On the Link Between New Stock Listings and Stock Delistings and Average Cross-Sectional Idiosyncratic Stock Volatility

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Log-return on stock $i$ is represented as:

$$\ln(R^i) = \text{drift} + \underbrace{\text{Systematic Risk}}_{\beta_i \times \sigma_m \times W_t} + \underbrace{\text{Idiosyncratic Risk}}_{\sigma_i \times Z^i_t}$$

- $W_t$: source of systematic risk (common across all stocks)
- $Z^i_t$: source of idiosyncratic risk (specific to stock $i$)

We study average of $\sigma_i$’s over all stocks and call it **average idiosyncratic volatility (AIVOL)**
Figure: AIVOL and Market Volatility, 1962–2011
Reasons to Study AIVOL

Average idiosyncratic volatility (AIVOL):

- influences effectiveness of portfolio diversification and performance of portfolio managers (Campbell et al., 2001; Bennett & Sias, 2006)

- affects efficiency of capital allocation via stock market (Durnev et al., 2003; Hamao et al., 2007)

- predicts future stock market returns (Goyal & Santa-Clara, 2003; Guo & Savickas, 2006)

- is a priced risk factor (Ang et al., 2006; Fu, 2009; Guo & Savickas, 2010)

- reflects intensity of "creative destruction" (Chun et al., 2008)
Previous Literature

- **Time-series behavior of AIVOL:**
  - Campbell et al. (2001): positive trend between 1962 and 1997
  - Bennett & Sias (2006), Brandt et al. (2010): reversal in trend around 2000
  - Bekaert et al. (2012): no evidence of positive trend overall

- **Factors influencing AIVOL dynamics:**
  - Pástor & Veronesi (2003), Fama & French (2004): number of new stock listings
  - Xu & Malkiel (2003): institutional stock ownership
  - Bennett & Sias (2006): stock market composition
  - Wei & Zhang (2006): level and volatility of return-on-equity
  - Brown & Kapadia (2007): riskiness of publicly traded subsample of the economy
  - Cao et al. (2008): level and variance of corporate growth options
  - Chun et al. (2008): intensity of "creative destruction" in the economy
  - Irvine & Pontiff (2009): idiosyncratic volatility of cash flows, intensity of competition
  - Bekaert et al. (2012): industry turnover, growth options, R&D spending, market variance, shocks to industrial production, bond yield spread
Main Findings

- AIVOL is positively associated with *contemporaneous* number of:
  - newly listed stocks
  - delisted stocks

- AIVOL is positively associated with *lagged* number of:
  - newly listed stocks
  - delisted stocks

- The results for stock delistings are novel, strong, and robust:
  - we account for autocorrelation of AIVOL
  - we control for aggregate financial/economic variables
  - we perform several specification tests

*Note:* our AIVOL measure represents average idiosyncratic volatility among *surviving* stocks
Important Attributes of AIVOL Estimation Approach

- \( AIVOL_{t,t+\tau} \) is average cross-sectional idiosyncratic stock volatility over time period \([t, t + \tau]\)

- \( AIVOL_{t,t+\tau} \) is unobservable and must be estimated

- To estimate \( AIVOL_{t,t+\tau} \), stock prices need to be observed only at two time moments: \( t \) and \( t + \tau \)

- When estimating \( AIVOL_{t,t+\tau} \), we do not consider stocks that were:
  - newly listed between \( t \) and \( t + \tau \)
  - delisted between \( t \) and \( t + \tau \)

- We use stock prices adjusted for stock splits, reverse splits, etc.
Our financial market model features three types of assets:
- many risky assets called **stocks**
- a diversified portfolio of stocks called **market index**
- a riskless asset (e.g., T-Bill) with risk-free interest rate \( r > 0 \)

Market index’s price, \( M_t \), follows a geometric Brownian motion:
\[
\frac{dM_t}{M_t} = \mu_m dt + \sigma_m dW_t
\]
- drift \( \mu_m = r + \delta \sigma_m \)
- \( \delta \): market risk premium
- \( \sigma_m > 0 \): market volatility
- \( W_t \): standard Brownian motion (source of systematic risk)
Stock Price Dynamics

- Price of stock $i$, $S_t^i$, follows a geometric Brownian motion:

$$\frac{dS_t^i}{S_t^i} = \mu_i dt + \beta_i \sigma_m dW_t + \sigma_i dZ_t^i$$

- $i = 1, 2, \ldots$ indexes stocks
- $W_t$: standard Brownian motion, source of systematic risk
- $Z_t^i$: standard Brownian motion, source of idiosyncratic risk
- $W_t$ and $Z_t^i$ are independent $\forall i$, $Z_t^i$ and $Z_t^j$ are independent $\forall i \neq j$
- Drift $\mu_i = r + \delta \beta_i \sigma_m + \gamma \sigma_i$
- $\gamma$: idiosyncratic risk premium
- $\beta_i$: beta of stock $i$, $\beta_i \sim i.i.d. UNI[\kappa_\beta, \kappa_\beta + \lambda_\beta]$
- $\sigma_i$: idiosyncratic volatility of stock $i$, $\sigma_i \sim i.i.d. UNI[0, \lambda_\sigma]$

- $AIVOL = \lambda_\sigma/2$, where $\lambda_\sigma$ is estimated using GMM-based approach of Khovansky & Zhylyevskyy (2013)
Source of stock data: Center for Research in Security Prices (CRSP)

Time frame: 1962–2011

We construct 12 time series of annual AIVOL estimates. Each series has 49 observations and is based on non-overlapping periods falling on a particular month:

- **January series, 49 periods:**
  - first Wednesday of January 1962–first Wednesday of January 1963
  - first Wednesday of January 1963–first Wednesday of January 1964
  - ...
  - first Wednesday of January 2010–first Wednesday of January 2011
  - ...

- **December series, 49 periods:**
  - first Wednesday of December 1962–first Wednesday of December 1963
  - ...
  - first Wednesday of December 2010–first Wednesday of December 2011

For same periods, we construct time series of numbers of new stock listings and delistings using CRSP stock header files
Before running regressions, we test all time series for unit root and find them to be stationary.

Contemporaneous regressions have following form:

$$\ln(AIVOL_t) = a_0 + a_1 \cdot \ln(n_t) + a_2 \cdot \ln(AIVOL_{t-1}) + a_3 \cdot nasdaq_t + \epsilon_t$$

$n_t$: number of new listings OR number of delistings during period $t$

<table>
<thead>
<tr>
<th>Log of Stock Numbers</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Newly Listed</strong></td>
</tr>
<tr>
<td>Coeff.($a_1$) (Std.Err.)</td>
</tr>
<tr>
<td>January series</td>
</tr>
<tr>
<td>February series</td>
</tr>
<tr>
<td>March series</td>
</tr>
<tr>
<td>...</td>
</tr>
<tr>
<td>December series</td>
</tr>
</tbody>
</table>

| **Delisted**        |
| Coeff.($a_1$) (Std.Err.) |
| January series  | 0.4350*** (0.0848) |
| February series  | 0.3304*** (0.0795) |
| March series      | 0.3591*** (0.1036) |
| ...               | ... (0.0935)        |
| December series   | 0.3972*** (0.0935)  |
We regress AIVOL on first lag of number of new listings and delistings. Regressions have following form:

\[
\ln(AIVOL_t) = b_0 + b_1 \cdot \ln(n_{t-1}) + b_2 \cdot \ln(AIVOL_{t-1}) + b_3 \cdot \text{nasdaq}_{t-1} + \epsilon_t
\]

\(n_{t-1}\): number of new listings OR number of delistings during \(t - 1\)

<table>
<thead>
<tr>
<th>First Lag of Log of Stock Numbers</th>
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<tr>
<td><strong>Newly Listed</strong></td>
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<tr>
<td></td>
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<tr>
<td>March series</td>
</tr>
<tr>
<td>...</td>
</tr>
<tr>
<td>December series</td>
</tr>
</tbody>
</table>

Regressions are also run for delistings differentiated by delisting reason: merger, stock-issue exchange, pre-announced liquidation, drop
Selected Aggregate Variables That May Affect AIVOL

- **MABA**: average ratio of market value of assets to book value of assets among publicly traded firms
- **RD**: average ratio of research and development expenditures to sales
- **Small**: percentage of total market capitalization attributable to smallest (by market value) quartile of firms
- **Std(SP500)**: standard deviation of daily returns on S&P 500 index
- **VIX**: VIX index (measures implied volatility of S&P 500 index options)
Contemporaneous Regression with New Listings and AV Controls

Estimated regressions:

\[ \ln(AIVOL_t) = a_0 + a_1 \cdot \ln(n_t) + a_2 \cdot av_t + a_3 \cdot \ln(AIVOL_{t-1}) + a_4 \cdot \text{nasdaq}_t + \epsilon_t \]

\( n_t \): number of newly listed stocks during period \( t \)

\( av_t \): aggregate variable for period \( t \)

<table>
<thead>
<tr>
<th>Aggregate Variable</th>
<th>Coeff. ( a_2 ) (Std.Err.)</th>
<th>Log # of New Listings</th>
</tr>
</thead>
<tbody>
<tr>
<td>( \ln(MABA) )</td>
<td>-0.0470 (0.1331)</td>
<td>0.1951** (0.0868)</td>
</tr>
<tr>
<td>( \ln(RD) )</td>
<td>0.0871** (0.0331)</td>
<td>0.1397** (0.0655)</td>
</tr>
<tr>
<td>Small</td>
<td>-0.6094** (0.2803)</td>
<td>0.2089** (0.0784)</td>
</tr>
<tr>
<td>Std(SP500)</td>
<td>0.4216*** (0.1508)</td>
<td>0.2733*** (0.0926)</td>
</tr>
<tr>
<td>VIX</td>
<td>0.0296** (0.0121)</td>
<td>0.2511*** (0.0897)</td>
</tr>
</tbody>
</table>

*Note: We use time series for annual periods starting in January*

- Each regression fails at least one specification test: RESET, alternative Durbin, or Fan & Li (1999) test
Contemporaneous Regression with Delistings and AV Controls

Estimated regressions:

\[ \ln(AIVOL_t) = a_0 + a_1 \cdot \ln(n_t) + a_2 \cdot av_t + a_3 \cdot \ln(AIVOL_{t-1}) + a_4 \cdot nasdaq_t + \epsilon_t \]

\( n_t \): number of delisted stocks during period \( t \)

\( av_t \): aggregate variable for period \( t \)

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<th>Aggregate Variable</th>
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</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Coeff. ( (a_2) )</td>
</tr>
<tr>
<td>ln(MABA)</td>
<td>-0.0777</td>
</tr>
<tr>
<td>ln(RD)</td>
<td>0.0476**</td>
</tr>
<tr>
<td>Small</td>
<td>0.0633</td>
</tr>
<tr>
<td>Std(SP500)</td>
<td>0.1840***</td>
</tr>
<tr>
<td>VIX</td>
<td>0.0142*</td>
</tr>
</tbody>
</table>

*Note: We use time series for annual periods starting in January*

- Log # of delistings remains statistically significant in all cases
- Regressions for ln(MABA) and Small fail alternative Durbin test (at 5% level)
Lagged Regression with New Listings and AV Controls

Estimated regressions:

$$\ln(AIVOL_t) = b_0 + b_1 \cdot \ln(n_{t-1}) + b_2 \cdot av_{t-1} + b_3 \cdot \ln(AIVOL_{t-1}) + a_4 \cdot nasdaq_{t-1} + \epsilon_t$$

- $n_{t-1}$: number of newly listed stocks during period $t - 1$
- $av_{t-1}$: aggregate variable for period $t - 1$

<table>
<thead>
<tr>
<th>Lagged:</th>
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</thead>
<tbody>
<tr>
<td></td>
<td>Coeff.($b_2$)</td>
<td>(Std.Err.)</td>
</tr>
<tr>
<td>ln(MABA)</td>
<td>0.2643</td>
<td>(0.1823)</td>
</tr>
<tr>
<td>ln(RD)</td>
<td>0.0871**</td>
<td>(0.0343)</td>
</tr>
<tr>
<td>Small</td>
<td>-0.4768**</td>
<td>(0.2002)</td>
</tr>
<tr>
<td>Std(SP500)</td>
<td>0.0956</td>
<td>(0.2161)</td>
</tr>
<tr>
<td>VIX</td>
<td>0.0073</td>
<td>(0.0153)</td>
</tr>
</tbody>
</table>

*Note: We use time series for annual periods starting in January*

- Lagged log # of new listings loses statistical significance when a lagged aggregate variable is added to the regression
- Each regression fails at least two specification tests out of three performed
Lagged Regression with Delistings and AV Controls

Estimated regressions:

\[
\ln(AIVOL_t) = b_0 + b_1 \cdot \ln(n_{t-1}) + b_2 \cdot av_{t-1} + b_3 \cdot \ln(AIVOL_{t-1}) + b_4 \cdot nasdaq_{t-1} + \varepsilon_t
\]

- \(n_{t-1}\): number of delisted stocks during period \(t - 1\)
- \(av_{t-1}\): aggregate variable for period \(t - 1\)

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<th>Log # of Delistings</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Coeff.((b_2))</td>
<td>(Std.Err.)</td>
</tr>
<tr>
<td>ln(MABA)</td>
<td>0.0791</td>
<td>(0.1231)</td>
</tr>
<tr>
<td>ln(RD)</td>
<td>0.0343</td>
<td>(0.0226)</td>
</tr>
<tr>
<td>Small</td>
<td>0.1775</td>
<td>(0.2597)</td>
</tr>
<tr>
<td>Std(SP500)</td>
<td>-0.0054</td>
<td>(0.1142)</td>
</tr>
<tr>
<td>VIX</td>
<td>-0.0018</td>
<td>(0.0096)</td>
</tr>
</tbody>
</table>

\textit{Note:} We use time series for annual periods starting in January

- Lagged log # of delistings remains statistically significant in all cases
- Each regression passes all performed specification tests
Number of stock delistings explains and predicts the dynamics of AIVOL among surviving stocks

- An increase in the number of delistings may disrupt investor learning about future prospects of surviving stocks
- In that case, the model of Pástor & Veronesi (2003) would predict a rise in idiosyncratic volatilities among surviving stocks

Our results for delistings are robust to accounting for other variables that can explain or predict AIVOL

Number of delistings may be indicative of the intensity of "creative destruction." Because of the link to AIVOL, financial investors may be negatively affected by economic forces contributing to long-run growth
Thank you!
Questions?
Figure: # of new listings for annual periods starting in December
Appendix: Number of Stock Delistings, 1962–2011

Figure: # of delistings for annual periods starting in December
Appendix: Selected Aggregate Variables and AIVOL

These regressions focus on aggregate variables and do not include log numbers of new listings and delistings as regressors.

- Contemporaneous regressions:
  \[
  \ln(AIVOL_t) = a_0 + a_1 \cdot av_t + a_2 \cdot \ln(AIVOL_{t-1}) + a_3 \cdot nasdaq_t + \epsilon_t
  \]

- Lagged regressions:
  \[
  \ln(AIVOL_t) = b_0 + b_1 \cdot av_{t-1} + b_2 \cdot \ln(AIVOL_{t-1}) + b_3 \cdot nasdaq_{t-1} + \epsilon_t
  \]

<table>
<thead>
<tr>
<th></th>
<th>Contemporaneous</th>
<th></th>
<th>Lagged</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Coeff. ((a_1))</td>
<td>(Std.Err.)</td>
<td>Coeff. ((b_1))</td>
<td>(Std.Err.)</td>
</tr>
<tr>
<td>ln(MABA)</td>
<td>0.0945</td>
<td>(0.1336)</td>
<td>0.3672**</td>
<td>(0.1497)</td>
</tr>
<tr>
<td>ln(RD)</td>
<td>0.0997***</td>
<td>(0.0360)</td>
<td>0.0936**</td>
<td>(0.0354)</td>
</tr>
<tr>
<td>Small</td>
<td>-0.5328**</td>
<td>(0.2471)</td>
<td>-0.4306**</td>
<td>(0.1873)</td>
</tr>
<tr>
<td>Std(SP500)</td>
<td>0.2877***</td>
<td>(0.1031)</td>
<td>0.0015</td>
<td>(0.1418)</td>
</tr>
<tr>
<td>VIX</td>
<td>0.0205*</td>
<td>(0.0107)</td>
<td>0.0010</td>
<td>(0.0124)</td>
</tr>
</tbody>
</table>

*Note:* We use time series for annual periods starting in January.