THE DETERMINANTS OF ISSUE CYCLES FOR INITIAL PUBLIC OFFERINGS

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Abstract. This paper identifies the determinants of market-wide and industry-specific security issue cycles using an autoregressive conditional duration model. We examine the business conditions, investor sentiment, and time-varying asymmetric information hypotheses and show that issue activity in different industries is consistent with different explanations. We find that the business conditions and sentiment hypotheses explain issue activity by manufacturing companies, while issue activity by financial institutions is partly explained by the sentiment hypothesis. On the other hand, none of these explanations are capable of explaining issue activity in the business services industry. Surprisingly, when all of the industries are pooled to examine market-wide activity, we find that none of these hypotheses are significantly related to issue activity. One explanation is that market-wide aggregation washes out much of the industry-specific information because issue activity is not perfectly correlated across industries. Using this observation, we then consider whether technological innovations are important determinants of industry-specific activity. We test for industry "contagion" by examining the periods before and after the Netscape initial public offering. Consistent with the technological innovations hypothesis, we find evidence of an increase in the correlation of issue activity in related industries.

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1. Introduction

The Initial Public Offering (IPO) market is highly cyclic. When the market for new issues is hot, it tends to stay hot. And when it cools off, new issues virtually disappear. The persistent nature of this time-series variation has sparked academic interest and this attention has produced a number of explanations for equity issue cycles. The IPO literature (see Lowry (2002) and Helwege and Liang (2004)) categorizes them into three groups: business conditions, time-varying asymmetric information, and investor sentiment.

The business conditions explanation asserts that issue activity simply reflects the current conditions in the economy and will therefore be positively correlated with various macroeconomic measures. When the economy is expanding, investment capital is readily available and the cost of equity capital is low by historical standards. The ability to issue new equity at relatively low rates motivates private firms to go public. There also may be a demand effect. Holding the cost of capital constant, firms are more likely to have positive net present value projects when business conditions are better (consumer demand for products increases, etc.) The business conditions explanation is so widely accepted that some studies (see Choe, Masulis, and Nanda (1993) and Fama and French (1989)) use monthly Industrial Production to identify hot and cold issue markets.

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There are two separate explanations for issue cycles based on models of time-varying asymmetric information. The first argues that time-varying adverse selection costs (Choe, Masulis, and Nanda (1993)) motivate investors to demand large price discounts in periods when asymmetric information is high. During these periods, it is less attractive for issuers to pursue new investments because the marginal cost of new capital is relatively high. This results in a cyclic pattern in the new issues market as issuers postpone new investment opportunities until they can obtain funds at cheaper rates.

The second explanation (see Allen and Faulhauber (1989), Grinblatt and Huang (1989), and Welch (1989)) predicts that periods of heightened issue activity will reflect the issue decisions of firms in industries that have recently experienced technological innovations or favorable productivity shocks. Such events reduce asymmetric information about the entire industry's future prospects and allow firms to issue equity at relatively attractive rates. Since technological innovations are unlikely to be highly correlated across industries, increases in issue activity are likely to be concentrated within particular industries. That is, hot issue periods are likely to be dominated by issues from a relatively small number of industries.

An analogous argument can be made for firms that experience negative productivity shocks. A negative shock reduces asymmetric information, but it now signals bad news about industry prospects. Investor demand for new shares will decline which leads to a corresponding reduction in issue activity for this industry.

The investor sentiment explanation is essentially an irrational investor explanation (see Loughran and Ritter (1995) and Lerner (1994)). It argues that there are periods when capital providers become particularly enthusiastic about new investment opportunities. This exuberance translates into periods of high demand for new security issues. As the marginal cost of obtaining new funds drops, firms find that previously unacceptable projects are now attractive at the margin, and they pursue these investments using newly obtained equity capital. This results in a cyclic pattern in the new issues market as investor optimism changes over time.

Issue cycles can be measured at the aggregate or the industry level. Aggregate measures are intuitively appealing because they attempt to characterize the state of the entire market in a relatively simple way. The problem is that certain sectors of the economy may be expanding while others are contracting. Since a single measure of issue activity is unlikely to capture this heterogeneity, it may be more sensible to characterize issue activity at the industry level. For example, during the hot issue period in the late 1990's, internet and software offerings in the business services industry (SIC 73) dominated the market for IPOs, yet at the same time, industrial offerings were experiencing a relatively cold period.

Prior research implicitly recognizes that too much heterogeneity is undesirable. Most notably, it is standard practice to exclude financial institutions from studies of hot and cold markets in order to focus on a relatively homogeneous set of industrial offerings.[1] However, these same studies include issues from the business services industry (SIC 73), which contained a significant proportion of market-wide issue activity during the "internet bubble" period. This is potentially problematic for more recent studies of market-wide activity because the same logic that is used to exclude financial institutions can also be applied to the business service industry (SIC 73).

[1]It is common to exclude financial institutions in other studies of corporate finance.

The purpose of this paper is to examine alternative explanations for issue activity and determine which of them best characterize the data. We do this in three steps. First, we examine the primary explanations for IPO cycles at the market-wide level. We then consider industry-specific issue activity and evaluate whether the determinants and timing of IPOs are similar across industries. Finally, we test the technological innovations hypothesis by examining the cross-industry correlation structure of issue activity.

Lowry (2002) is the first paper to conduct a comprehensive empirical examination of issue activity and finds support for the business cycle and investor sentiment explanations. She also concludes that proxies for adverse selection costs are statistically significant but economically unimportant. More recently, Helwege and Liang (2004) find that the proportions of new issues across industries are stable over time, which they interpret as being inconsistent with the hypothesis that industry innovations explain industry-specific issue activity. They conclude that the business conditions explanation best characterizes the data.[2]

We find that issue activity among firms in similar industries can be explained by common factors and that these factors differ across industries. The business conditions and sentiment hypotheses explain issue activity by manufacturing companies, while issue activity by financial institutions is partly explained by the sentiment hypothesis. On the other hand, none of these explanations are capable of explaining issue activity in the business services industry. In contrast to Lowry (2002), when all of the industries are pooled to examine market-wide activity, none of these hypotheses are significantly related to issue activity. We conclude that issue activity is better understood at the industry level and that theories of issue activity should be tested in settings where there is more power to test competing hypotheses.

With this in mind, we then test the technological innovations hypothesis. We show that they are significant differences in the contemporaneous correlations of issue activity across industries. In contrast to Helwege and Liang (2004), this indirectly supports the industry innovations hypothesis. We then perform a second more direct test of this hypothesis by examining changes in cross-industry correlations in issue activity following the Netscape IPO. We find evidence of industry "contagion" effects in that the correlation among *related* industries increases following the offer.

In addition to increasing our understanding of equity issue cycles, this study provides a new approach for identifying hot and cold periods that is based on the expected time to the next issue. Using recent developments in time-series econometrics (see Engle and Russell (1998), Hamilton and Jorda(1999) and Grammig and Mauer (2000)), we model IPO activity as an autoregressive conditional duration (ACD). This approach has two attractive properties.

First, it is a natural way to classify issue periods as "hot" or "cold". A market is considered hot or cold when the respective expected conditional durations are short or long. Since the conditional hazard rate of a new issue is inversely related to the conditional duration, a market is considered hot when the expected rates of new issues are high. The forward looking nature of our approach compares favorably

[2]There are relatively few studies that examine issue activity in specific industries. Masulis (1987) and Hogue and Loughran (1999) study financial institutions and find that banks and thrifts had IPOs when regulatory and market conditions became favorable. Lerner, Shane, and Tsai (2003) examine biotechnology alliances and find that larger corporate partners are allocated more control rights in cold issue periods.

to a number of proxies that have been used in other studies such as monthly issue volume (Bayless and Chaplinsky (1996)) and summary measures of macroeconomic activity (Choe, Masulis, and Nanda (1993) and Fama and French (1989)).

The second benefit of the ACD approach is that it simultaneously incorporates numerous factors to produce a single multivariate measure of issue activity. Not only do we use more information than other univariate approaches (Lowry (2002) and Helwege and Liang (2004)), but we use the entire time series of issue durations rather than aggregating at a lower frequency. As a result, our sample is significantly larger than those employed in previous studies, and our statistical tests have greater power to distinguish among the alternative hypotheses.

2. Autoregressive Conditional Duration Models

The ACD model of Engle and Russell (1998) is used to describe the temporal clustering of events. ACD models specify the time between initial public offerings (the "issue duration") as

$$x_i = f(\varepsilon_i)\psi_i \tag{1}$$

where ε_i (for $i = 1, \dots, n$) is an IID sequence with $E(\varepsilon_i) = \mu$, such that $E(x_i|\Omega_i) = \psi_i\mu$. The conditional duration, ψ_i, is specified as a linear function of past durations and past conditional durations. The most common specification is the $ACD(1,1)$, i.e.,

$$\psi_i = \omega + \alpha x_{i-1} + \beta\psi_{i-1} \tag{2}$$

where $\omega > 0$, $\alpha \geq 0$,and $\beta \geq 0$. To ensure stationarity, it also is required that $\alpha + \beta \leq 1$. The autoregressive structure implies that active issue periods have short durations which tend to be persistent. It is possible to add exogenous variables to (2) as follows:

$$\psi_i = \omega + \alpha x_{i-1} + \beta\psi_{i-1} + \sum_{j=1}^{J}\gamma_j(z_{ji-1} - \beta z_{ji-2}) \tag{3}$$

where z_j is the jth exogenous variable, $j = 1, \dots, J$.[3] This specification for the exogenous variables (i.e., $z_{ji-2} - \beta z_{ji-2}$) isolates the independent effects of the exogenous variables on conditional duration. The long-run duration implicit in the $ACD(1,1)$ model is

$$\psi_0 = \omega/(1 - \alpha - \beta). \tag{4}$$

2.1. **The Exponential-ACD (EACD) Model.** Under the assumption that durations are conditionally exponential and $f(\varepsilon_i) = \varepsilon_i$, the conditional density of x_i is

$$g(x_i|\Omega_i) = \frac{1}{\psi_i}\exp\left\{-\frac{x_i}{\psi_i}\right\}. \tag{5}$$

and the corresponding conditional hazard is constant, i.e.,

$$h(x_i|\Omega_i) = \psi_i^{-1}. \tag{6}$$

[3]Since there are no *a priori* restrictions on the coefficients for the control variables, there is nothing to prevent ψ_i from taking a negative and therefore inadmissable value. Bauwens and Giot (2000) propose a logarithmic version of the ACD ($LACD$) that constrains expected conditional durations to be nonnegative. We estimate the models using the logarithmic specification and obtain similar results.

The log likelihood function for the Exponential-ACD model can be expressed as

$$L(\theta) = -\sum_{i=1}^{N(t)} \left\{ \ln(\psi_i) + \frac{x_i}{\psi_i} \right\} \tag{7}$$

where $N(t)$ is a counting function that denotes the number of events that have occurred by time t.

2.2. **The Burr-ACD (BACD) Model.** The assumption that the conditional hazard rate of a new issue is constant until the next issue seems particularly restrictive in the case of IPOs.[4] A model that permits the hazard function to be non-monotonic may be more realistic. Figure 1 shows a representative hazard function for the BACD model that is calculated from parameter estimates obtained in Section 5. It demonstrates that the hazard rate increases in the period immediately following a new issue. After a sufficiently long period without a new issue (the IPO market has possibly cooled off), the conditional hazard rate of a new issue declines. This contrasts sharply to the EACD model which assumes that the hazard rate is constant between event arrivals.

The Burr-ACD model proposed by Grammig and Mauer (2000) allows hazard functions to be non-monotonic and has the property that commonly used waiting-time distributions like the Exponential and Weibull are special cases under appropriate restrictions of the parameter space.[5] It uses the following specification for the duration x_i,

$$x_i = \varepsilon_i f(\psi_i) \tag{8}$$

where $0 < \sigma^2 < \kappa$ and

$$f_i = \psi_i \cdot \frac{\sigma^{2(1+\frac{1}{\kappa})} \cdot \Gamma(\frac{1}{\sigma^2}+1)}{\Gamma(\frac{1}{\kappa}+1)\cdot\Gamma(\frac{1}{\sigma^2}-\frac{1}{\kappa})}. \tag{9}$$

The conditional density of x_i is

$$g(x_i|\Omega_i) = \frac{\kappa f_i^{-\kappa} x_i^{(\kappa-1)}}{(1+\sigma^2 f_i^{-\kappa} x_i^{\kappa})^{(\frac{1}{\sigma^2}+1)}}, \tag{10}$$

the conditional hazard function can be expressed as

$$h(x_i|\Omega_i) = \frac{\kappa f_i^{-\kappa} x_i^{(\kappa-1)}}{1+\sigma^2 f_i^{-\kappa} x_i^{\kappa}}, \tag{11}$$

and the corresponding log likelihood function is

$$L(\theta) = -\sum_{i=1}^{N(t)} \left\{ \ln\kappa - \kappa\ln f_i + (\kappa-1)\ln x_i - \left(\frac{1}{\sigma^2}+1\right)\ln(1+\sigma^2 f_i^{-\kappa} x_i^{\kappa}) \right\}. \tag{12}$$

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[4] Papers by Bauwens and Verdas (1999), Lunde (1999), Hamilton and Jorda (1999), and Zhang, Russell, and Tsay (2001), Grammig and Mauer (2000) all question this assumption.

[5] The Burr-ACD reduces to the Weibull-ACD as σ^2 approaches 0. It also reduces to the EACD model as σ^2 approaches 0 and κ equals 1.

3. Sample Description

The sample consists of all IPOs available in the Securities Data Corporation (SDC) New Issues database. The data base includes 11,309 offerings over the period 1970 through 2001. We exclude non-firm-commitment offerings, offerings from closed-end mutual funds, ADRs, REITs, unit offerings, mutual-to-stock conversions, issues in which the offer price is less than 5 dollars, and issues in which 75-percent or more of the shares sold represent a secondary issue. This yields a sample of 8,131 offers. We also require the firms to be available on the Chicago Research Security Price (CRSP) and the annual Compustat databases, which further reduce the sample to 6,444 observations.

3.1. **Market-wide issue activity.** After applying these data restrictions, we find that there is little time series variation in issue durations due to the large number of relatively small IPOs. Since the inclusion of small IPOs result in a security offering almost every day, the vast majority of the issue durations are 1 day. To deal with this, we 'thin' the process by 'marking' all security issues of at least 25 million dollars in terms of years 1982-1984 purchasing power. The issue durations are then defined as the time between issues of at least 25 million dollars.[6] This yields a sample of 2,071 offerings. Table 1 provides summary statistics for issue size and issue durations.

Figure 2 illustrates the monthly number of new equity issues over the sample period, which clearly displays the cyclic behavior that has been characterized in the IPO literature as hot and cold periods. There appears to be three major episodes of heightened issue activity.

3.2. **Industry issue activity.** We present results for the six industries that have the most issue activity over the sample period. Industry classifications are based on two-digit SIC codes. These are Chemicals (SIC 28), Industrial Machinery and Equipment (SIC 35), Electronic Equipment (SIC 36), Instruments (SIC 38), Depository Institutions (SIC 60), and Business Services (SIC 73). The Business Service industry includes software and internet companies. The respective sample sizes are 471, 591, 669, 556, 440, and 1,123 offerings.[7]

Unlike the market-wide sample, there is sufficient time-series variation in the industry-specific issue durations so that we are able to analyze the unmarked processes. Figure 3 illustrates the number of monthly issues over the sample period for the six industry classifications. The time-series variation in the four manufacturing industries displays a cyclic pattern that is very similar across industries but rather moderated when compared to market-wide activity in Figure 2.

Casual observation also indicates that banking (depository institutions) and business services offerings differ from those by industrial firms as they are characterized instead by one or two periods of heightened issue activity. The timing of the peaks in these industries appears to coincide with some of the larger spikes in market-wide issue activity in Figure 2.

Figure 3 also suggests that hot and cold periods are not perfectly correlated across all industries. One of the more notable examples occurs at the end of the sample period. One can see that there is an explosive hot issue market for the

[6]We also look at cutoffs of 50, 75, and 100 million dollars are obtain similar results.

[7]We classify all remaining issues by sector (1-digit SIC code). The results of this analysis are available upon request

business services industry due to the hot issue market for internet companies. Yet, at the same time, there are very few industrial companies accessing equity markets.

Table 2 reports the cross-industry correlations of monthly issue volume across different industries. It is immediately apparent that industry issue volume is not perfectly correlated over the sample period. For example, issue activity across industrial companies is more highly correlated than that associated with the banking industry.

Table 1 presents industry-specific summary statistics for issue size and durations. As one expects, the average time between issues is a decreasing function of the number of issues over the sample period. Interestingly, the average issue size for the six most active industries is smaller than the average issue size across all industries.

4. Hypothesis Development, the Measurement of Proxy Variables and Data Sources

We describe and group the variables used in our analysis according to whether they are proxies for the business conditions, time-varying adverse selection costs, and the investor sentiment hypotheses. Note that, by definition, the time between offers is *shorter* in periods of high issue activity.

A number of the proxy variables have unit roots. If the augmented Dickey-Fuller test does not reject the hypothesis that there is a unit root in the levels, we use first differences. (The 10% critical value is 2.571.) In the following discussion, variables that have a unit root are referred to as *Change* variables.[8]

Typically, there are a number of variables that can be used as proxies for one of the explanations of issue activity. For example, leading indicators, industrial production, the credit spread, and the term spread are proxies for an underlying common factor that represents Business Conditions. Rather than estimate each variable separately, we construct a single factor that is a linear combination of these variables. This approach is commonly used in the corporate finance literature (see Eckbo and Thorburn (2003) and Gillan, Hartzell, and Starks (2002)) when there are a number of proxies available to model a common underlying factor and none of them are clearly superior to the others.[9] The factor realizations are then standardized by subtracting their mean and scaling by the corresponding standard deviation. This allows us to interpret the coefficient estimate as the marginal change in the number of days to the next IPO if the factor is one standard deviation from its mean.[10]

4.1. **Business Conditions Variables.** The Business Conditions (BC) hypothesis predicts a negative relation between issue durations and business conditions because firms find equity markets attractive when the cost of capital is relatively

[8] Although we require each exogenous variable to be individually stationary, it is not strictly necessary. When more than one nonstationary variable are used simultaneously, it is possible that they are cointegrated. We do not pursue this possibility because it is easier to interpret individual first differences. Hence, there is no particular econometric advantage to testing for cointegration.

[9] As an alternative, we have also identified the weights in the linear combination by estimating the first principal component of the data matrix, X_F. The advantage of this approach is that the first eigenvector of X_F is the linear combination of the data matrix that maximizes the sample variance. The vector of factor loadings, υ is then used to calculate the factor realizations, i.e., $F = \upsilon' X_F$. We obtain similar results using the principal components approach.

[10] It also improves the convergence properties of the ACD estimations.

low. Summary statistics for the variables used to evaluate the BC hypothesis are reported in Panel A of Table 3.

To test for a significant relation between IPO cycles and economic conditions we form a business conditions factor using the following macroeconomic variables:[11]

Change in Leading Indicators ($\Delta Lead$). This variable is calculated as the first-difference in monthly levels of the index of leading indicators. (The augmented Dickey Fuller test statistic for the levels is 1.973, which is insignificant at the 10% level.) Since increases in leading indicators indicate an improving economy, we expect a negative relation between $\Delta Lead$ and expected durations.

Change in Industrial Production (ΔIP). This variable is calculated as the first-difference in monthly levels of the index of industrial production. (The augmented Dickey Fuller test statistic for the levels is 0.176.) Since increases in industrial production also indicate an improving economy, we expect a negative relation between ΔIP and expected durations.

Credit Spread ($\Delta Credit$). This variable is measured as the first-difference in monthly levels of the credit spread. The credit spread is calculated as the difference between the interest rates of Moody's Baa- and Aaa-rated corporate bonds. The credit spread is available on a monthly basis. Similar to the other macroeconomic variables, changes are used because we cannot reject the hypothesis that the levels have a unit root. (The augmented Dickey Fuller test statistic for the levels is -2.223.)

Since we are looking at *changes* in the credit spread rather than than *levels*, a positive change indicates that capital markets have become less attractive at the margin. This should reduce demand for equity and lead to fewer equity issues with longer durations.

Term Spread ($\Delta Term$). This variable is measured as the first-difference in monthly levels of the term spread. The term spread is calculated as the difference between the yield on a long-term (20-year) U.S. Treasury bond and the yield on a six-month U.S. Treasury bill and is available on a monthly basis. (The augmented Dickey Fuller test statistic for the levels is -1.563.) Increases in the term spread suggest that capital markets are less attractive at the margin, which should lead to longer durations between IPOs.

Based on the theoretical predictions discussed above, the Business Conditions factor ($BusCond$) is estimated as

$$BusCond_i = \Delta Lead_i + \Delta IP_i - \Delta Credit_i - \Delta Term_i. \tag{13}$$

This factor is constructed so that, if the $BusCond$ hypothesis is valid, it will be *negatively* related to issue durations.

4.2. **Time-Varying Asymmetric Information Variables.** There are two explanations of issue cycles based on time-varying asymmetric information. The first is the time-varying adverse selection cost ($TVASC$) explanation, and the second is the technological innovation (TI) explanation. Only the time-varying adverse selection cost explanation is discussed here. We describe and test the technological innovation hypothesis in Section (6.2).

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[11]Macroeconomic data is obtained from www.FreeLunch.com. We use other measures of macroeconomic conditions such as Gross Domestic Product and Coincident Indicators and obtain similar results. We choose not to include them in the construction of the Business Conditions factor because they are highly collinear with other variables that are already included.

The $TVASC$ hypothesis predicts a positive relation between issue durations and adverse selection costs because firms are less likely to issue equity when the cost of capital is high due to high levels of asymmetric information between managers and shareholders. Summary statistics for the variables used to evaluate the $TVASC$ hypothesis are reported in Panel B of Table 3.

We use the following three variables as proxies for time-varying adverse selection costs:

Volatility. This variable is calculated as the standard deviation of the S&P 500 returns over the 180 day period immediately preceding the issue date. The S&P 500 index level is obtained from the CRSP (Center for Research in Security Prices) database. Adverse selection costs are expected to be high during periods of high volatility. As a result, *Volatility* is expected to be positively related to issue durations.

Industry Dispersion (IndDisp). Industry dispersion measures the aggregate level of uncertainty among equity research analysts. It is calculated as the average of the standard deviations of the consensus forecast for each firm in the same two-digit SIC code. This variable is measured on a daily basis using the US Detail History file from the I/B/E/S database. Adverse selection costs are expected to be high during periods of high analyst uncertainty, which implies that *IndDisp* is expected to be positively related to issue durations.

Industry Diffusion (IndDiff). Industry diffusion is another proxy for analyst uncertainty. It is calculated as the difference between the number of upward revisions and the number of downward revisions divided by the total number of analysts making revisions in the past 120 days. Analyst uncertainty is high when diffusion is close to zero because equity analysts disagree about the firm's future earnings prospects. Since this variable is distributed between -1 and 1, we calculate the absolute value of analyst diffusion so that lower values indicate greater uncertainty about future earnings prospects. To estimate *IndDiff*, we then calculate the average absolute value of analyst diffusion by two-digit SIC code. This variable is measured on a daily basis using the US Detail History file from the I/B/E/S database. Since analyst uncertainty is high when *IndDiff* is low, issue durations are expected to be long when *IndDiff* is low.

Based on the theoretical predictions associated with each variable, the $TVASC$ factor is calculated as

$$TVASC_i = Volatility_i + IndDisp_i - IndDiff_i. \tag{14}$$

This factor is constructed so that, if the $TVASC$ hypothesis is valid, it will be *positively* related to issue durations.

4.3. **Sentiment Variables.** The Sentiment hypothesis predicts that equity issue activity will be higher when investors are optimistic. This implies that there is a negative relation between issue durations and sentiment. Summary statistics for the variables used to evaluate the sentiment hypothesis are reported in Panel C of Table 3.

To test for a significant relation between IPO issue cycles and sentiment, we form a sentiment factor using the following variables:

Investor Sentiment ($\Delta InvSent$). The investor sentiment proxy is the three-month change in the monthly index of closed-end fund discounts as proposed by Lee, Shleifer, and Thaler (1991). It is calculated as the value-weighted discount across all domestic equity and convertible debt closed-end funds at the end of each quarter, where fund discounts are weighted by fund net asset value times shares outstanding. Data on closed-end fund discounts is obtained from two sources: the sample of Lee, et al. (1991),[12] which has data from 1965 to 1985, and the Wall Street Journal for the period January 1986 until December 2001. We use the three-month change because we cannot reject the hypothesis that Investor Sentiment has a unit root (the augmented Dickey Fuller test statistic = -1.993)

Lee, et al. (1991) argue that closed-end funds are mostly owned by individual investors who tend to be noise traders. Noise traders create risk that cannot be diversified away and hence the assets that are subject to this risk (closed-end fund shares) should be underpriced relative to their fundamental values. The discounts reflect the changes in the sentiment of a clientele of individual investors that invest in these funds relative to a clientele that invests in the underlying assets. Since investors pay more for closed-end funds when sentiment is high, we expect a positive relation between sentiment and expected conditional duration.

Consumer Sentiment ($\Delta ConSent$). The consumer sentiment proxy is the Index of Consumer Sentiment (ICS) constructed by the Survey Research Center of the University of Michigan. This variable is measured by the the Index level. We use first-differences because we cannot reject the hypothesis that the levels have a unit root (augmented Dickey Fuller test statistic = -2.812, 5%). The ICS is available on a monthly basis after 1979. Prior to this time it was published quarterly (February, May, August, and November).

The ICS reflects the perceptions of the general public. Charoenrook (2002) shows that changes in consumer sentiment predict one-month and one-year stock market returns. One possible explanation that she offers is that ICS proxies for general investor's waves of optimism and pessimism. We expect that increases in consumer sentiment lead to shorter issue durations.

The Sentiment factor ($Sent$) is designed to be negatively related to issue durations. It is calculated as [13]

$$Sent_i = \Delta ConSent_i - \Delta InvSent_i. \tag{15}$$

4.4. **A Direct Test of the Time-Varying Adverse Selection Costs and Sentiment Hypotheses.** In general, the proxies that are available to examine the different explanations of issue activity result in empirical specifications that allow us to determine whether issue activity is consistent with a particular explanation, but they do not permit a direct test of one explanation against the other. We describe here an exception that permits us to test whether the time-varying adverse selection cost or sentiment explanation best characterizes the data.

According to the time-varying adverse selection cost explanation, issue activity will be higher when investors are better informed. It has been suggested (see Gompers and Lerner (1999) and Megginson and Weiss (1991)) that since venture

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[12] Charles Lee graciously provided the sentiment index data for the 1965-1985 period.

[13] Since Lowry (2002) finds that sentiment (lagged by four quarters) is a significant determinant of quarterly issue activity, we construct an alternative version of this factor that uses lags of the sentiment variables at four quarters, i.e.,

$$Sent_i = \Delta ConSent_i + \Delta ConSent_{i-3} - \Delta InvSent_i - \Delta InvSent_{i-3}.$$

Although not reported here, we obtain similar results to those presented using Equation (15) using this factor.

capitalists (VCs) have expertise in particular industries, they are expected to make superior investments relative to other investors. In essence, VCs certify the quality of an IPO and their presence signals that asymmetric information is relatively low for this issue. In the context of the TVASC hypothesis, this implies that VC-backed IPOs are likely to have a relatively large market share during periods when adverse selection costs are particularly high. Thus, the time-varying adverse selection cost explanation predicts that the proportion of VC-backed IPOs will be positively related to issue durations.

The $TVASC$ explanation also predicts that there will be less underpricing when investors are better informed. Since issue activity is expected to be high when there is less asymmetric information, we expect to find a positive relation between underpricing and issue durations.

By contrast, Lerner (1994) documents that venture capitalists are experts at timing the market and wait until sentiment levels are high before taking firms public. Since issue durations are short when markets are hot, the sentiment explanation predicts that the proportion of IPOs with VC-backing will be negatively related to issue durations.

It also predicts that investor enthusiasm will cause initial returns to be high as they compete for the newly issued shares in the secondary market. This motivates firms to take advantage of these temporary windows of opportunity (Loughran and Ritter (1995). Since underpricing is expected to be highest during periods when investor enthusiasm creates a hot issue market, we expect to find that underpricing is negatively related to issue durations.

To summarize, the $TVASC$ hypothesis predicts that issue durations are positively related to the proportion of VC-backed IPOs and underpricing. The sentiment hypothesis makes the opposite predictions. These differences allow us to formally test whether time-varying adverse selection costs or sentiment hypotheses characterize the data best. We measure the control variables as follows:

Prop VC. The proportion of venture capital (VC)-backed IPOs is calculated as the number of IPOs that received VC funding during a given month divided by the total number of IPOs during that same month using the SDC New Issues database.

Underpricing. Using the SDC New Issues database, we identify all IPOs for a given month that are available on the CRSP database.[14] Using the CRSP daily stock returns file, we calculate the initial return using the closing price on the offer date or, if it is not available, the first available closing price in the 14 trading days after the IPO and the offer price. The *Underpricing* variable is then computed as the equally-weighted mean initial return for all issues during a given month.

The TVASC/Sentiment factor ($AdSent$) is then estimated as

$$AdSent_i = Prop\ VC_i + Underpricing_i. \tag{16}$$

4.5. **Activity Variables.** We include a number of additional control variables that measure general conditions in the the stock market but are not specifically related to a particular hypothesis. Summary statistics for the activity variables are reported in Panel D of Table 3.

The activity variables are constructed as follows:

S&P 500 Return (S&P Ret). The S&P 500 return is calculated as the buy-and-hold return on the S&P 500 index over the 180 period immediately preceding the

[14] Of the 9,858 firms available in SDC, we find matches for 8,680 firms

issue. The index level is obtained from the CRSP daily return file. It measures market-wide stock performance and is used in our market-wide tests. We expect a negative relation between stock market returns and issue durations.

Industry Return (Ind Ret). This variable is calculated as the buy-and-hold return on an equally-weighted portfolio of all firms in the same two-digit SIC code over the 180 period immediately preceding the issue. The returns are obtained from the CRSP daily return file. We use *Ind Ret* as the measure of stock market conditions in our industry tests. We expect a negative relation between industry returns and issue durations.

Quarterly IPO Dollar Volume (IPO $ Volume). This variable is calculated as the total dollar amount of IPOs issued in the past three months (SDC New Issues database). It provides a measure of past issue activity. In our market-wide test, this measure reflects all IPO activity, while in the industry-specific tests, it represents the number of IPOs for each two-digit SIC code. We expect a negative relation between the *IPO $ Volume* and expected durations.

Offers per Day. This variable is calculated as the number of IPOs that occur on the same day. Since the SDC New Issues file only records issues at a daily frequency, it possible for there to be multiple offerings on the same day. As with the $IPOActivity$, market-wide tests reflect the entire sample, while industry tests reflect the number of offers per day in each two-digit SIC code. Since multiple issues on the same day indicate that a market is hot, we predict a negative relation between issue durations and *Offers per Day.*

Venture Capital Investments (VC Invest). This variable is calculated as the three-month moving average of the dollar volume of VC investments from the VentureExpert database (each monthly amount is deflated to constant 1980 dollars).

Proportion of Early Stage VC Investments (Early). This variable is calculated as the proportion of early stage VC investments to all VC investments. An investment is classified as "Early" if it is identified as being at the "Seed", "Startup", or 'Early Stage" by the VentureExpert database.

Proportion of Late Stage VC Investments (Late). This variable is calculated as the proportion of late stage VC investments to all VC investments. An investment is classified as "Late" if it is identified as being at the "Third Stage", "Bridge Loan", "Acquisition", "Secondary Purchase", or "Other Later Stage" by the VentureExpert database.

Since the three VC proxies all measure VC activity, we create a venture capital activity factor as follows:

$$VCActivity_i = VC\ Invest_i + Early_i + Late_i. \tag{17}$$

We expect that VC activity will be *negatively* related to issue durations.

5. Market-Wide Determinants of IPO Issue Cycles

5.1. **The Exponential-ACD model.** Panel A of Table 4 reports the results of our estimations of six Exponential-ACD models. The Baseline model estimates the model without exogenous variables. The first thing to note is that the model has strong moving average and autoregressive components. For example, the estimates of α and β for the Baseline model are 0.1185 and 0.8496, respectively. Based on equation (4), the long-run duration for this model is 3.878 days, which lies between the sample mean (5.65 days) and median (2.00 days) for the actual durations.

The parameter estimates for α and β suggest that there is substantial mean reversion in expected conditional durations. A calculation of the duration "half-life" provides some indication of the speed at which the conditional duration forecast reverts to its long-run mean ψ_0 (see equation (4)). The half-life is defined as the number of issues required for the expected conditional duration to revert halfway to the long-run mean. It is determined by finding the number of events, s, for which the s^{th} step-ahead forecast from the EACD(1,1) model (ψ^F_{t+s}) satisfies the following:[15]

$$\psi^F_{t+s} = (1 - w_s)\ \psi_0 + w_s \psi_t = \frac{1}{2}(\psi_0 + \psi_t). \tag{18}$$

where

$$w_i = \frac{(\alpha+\beta)^{i-1} - (\alpha+\beta)^i}{1-\alpha-\beta} \tag{19}$$

The duration half-life is found by finding the value for s that sets w_s equal to one-half. Given the estimates of α and β for the Baseline model in Table 4, the expected number of issues before the expected conditional duration of ψ_t reverts to its long-run mean is 22.38.

We can gain further intuition for the time series properties of our estimates by plotting estimates of expected conditional duration and monthly issue volume. Figure 4 demonstrates that periods of low issue activity are positively correlated with periods when the expected time to the next IPO is long.

Next, we add the Activity variables described in Section 4.5 to the *Baseline* model. As expected, the *Activity* model indicates that our proxies of aggregate issue activity are negatively related to time between equity issues. That is, the market for new issues becomes active when there is more than one IPO on a given day, the return to the stock market is high, and venture capital investment is high.

The next three models in Table 4 add either the business conditions (*BusCond*), time-varying asymmetric information (*TVASC*), or the sentiment (*Sentiment*) factors to the *Activity* model.

The *BusCond* model supports the business conditions hypothesis. As expected, the coefficient for the business conditions factor is negatively related to conditional durations. That is, as economic and credit market conditions improve and the cost of capital decreases, firms are more likely to raise new capital, which results in shorter durations between IPOs.

Contrary to the *TVASC* hypothesis, the results for the *TimeVar* model suggest that issue activity does not decrease as asymmetric information levels increase. The negative relation between the *TVASC* factor and conditional duration suggests that, when there is less market volatility and more agreement among equity research analysts, issuers are more likely to take a company public. However, the statistical insignificance of the coefficient estimate suggests that this interpretation should not be pursued aggressively.

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[15]Equation (18) shows that the step-ahead forecasts for duration are a weighted average of the long-run duration and the one-step ahead forecast ψ_t. The weighting factor (equation (19)) indicates that the weight on ψ_t declines exponentially as the length of the forecast horizon increases due to the mean-reverting nature of the *ACD* model.

Table 4 finds no support for the sentiment hypothesis. The *Sentiment* model indicates that the *Sentiment* factor is not significantly related to conditional duration. This result is inconsistent with Lowry (2002) who finds support for the sentiment hypothesis using lower frequency data.

The sixth model combines all the proxy variables from the first previous models. The results for the *Full* model reinforce the findings for the *BusCond*, *TimeVar*, and *Sentiment* models. The *Full* model also includes the results of the direct test of the *TVASC* and sentiment hypotheses. The coefficient for *AdSent* is negative and statistically significant, which indicates that the sentiment hypothesis explains issue activity better than time-varying asymmetric information.

5.2. **The Burr-ACD model.** Panel B of Table 4 provides estimates for the same six models under the assumption that durations follow a Burr distribution. The results are striking and stand in sharp contrast to those reported in Panel A. First, there is a dramatic improvement in statistical fit. Notice that the *Baseline* Burr-ACD model has a higher Log-likelihood function than any of the Exponential-ACD specifications we report in Panel A. More surprisingly, none of the exogenous variables are statistically significant in any of the six specifications. Consistent with this observation we find that none of the specifications with exogenous variables contain incremental explanatory power beyond that already reflected in the *Baseline* model.

One possible explanation for the superior performance of the Burr-ACD model is that the Exponential-ACD assumes a constant hazard function between issue dates, while the Burr-ACD makes continuous adjustments to the hazard rate as time passes. This adjustment mechanism is different from the one that incorporates information contained in the exogenous variables. Although exogenous variables allow the hazard rate to increase or decrease in response to time-varying market characteristics, these adjustments are based on information at the time of last issue and do not cause the hazard rate to update until the next event.[16]

For the EACD model, the "corrections" to the conditional hazard rate occur rapidly in "event" time and are symmetric across hot and cold markets. However, since the hazard rate only updates following an event, there are extended periods in "calendar" time where the environment evolves yet the hazard rate does not change. This is particularly problematic in cold issue periods that immediately follow a hot issue period because there is an extended period in "calendar" time where no issues occur. Unfortunately, the EACD model over-predicts the rate of new issues throughout this period.

The model also tends to under-predict new issues coming out of a cold period as well. However, the model adjusts more rapidly in calendar time because the issue durations are short. Taken together, the EACD model tends to over-predict conditional duration in calendar time.

The main benefit of the Burr distribution is that the conditional hazard rate changes in calendar time. Based on the parameter estimates in Table 4, Figure 1 shows that the estimated conditional hazard rates initially increase and, after a sufficient amount of time passes, decrease to reflect the reduced probability of a new issue.

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[16]Hamilton and Jorda (2001) propose the Autoregressive Conditional Hazard (ACH) model, which permits continuous updating of exogenous information between events.

The increase in the hazard rate immediately following a new issue captures the idea that the likelihood of another offer initially increases for a relatively short period of time. This feature allows the Burr-ACD model to capture transitions from cold to a hot markets faster than the Exponential-ACD model. The dynamic adjustments implied by this model also allow the conditional hazard rate to adjust downward even though there are no specific events that force the hazard rate to explicitly update. We can determine the time at which the hazard rate begins to decrease as the time t^* that sets $\partial h/\partial t|_{t=t^*} = 0$, i.e.,

$$t^* = \left(\frac{f_i(\kappa - 1)}{\sigma^2}\right)^{\frac{1}{\kappa}}. \tag{20}$$

6. Industry-Specific Determinants of Issue Cycles

One of the drawbacks of analyzing issue activity at the market-wide level is that aggregation may wash out important information. To illustrate this point, suppose that automobile manufacturers and internet/tech companies are at different points in their industry life cycles. The automotive industry represents a seasoned industry, while internet firms represent a nascent industry that has developed in response to a significant innovation.

In the automobile industry, innovations occur that require new capital. However, these innovations are comparatively modest and the timing of the decision to issue new shares is likely to be driven by the relative cost of capital.

By contrast, the commercialization of the internet represents an innovation that created many new business opportunities. Since the gains from early adoption tend to be large relative to later adoptions, many firms issue new equity so that they can make timely investments. If the gains are large enough, firms will issue new equity regardless of the state of the economy.

Pooling these two industries together and estimating them as a single process produces a situation where important economic conditions in the automotive industry may be masked by issue activity in the internet/tech industry, particularly when issue activity in one industry tends to dominate the other. The possibility that both types of issue decisions are being made contemporaneously but are driven by different economic factors motivates our examination of industry-specific issue activity.

The analysis proceeds in two stages. First, we repeat our analysis of the determinants of issue activity by estimating ACD models at the industry level. Second, we address the technological innovation hypothesis by examining cross-industry correlation in issue activity and show that industries are interdependent. We then extend our analysis of the technological innovation hypothesis by testing for issue "contagion" effects following the Netscape public offering in 1995.

6.1. **Testing Different Explanations of Issue Activity.** We estimate industry-specific models of issue activity for four manufacturing industries (SIC 28, 35, 36, and 38), financial institutions (SIC 60), and business services (SIC 73). Table 5 reports estimations of the *Full* version of the industry-specific Burr-ACD models. The parameter estimates of α and β indicate the industry-specific issue durations display the same mean-reverting behavior found at the market-wide level. Likewise, the estimates for κ and σ^2 indicate that all of the models have a "hump-shaped" conditional hazard rate. Consistent with the suggestion that aggregation may eliminate information, we find that the Burr-ACD estimates for different manufacturing industries have similar time series characteristics relative to each other, but that financial institutions (SIC 60) and business services (SIC 73) behave differently.

6.1.1. *Manufacturing Industries.* The estimations for Chemicals (SIC 28), Industrial Machinery and Equipment (SIC 35), Electronic Equipment (SIC 36), and Instruments (SIC 38) in Table 5 provide support for the business conditions and sentiment hypotheses, but not the time-varying adverse selection cost hypothesis. Specifically, we find that issue durations are significantly and negatively related to the business conditions factor. For example, the coefficient estimate for SIC 28 indicates that, all else equal, when the business conditions factor is one standard deviation higher than its average value, the expected time to the next IPO is 0.5607 days shorter. We also find that a one standard deviation shock to the $AdSent$ factor reduces issue durations by 2.1493 days. Since the sign of this coefficient is significantly and negatively related to issue durations, we reject the $TVASC$ hypothesis in favor of the *Sentiment* explanation. That is, relatively high levels of underpricing and low participation rates by venture capitalists occur in relatively hot markets. The likelihood ratio test statistics indicate that explanatory variables explain a significant amount of the time series variation in issue durations.

6.1.2. *Financial Institutions.* The factors that explain issue activity in the financial services industry are different from those in manufacturing industries. We find that issue activity in the financial services industry slows down when the general level of venture capital activity increases. Table 5 also reports that the coefficients for the $TimeVar$ and $AdSent$ factors are negative and statistically significant. Both of these findings are inconsistent with the predictions of the $TVASC$ hypothesis. By contrast, the negative sign on the $AdSent$ factor indicates that the rate of financial services offerings increases when investor sentiment is high. The likelihood ratio test statistic of 11.16 has a p-value of 19.28%, which indicates that the exogenous variables do not explain a significant amount of variation beyond that contained in the *Baseline* model.

As we noted before in Figure 3, the time series of issues for Depository Institutions displays a single episode of heightened activity over the sample period. Masulis (1987) describes how regulatory and competitive changes motivated a large number of banks and thrifts to convert to stock charters during the 1980s by conducting IPOs.[17] Consistent with the sentiment explanation, Hogue and Loughran (1999) find that "many of the offerings corresponded to a period when other bank stocks and the economy were posting strong gains."

6.1.3. *Business Services.* The results for the business services industry are very similar to the market-wide results reported in Table 4 in that none of the explanatory variables are statistically significant at conventional levels. Essentially, the

[17]Hogue and Loughran summarize the relevant legislation that made conversions to stock charters attractive. They note: "The Depository Institutions Deregulation and Monetary Control Act of 1980 enhanced the competitiveness of the US banking industry by removing interest rate ceilings, increasing deposit insurance limits, and expanding the investment opportunities available to banks and thrifts. The Garn-St. Germain Depository Institutions Act of 1982 continued the deregulation process by authorizing new sources of funds and allowing thrifts to convert from a mutual to stock form of organization. As a result of this legislation, a large number of banks and thrifts issued an initial public offering of stock."

Baseline model does as good a job explaining issue activity as the Full model. The likelihood ratio test statistic is 2.81, which has a p-value of 94.57%.

The business services industry has hot and cold periods that are unrelated to any of the proposed explanations for issue activity. Figure 3 shows that the hot and cold periods display an oscillating pattern that increase in intensity each time it cycles to a hot period, which is primarily driven by the large number of internet offerings that are included in this classification.

One possible explanation for the close correspondence between the market-wide and industry-specific results is that business service offerings dominate the market-wide measures of issue activity (1,066 issues), particularly in the later part of the sample. For example, the next most active industry (SIC 36) only has 589 offerings. The fact that business service offerings occur at relatively high rates compared to other industries suggests that the factors (or lack thereof) which explain industry activity may also explain aggregate issue activity.

6.2. **Tests of the Technological Innovations Hypothesis.** The technological innovations hypothesis predicts that periods of heightened issue activity reflect the issue decisions of firms in industries that have recently experienced technological innovations or favorable productivity shocks. Such events reduce asymmetric information about the entire industry's future prospects and allow firms to issue equity at relatively attractive rates. Since technological innovations are unlikely to be highly correlated across industries, increases in issue activity are likely to be concentrated within particular industries. That is, hot issue periods are likely to be dominated by issues from a relatively small number of industries. An analogous argument can be made for firms that experience negative productivity shocks. Negative shocks reduce asymmetric information, which signals bad news about industry prospects. As investor demand for new shares declines there is a corresponding reduction in issue activity.

We test this hypothesis by examining the correlation structure of issue intensity. If the technological innovations hypothesis is valid we expect to observe differences in cross-industry correlations. Industries that are related are likely to have positive feedback effects and relatively high cross-industry correlations. Industries that do not share similar underlying technologies are not expected to be as highly correlated.

If the technological innovations hypothesis does not hold, all industries are expected to make similar issue decisions because all firms respond in a similar way to incentives to issue equity. If the cost of equity is relatively low, all firms will issue high amounts of equity. If the cost of equity is high, firms postpone issue decisions together. This implies that cross-industry correlations will be very high. Consistent with this conjecture, Helwege and Liang (2004) find that the proportion of new issues from a given industry is stable over time.

6.2.1. *Measures of Issue Activity.* We use two related estimates of issue activity that are based on the Burr-ACD model. Since the ACD approach produces estimates in event time, cross-industry measures of issue activity are not aligned in calendar time and correlations cannot be calculated. To estimate cross-industry correlations, we convert our estimates of issue activity to calendar time by constructing a daily time series of expected issue activity for each industry.

The first measure of issue intensity is the rate at which new issues are expected to occur. For the Burr-ACD model, this rate is measured by the conditional hazard rate, which is calculated by evaluating Equation (11) at day t using the time that has elapsed since the last issue where $T = t - t_i$ and t_i is the day of the last issue, i.e.,

$$h(T|\Omega_{t_i}) = \frac{\kappa f_i^{-\kappa} (T)^{\kappa-1}}{1 + \sigma^2 f_i^{-\kappa} (T)^{\kappa}}. \tag{21}$$

The second measure uses the conditional expected duration to the next event. To calculate expected durations in calendar time, we calculate the expected duration at time t given that the last issue occurred at time t_i, $E(x_t|x_t > T)$. The expectation is taken with respect the conditional probability of x_t given that $x_t > T$ and is given by

$$g_{x>T}(x_t|\Omega_{t_i}) = \frac{g(x_i|\Omega_{t_i})}{S(T|\Omega_{t_i})}. \tag{22}$$

where $S(T|\Omega_{t_i})$ is the survivor function at time t evaluated at time T. For the Burr-ACD, the survivor function at $x_i = T$ is

$$S(T|\Omega_{t_i}) = \left(\sigma^2 f^{-\kappa} T^{\kappa} \left(1 + f_i^{\kappa} x_i^{-\kappa}/\sigma^2\right)\right). \tag{23}$$

The expected conditional duration given that no event has occurred for T periods is then given by

$$E(x_t|x_t > T) = \kappa T \cdot \left(1 + \frac{f^{\kappa} T^{-\kappa}}{\sigma^2}\right)^{1/\sigma^2} \cdot H_{2,1}(a, b, c, d) \tag{24}$$

where $H_{2,1}(a, b, c, d)$ is Gauss's hypergeometric equation, i.e.,

$$H_{2,1}(a, b, c, d) = \frac{\Gamma(c)}{\Gamma(b)\Gamma(c-b)} \int_0^1 \frac{t^{b-1}(1-t)^{c-b-1}}{(1-tz)^a} dt \tag{25}$$

and $a = 1 + \frac{1}{\sigma^2}, b = \frac{1}{\sigma^2} - \frac{1}{\kappa}, c = 1 - \frac{1}{\kappa} + \frac{1}{\sigma^2}$, and $d = -\frac{f^{\kappa} T^{-\kappa}}{\sigma^2}$.

6.2.2. *Cross-Industry Correlation Structure.* Panel A of Table 6 reports the correlation matrix for the conditional hazard rates across industry classifications. The correlations between hazard rates are all positive but closer to zero than one. This result provides evidence consistent with the technological innovations hypothesis.

Panel B of Table 6 reports Fisher Z-statistics for each correlation coefficient. Fisher showed that the transform

$$Z = \frac{0.5 * ln(1+p)}{1-p} \tag{26}$$

is asymptotically normal with $\sigma_Z = \sqrt{(1/(N-3)}$ where N is the number of days in the sample period. The Z-statistics reject the hypothesis that the correlations are equal to zero at conventional levels. They also reject the hypothesis that they are relatively large. For example, we can reject the hypothesis that any specific correlation coefficient is greater than 0.3 at the .001% level. This result is inconsistent with the findings reported in Helwege and Liang (2004). If we were able to replicate their findings in our sample, the correlations should be close to one.

We also test whether the correlations between industry i and the remaining $J-1$ industries are significantly different from each other, i.e. $\rho_{i1} = \cdots = \rho_{ii-1} = \rho_{ii+1} =$

$\ldots \rho_{iJ}$. Olkin and Finn (1990) show that a Wald statistic can be constructed that has the following quadratic form

$$\nu_i' \widehat{Var}(\nu_i)^{-1} \nu_i \tag{27}$$

which is asymptotically distributed χ^2 with $J-2$ degrees of freedom where $\nu_1 = (\hat{r}_{12} - \hat{r}_{13}, \hat{r}_{12} - \hat{r}_{14}, \ldots, \hat{r}_{12} - \hat{r}_{1J})$, $\widehat{Var}(\nu_i)$ is a consistent estimator of the covariance matrix of the correlation differences (ν_i), and $\hat{r}_{ij}$ is a consistent estimator for ρ_{ij}. The values of this test statistic are reported in Panel C of Table 6. For all six industries, the values are large and indicate that we can reject the hypothesis of equal correlation between conditional hazard rates. This provides additional evidence that is consistent with the technological innovations hypothesis.

Table 7 reports results based on the expected conditional duration estimates using Equation (24). The results are similar to those obtained using the conditional hazard rates.

6.2.3. *Contagion and the Cross-Industry Correlations Following the Netscape IPO.* Although our finding that issue activity is not perfectly correlated across industries is consistent with the TI hypothesis (and inconsistent with Helwege and Liang (2004)), it is not a particularly powerful test of this hypothesis. We propose a second test of the TI hypothesis that examines changes in cross-industry correlations following an important technological innovation.

A particularly interesting example of an industry "innovation" is the initiation of internet-related issue activity beginning with Netscape's decision to go public in August 1995. We posit that the development of the internet-related issues market within the Business Services industry is a significant financial event that signalled investor acceptance of the commercial viability of internet-based businesses.

The hot issue market that followed the Netscape IPO is consistent with the prediction that IPO clustering is related to the development of new products and industries. For example, internet-based firms like Yahoo, Priceline, and ebay found a ready market for their shares following Netscape's offering. They respectively raised \$33,800,000, \$160,000,000, and \$63,000,000, which reflected first day price run-ups of 153.8%, 331.3%, and 163.2%.

The TI hypothesis predicts that if positive externalities in one industry creates new opportunities in related industries, issue activity should become more correlated across related industries. For example, increased demand to expand networking capabilities made it possible for manufacturing firms like Copper Mountain (a manufacturer of broadband access and communications equipment) and Juniper Networks (a developer of backbone routers and other high-performance communications equipment) to expand their businesses and raise new equity capital. These companies were able to respectively raise \$84,000,000 and \$168,000,000.

To answer the question of whether correlation increases following the Netscape offer, we adopt an econometric approach that has been used to examine financial contagion across related countries following a financial crisis.[18] Forbes and Rigobon (FR, 2002) define contagion as significant increases in cross-industry linkages after a shock to one industry (or group of industries). If two related industries show a high degree of correlation prior to a technological innovation, even if industries

[18]Examples like the Asian crisis of 1997, the 1994 Mexican devaluation, and the 1987 U.S. market crash have shown that large movements in one market can significantly impact related markets.

continue to be highly correlated after the innovation, this may not constitute contagion. According to FR, it is only contagion if cross-industry correlation increases significantly after the shock. If the correlation does not increase significantly, any continued high level of correlation suggests that the industries continue to be interdependent but have not experienced a fundamental change.

In an examination of stock market returns, FR argue that estimates of contemporaneous correlations during more volatile periods could be biased upward and propose a bias-corrected correlation coefficient. Chakrabarti and Roll (2003) argue that this bias is a concern only if the underlying distribution is stationary and the measurement period happens to occur during a period when an estimate of sample variance is high. By contrast, if the true volatility happens to increase during the measurement period, no such bias exists. Since the technological innovation we consider here is hypothesized to represent a fundamental change that permanently alters cross-industry dynamics, it is appropriate to test for changes in contemporaneous cross-industry correlations without making a specific bias correction.

We determine whether the correlation structure changes following the Netscape offer by testing whether the pre- and post-offer correlation matrices are the same. Jennrich (1970) develops a test statistic for the equality of two J-variate sample correlation matrices R_1 and R_2 with sample sizes N_1 and N_2 that has the following quadratic form

$$\chi^2_{Jenn1} = \left(\frac{N_1 N_2}{N_1 + N_2}\right) x' \widehat{var}(x)^{-1} x \tag{28}$$

where x denotes the column vector of the $J(J-1)/2$ cross-correlation differences $R_1 - R_2$ of the two sample correlation matrices in lexographic order. Jennrich (1970) provides an explicit solution to $\widehat{var}(x)^{-1}$ based on the inverse of the information matrix. Under the null hypothesis that R_1 and R_2 are equal, χ^2_{Jenn1} is asymptotically distributed as χ^2 with $J(J-1)/2$ degrees of freedom.

This test can be easily modified to accommodate any arbitrary set of correlation coefficients from the same correlation matrices used in Equation (28) by constructing the following Wald-statistic,

$$\chi^2_{Jenn2} = \left(\frac{N_1 N_2}{N_1 + N_2}\right) \omega(x)' \left(\frac{\partial \omega(x)}{\partial x}' \widehat{var}(x)^{-1} \frac{\partial \omega(x)}{\partial x}\right) \omega(x) \tag{29}$$

where $\omega(x_m) = \iota_m * x_m$ and ι_m takes the value 1 if the correlation coefficient is to be included in the test and zero otherwise. Under the null hypothesis that R_1 and R_2 are equal, χ^2_{Jenn2} is asymptotically distributed as χ^2 with M degrees of freedom where M is the number of cross-correlation differences included in the test, i.e. $M = \sum_{m=1}^{J(J-1)/2} \iota_m$.

Table 8 presents results for industry contagion based on the conditional hazard rate. Panel A presents cross-industry correlations before the Netscape offer, Panel B presents cross-industry correlations following the Netscape offer, and Panel C reports test statistics for three different χ^2 statistics that progressively focus more directly on the contagion hypothesis as it relates to internet/tech-induced contagion.

The first statistic tests the null hypothesis that there is no change in cross-industry correlation following the Netscape offer across all industries. Causal observation of panels A and B suggest that correlations have increased across most but not all industries. The χ^2_{Jenn1} statistic of 216.4 rejects the hypothesis of no change at the 000% level. A limitation of this test is that it not only considers how correlations relative to the Business Service (SIC 73) industry change but also how correlations among industries not directly related change as well.

The second test considers whether cross-industry correlations relative to Business Services change across all six industries. Essentially, this test only considers whether there are significant changes in correlations in the last column of Table 8. The χ^2_{Jenn2} statistic is 92.5 which rejects the null hypothesis of no change at the 0.000% level.

Since Chemicals (SIC 28) and Financial Services (SIC 60) are not expected to display as much interdependence as Industrial Machinery and Equipment (SIC 35), Electronic Equipment (SIC 36), and Instruments (SIC 38), the third statistic tests for contagion on the subset of industries that are expected to be most closely related to Business Services (SICs 35, 36, and 38). Consistent with the TI hypothesis, there is a substantial increase in the correlation between SIC 35 and SIC 38 relative to SIC 73. This suggests that cross-industry linkages which were not particularly strong prior to the Netscape offer become stronger afterward. By contrast, the correlation between SIC 36 and SIC 73 actually decreases following the Netscape offer. However, since these industries were highly correlated in the pre-issue period, the finding that correlation levels decrease but remain high in absolute terms suggests that these two industries are interdependent. The χ^2_{Jenn2} for this third test is 67.8, which rejects the null hypothesis at the 0.000% level.

Table 9 reports results based on expected conditional durations. The results are similar to those obtained using the conditional hazard rates.

7. Conclusion

This paper examines the determinants of issue cycles for initial public offerings by modelling the time between IPOs with an autoregressive conditional duration model. By including proxies for different explanations of issue activity, we evaluate whether the data supports the business conditions, time varying adverse selection costs, or sentiment hypotheses. The estimates from these models provide a simple way to characterize hot and cold issue cycles that rely on a multidimensional set of factors.

We find that models like the Burr-ACD that allow the hazard rate to be a non-monotonic function of the time between issue dates have significant incremental explanatory power relative to models that assume the hazard rate is constant (e.g. the Exponential-ACD). One explanation is that a constant hazard rate updates rapidly in "event" time, but there are extended periods in "calendar" time when the hazard rate does not change. This is a problem in cold issue periods that immediately follow a hot issue market because the hazard rates tend to remain high for a long period of time (they only change after an issue has occurred). By contrast, a non-monotonic hazard rate continuously updates in calendar time, even if no issues occur. As a result, the hazard rate naturally declines to reflect this lower level of issue activity.

Market-wide models of issue activity can be explained by a simple Burr-ACD model that does not include exogenous variables. Since our tests of the various theories of issue activity are based on these exogenous factors, one might conclude that none of these theories are capable of explaining issue activity. We prefer an alternative interpretation that illustrates the importance of industry modelling. We argue that issue activity among related firms is more likely to be driven by common factors. Since different industries have different rates of technological innovation and different needs for capital, the factors that explain issue activity are likely to be different for different industries. For example, we find that issue cycles in manufacturing industries can be partly explained by the business conditions hypothesis. By contrast, firms in industries that do not have significant capital spending requirements are not affected by business conditions.

We also find that issue activity in manufacturing industries and the financial institution industry are explained by the sentiment hypothesis. Surprisingly, none of these factors explain issue activity in the business service industry. This is likely due to the significant technological innovations related to the development of the internet, which spurred significant demand for new shares that was independent of general market conditions.

We pursue the issue of industry activity further by considering whether technological innovations create investment opportunities in certain industries and whether these innovations spillover to other industries. We provide evidence consistent with this hypothesis. Using the Netscape initial public offer date to "mark" the beginning of a significant innovation in the internet, we examine the cross-correlation of industry issue activity and document evidence consistent with internet-related industry contagion.

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TABLE 1. Summary statistics for issues size and issue durations for all issues, all issues that exceed $25 million and the six most active industries based on issue activity.

Entries report the mean, median, standard deviation, minimum, and maximum of the indicated variables. Panel A reports statistics for issue size. Panel B reports statistics for issue durations.

	Statistics				
Variable definition	Mean	Median	Std. Dev.	Min	Max
Panel A. Issue Size					
All issues	34.48	12.81	112.78	0.10	5,278.95
Issues (> $25 mil.)	75.83	42.86	161.15	25.00	4,118.34
SIC 28	22.52	12.11	46.78	0.70	792.08
SIC 35	19.59	10.17	30.48	0.42	332.13
SIC 36	23.20	12.17	71.78	0.19	1,711.70
SIC 38	15.79	8.22	47.41	0.41	1,079.74
SIC 60	18.20	8.92	36.25	0.32	511.73
SIC 73	22.27	17.65	22.99	0.27	275.79
Panel B. Issue Durations					
All issues	1.88	1.00	4.62	1.00	248
Issues (> $25 mil.)	5.60	2.00	18.71	1.00	270
SIC 28	15.83	5.00	42.60	1.00	701
SIC 35	12.70	6.00	24.70	1.00	330
SIC 36	10.78	5.00	29.11	1.00	576
SIC 38	13.27	5.00	34.44	1.00	675
SIC 60	14.00	4.00	39.78	1.00	718
SIC 73	5.47	1.00	20.98	1.00	578

TABLE 2. Correlation matrix for the monthly dollar volume of initial public offerings across industry classifications.

	Industry Classifications				
	SIC 35	SIC 36	SIC 38	SIC 60	SIC 73
			Correlation Matrix		
SIC28	0.1860	0.1839	0.2398	0.0731	0.2018
SIC35		0.1644	0.1571	0.2425	0.2282
SIC36			0.1709	-0.0213	0.3110
SIC38				0.0348	0.1979
SIC60					-0.0245

Table 3. Summary statistics for variables that proxy for the business conditions, time varying adverse selection costs, sentiment, and activity variables.

We report the mean, median, standard deviation, minimum, and maximum of the variables. The statistics are categorized according to the different hypotheses under consideration. Panel A reports statistics for the business conditions proxies. Panel B reports statistics for the time-varying asymmetric information variables. Panel C reports statistics for the sentiment variables. Panel D reports statistics for the activity variables.

	Statistics				
Variable definition	Mean	Median	Std. Dev.	Min	Max
Panel A. Business Condition Variables					
Index of leading indicators	99.5	98.4	7.4	72.4	111.3
Index of industrial production	88.8	88.5	17.1	48.1	116.2
Index of coincident indicators	95.5	96.6	14.3	53.3	116.6
Credit spread	0.9	0.8	0.3	0.6	2.6
Term spread	1.4	1.2	1.2	-2.6	4.2
Panel B. Time-Varying Asymmetric Information Variables					
Volatility	0.01	0.01	0.01	0.00	0.10
Dispersion	0.63	0.67	0.48	0.00	1.40
Industry diffusion	0.35	0.44	0.21	0.00	0.69
Panel C. Sentiment Variables					
Investor sentiment	7.7	8.4	4.5	-8.2	23.3
Consumer sentiment	93.3	92.7	11.1	62.3	112.0
Panel D. Activity Variables					
S&P500 ret	0.08	0.07	0.08	-0.26	0.35
Offers per day	1.48	1.00	0.87	1.00	7.00
IPO $ volume	3,345.00	3,111.90	2,190.20	0.00	11,827.80
VC investments	4,119.80	1,473.05	5,394.88	9.96	20,852.61
Proportion of early stage	0.42	0.41	0.10	0.00	1.00
Proportion of late stage	0.16	0.14	0.09	0.00	0.67

TABLE 4. Estimations of autoregressive conditional duration (ACD) models.

The Table presents estimates for the business conditions (BC), time varying adverse selection costs (TV), sentiment (S), and combined (C) models. We report the coefficient estimates and t-statistics.

	Models											
	Baseline		Activity		BusCond		TimeVar		Sentiment		Full	
Variable definition	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat
Panel A. Exponential-ACD												
Omega (ω)	0.1237	5.87	0.2267	4.58	0.2318	4.51	0.2177	4.46	0.2344	4.51	0.3071	4.31
Offers per day			-0.4683	-9.50	-0.4144	-7.43	-0.4528	-9.04	-0.4617	-9.45	-0.3957	-6.28
S&P Ret			-0.1739	-2.76	-0.1592	-2.45	-0.1903	-2.76	-0.1815	-2.94	-0.2455	-3.07
IPO $ Volume			0.0898	1.02	0.1022	1.10	0.1033	1.18	0.0748	0.86	-0.1291	-1.31
VC activity			-0.2025	-1.94	-0.2229	-2.02	-0.1482	-1.39	-0.2013	-1.99	-0.0207	-0.17
Business Conditions					-0.1410	-4.85					-0.1739	-5.14
TimeVar							-0.0709	-1.45			-0.0740	-1.38
Sentiment									-0.0359	-0.90	0.0314	0.66
AdSent											-0.3696	-4.62
Alpha (α)	0.1185	10.82	0.1079	8.81	0.0982	8.32	0.1075	8.77	0.1096	8.71	0.1063	7.79
Beta (β)	0.8496	64.99	0.8343	39.14	0.8424	38.42	0.8358	39.44	0.8307	37.35	0.8088	27.47
Log-Likelihood	-2976.35		-2954.28		-2945.46		-2953.58		-2954.06		-2936.77	
Panel B. Burr-ACD												
Omega (ω)	4.4898	3.33	4.9566	3.24	4.9669	3.21	5.0024	3.20	4.9599	3.20	5.0231	3.06
Offers per day			-0.0371	-0.49	-0.0364	-0.48	-0.0421	-0.50	-0.0366	-0.48	-0.0407	-0.45
S&P Ret			-0.0792	-0.58	-0.0759	-0.52	-0.0842	-0.62	-0.0781	-0.57	-0.0814	-0.54
IPO $ Volume			-0.1192	-0.65	-0.1166	-0.64	-0.1112	-0.60	-0.1176	-0.64	-0.1109	-0.58
VC activity			-0.1034	-0.45	-0.1015	-0.45	-0.1229	-0.47	-0.1020	-0.45	-0.1198	-0.44
Business Conditions					-0.0025	-0.04					-0.0049	-0.07
TimeVar							0.0175	0.15			0.0154	0.11
Sentiment									0.0000	0.00	0.0012	0.01
AdSent											-0.0090	-0.05
Alpha (α)	0.0364	2.11	0.0260	1.67	0.0254	1.65	0.0246	1.61	0.0255	1.66	0.0243	1.60
Beta (β)	0.4010	6.17	0.3450	3.30	0.3416	3.10	0.3384	3.07	0.3426	3.13	0.3354	2.69
κ	15.8877	4.80	15.8877	4.70	16.0566	4.68	16.1377	4.67	16.0551	4.68	16.1377	4.67
σ^2	14.0406	4.57	13.9953	4.46	14.1374	4.44	14.2046	4.43	14.1360	4.44	14.2044	4.43
Log-Likelihood	-2326.09		-2321.88		-2320.15		-2319.27		-2320.17		-2319.25	

TABLE 5. Industry-specific estimations of autoregressive conditional duration (ACD) models.

The Table presents estimates combined (C) models for issues in SIC codes 28, 35, 36, 38, 60, and 73. We report the coefficient estimates and t-statistics. Log-likelihood functions for the combined and base models, the likelihood ratio test statistic, the probability value from the likelihood ratio test and the number of observations also are presented.

	Models											
	SIC 28		SIC 35		SIC 36		SIC 38		SIC 60		SIC 73	
Variable definition	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat
Omega (ω)	1.9698	1.98	0.9508	1.90	0.4154	1.87	1.0143	2.57	0.0089	0.04	1.2698	0.83
Offers per day	-0.2775	-1.06	-0.2880	-1.44	-0.3074	-1.67	-0.1275	-0.80	0.4909	2.15	-0.1299	-0.34
SIC Ret	-3.2973	-1.38	-1.8314	-0.72	-1.3017	-0.84	-3.3662	-1.89	-3.3676	-1.10	-1.4185	-0.48
IPO $ Volume	-0.7165	-1.02	0.2403	0.45	-0.7793	-1.73	-0.4609	-1.01	-0.3754	-0.70	0.0204	0.03
VC activity	0.0710	0.08	2.0831	1.83	-0.1884	-0.27	0.1827	0.24	2.4742	2.01	0.3960	0.33
Business Conditions	-0.5607	-1.93	-0.4222	-2.18	-0.4708	-2.26	-0.5395	-2.74	-0.1636	-0.82	-0.0731	-0.23
TimeVar	-0.1307	-0.23	-0.1852	-0.37	-0.1164	-0.26	-0.5005	-1.41	-1.5638	-2.90	-0.1057	-0.16
Sentiment	0.3460	0.91	0.2852	1.08	0.0553	0.22	0.3656	1.40	0.1632	0.57	-0.2350	-0.45
AdSent	-2.1493	-2.85	-1.4364	-2.74	-1.1336	-2.31	-1.6681	-3.53	-0.7359	-1.73	0.1673	0.20
Alpha (α)	0.0890	2.41	0.1070	3.25	0.0422	2.35	0.0914	3.50	0.1735	3.71	0.0522	0.80
Beta (β)	0.7860	8.85	0.8065	11.81	0.9296	33.92	0.8282	16.03	0.8057	20.87	0.9460	126.83
κ	1.5425	9.73	1.5325	11.01	1.5629	10.17	1.3384	12.62	1.7132	8.79	9.4809	18.00
σ^2	0.8512	3.58	0.6413	3.29	0.8734	3.95	0.3632	2.84	0.9669	3.25	9.1617	13.70
Log-Likelihood (Full)	-1450.29		-1583.16		-1814.48		-1612.35		-1268.68		-2312.97	
Log-Likelihood (Base)	-1467.79		-1597.11		-1826.66		-1635.09		-1274.26		-2314.37	
Likelihood ratio test (8 d.f.)	35.00		27.89		24.36		45.49		11.16		2.81	
Probability value	0.0000		0.0005		0.0020		0.0000		0.1928		0.9459	
Observations	440		490		589		505		402		1066	

Table 6. Correlation matrix for conditional hazard rates across industry classifications.

	Industry Classifications				
	SIC 35	SIC 36	SIC 38	SIC 60	SIC 73
	Panel A. Correlation Matrix				
SIC 28	0.1235	0.1601	0.1903	0.0683	0.1914
SIC 35		0.1240	0.1567	0.1179	0.0837
SIC 36			0.1432	0.0563	0.2259
SIC 38				0.0352	0.1360
SIC 60					0.0221
	Panel B. Fisher Z-statistic for $H_0 : \rho = 0$				
SIC 28	9.0799	11.8137	14.0923	5.0057	14.1737
SIC 35		9.1140	11.5543	8.6605	6.1371
SIC 36			10.5444	4.1219	16.8168
SIC 38				2.5754	10.0059
SIC 60					1.6147
	Panel C. Olkin-Finn Wald statistic and the associated p-values				
SIC 28	66.4	0.001			
SIC 35	19.3	0.000			
SIC 36	97.4	0.000			
SIC 38	79.7	0.000			
SIC 60	34.0	0.000			
SIC 73	157.7	0.000			

TABLE 7. Correlation matrix for autoregressive conditional duration forecasts across industry classifications.

	Industry Classifications				
	SIC 35	SIC 36	SIC 38	SIC 60	SIC 73
			Panel A. Correlation Matrix		
SIC 28	0.3198	0.3620	0.1644	0.5112	0.2807
SIC 35		0.2704	0.2135	0.4038	0.1610
SIC 36			0.2102	0.1652	0.3902
SIC 38				0.1524	0.1433
SIC 60					0.1247
			Panel B. Fisher Z-statistic for $H_0 : \rho = 0$		
SIC 28	24.2417	27.7370	12.1385	41.2744	21.0977
SIC 35		20.2785	15.8614	31.3209	11.8772
SIC 36			15.6066	12.1976	30.1415
SIC 38				11.2365	10.5509
SIC 60					9.1717
			Panel C. Olkin-Finn Wald statistic and the associated p-values		
SIC 28	723.0	0.000			
SIC 35	369.0	0.000			
SIC 36	268.6	0.000			
SIC 38	33.4	0.000			
SIC 60	1584.0	0.000			
SIC 73	445.4	0.000			

Table 8. Correlation matrix for conditional hazard rates across industry classifications in the two-year period immediately before and after the Netscape IPO.

	Industry Classifications				
	SIC 35	SIC 36	SIC 38	SIC 60	SIC 73
Panel A. Cross-industry correlation matrix before Netscape offer					
SIC 28	0.1027	0.1137	0.0645	0.1278	0.0943
SIC 35		0.1036	0.1372	0.1207	0.0461
SIC 36			0.0695	0.0425	0.1822
SIC 38				0.0763	-0.0147
SIC 60					-0.0571
Panel B. Cross-industry correlation Matrix after Netscape offer					
SIC 28	0.1310	0.1683	0.2175	-0.0220	0.1398
SIC 35		0.0920	0.1225	-0.0460	0.0733
SIC 36			0.1583	-0.0531	0.1233
SIC 38				0.0078	0.1764
SIC 60					0.0037
Panel C. Jennrich (1970) χ^2 statistics and the associated p-values					
All industries	13.4	0.0199			
All relative to SIC 73	12.2	0.0324			
Related relative to SIC 73	11.4	0.0098			

TABLE 9. Correlation matrix for daily expected conditional duration forecasts across industry classifications in the two-year period immediately before and after the Netscape IPO.

	Industry Classifications				
	SIC 35	SIC 36	SIC 38	SIC 60	SIC 73
Panel A. Cross-industry correlation matrix before Netscape offer					
SIC 28	0.0063	-0.0142	-0.1022	0.1370	0.1401
SIC 35		0.0748	-0.0714	0.1099	0.0484
SIC 36			-0.0966	-0.0956	0.4286
SIC 38				-0.0040	-0.0342
SIC 60					-0.1607
Panel B. Cross-industry correlation Matrix after Netscape offer					
SIC 28	0.1769	0.2786	0.3117	-0.1056	0.0677
SIC 35		0.0170	0.3604	0.1167	0.2813
SIC 36			0.1129	-0.0293	0.1809
SIC 38				-0.0148	0.3345
SIC 60					0.1495
Panel C. Jennrich (1970) χ^2 statistics and the associated p-values					
All industries	216.4	0.0000			
All relative to SIC 73	92.5	0.0000			
Related relative to SIC 73	67.8	0.0000			

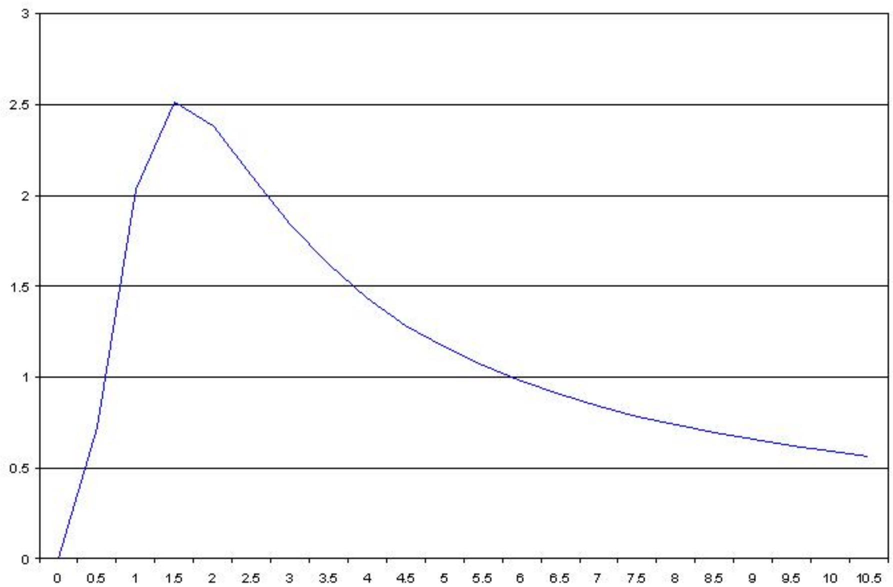

Figure 1. Conditional hazard rate for the Burr ACD model as a function of the time since the last issue. It is calculated using the parameter estimates from the Baseline Model in Panel B of Table 4.

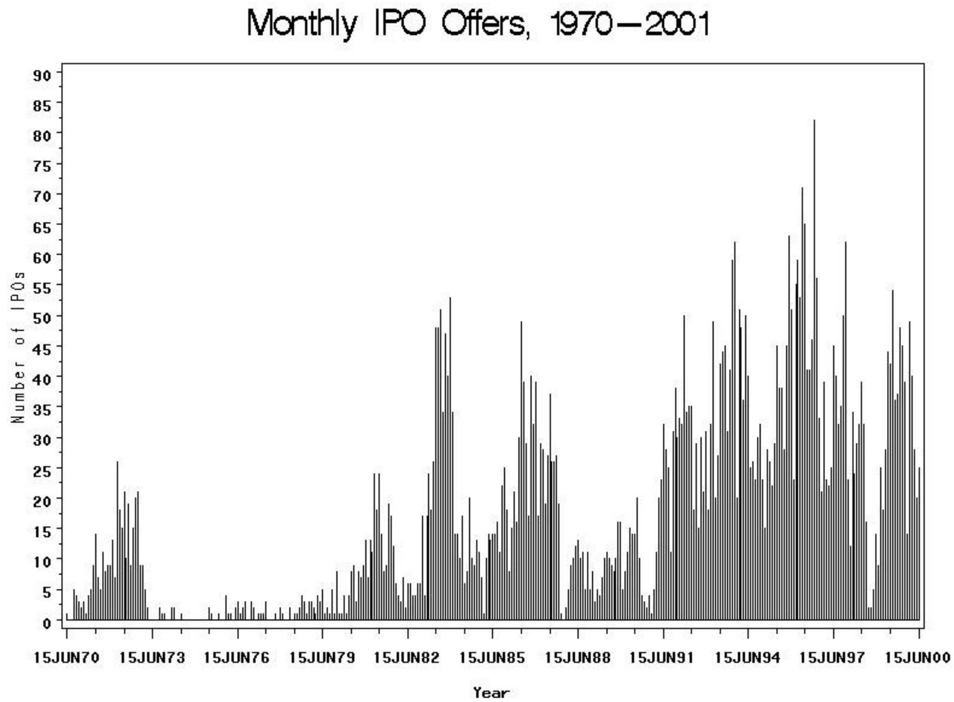

FIGURE 2. Monthly number of issues for the period 1970 through 2001.

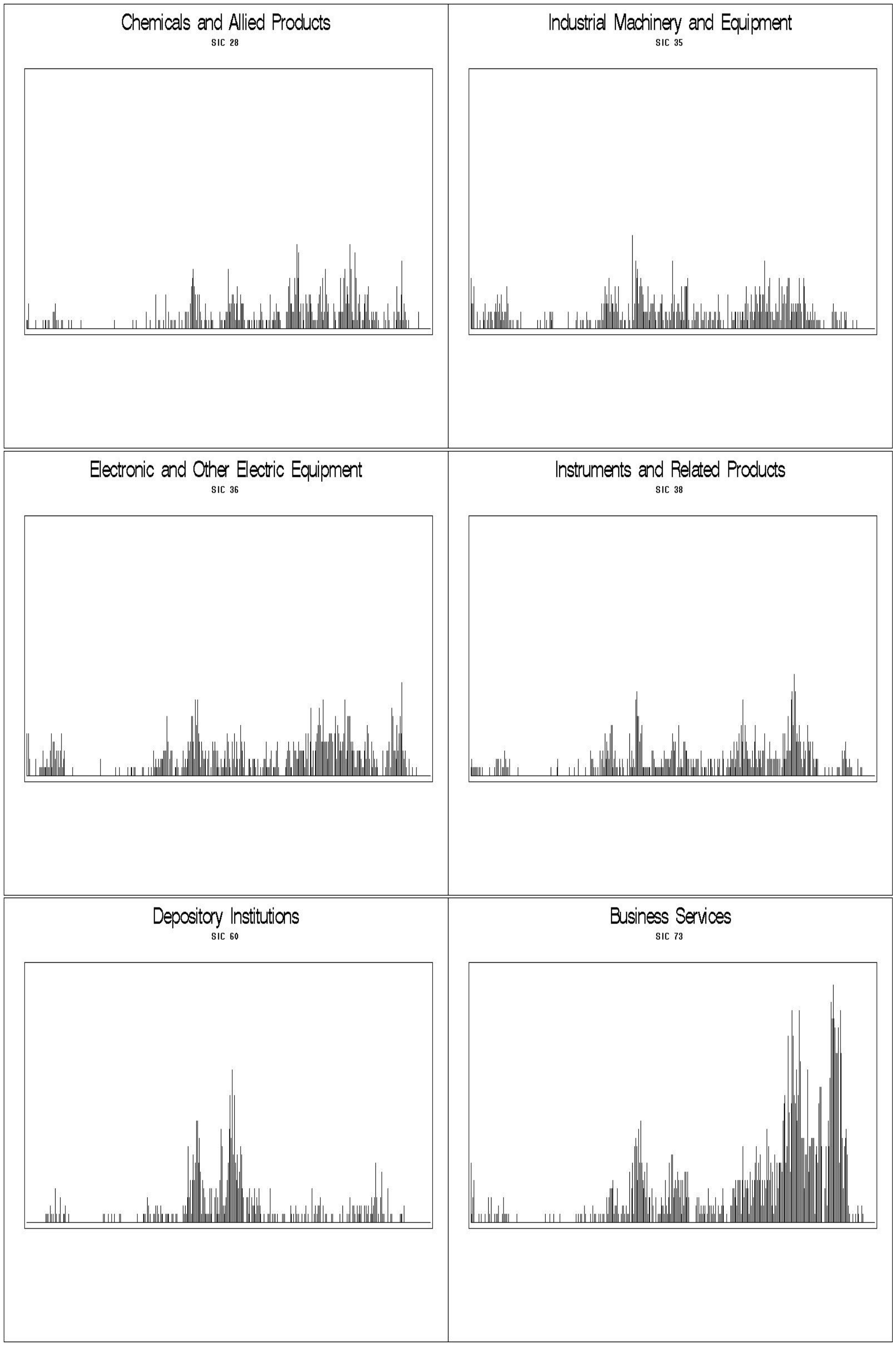

FIGURE 3. Monthly number of issues for the six industries with the greatest issue volume over the period 1970 through 2001.

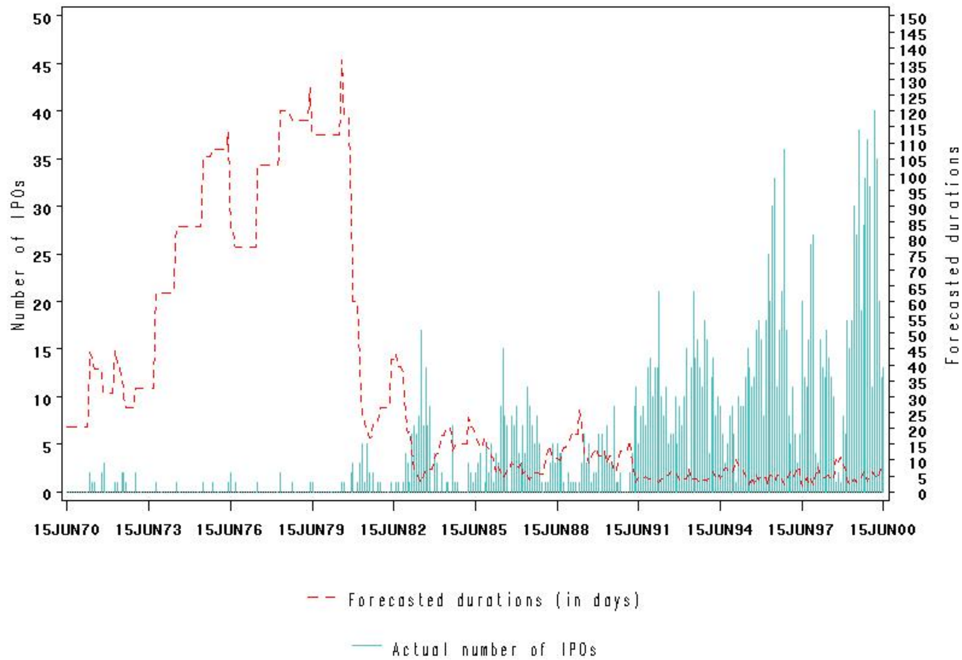

FIGURE 4. Estimates of the expected conditional durations at month-end and the number of issues each month for the period 1970 through 2001.