, SMB, MKTRF) from WRDS. We compute Spiegel and Wang's (2006) EGARCH forecasted idiosyncratic risk measure, LGVGRCH, as they did but using daily data. We calculate Ang, Hodrick, Xing, and Zhang's (2006) innovation in aggregate volatility measure, FVIX, using the VIX (VXO) index as they did. All regressions use Rogers' estimators for the standard deviations adjusted for clustering on the firm. We report within parentheses p-values associated with the hypothesis that the coefficient equals zero.

	$E(R_i) - R_f$	$E(R_i) - R_f$
Constant	-0.0003 (0.42)	-0.00008 (0.70)
HML	0.447 (0.00)	0.538 (0.00)
SMB	0.609 (0.00)	0.575 (0.00)
MKTRF	0.959 (0.00)	0.891 (0.00)
LGVGRCH	0.269 (0.47)	
FVIX		-0.0002 (0.35)
R^2	0.03	0.025

Table 8
Test of Idiosyncratic Risk Equivalence

This table reports differences in the residual variances for each class of stock identified by the Fama and French three-factor model using a panel of firms with traded dual class stock during 1980, firms that went public with traded dual class stock during 1980-2004, and firms that recapitalized from single to dual class stock during the 1980-2004 period. We use the Levene test to determine whether the residual variances differ from each other. In the table below, we list the number of cases pertaining to a probability level that the null hypothesis of equal variance is violated.

Test	Number of Cases Rejecting the Null at the:		
	1% level	5% level	10% level
Levene – mean test	19	26	29
Levene – median test	19	25	29