regression

December 4, 2025

[2]:
```
%reload_ext autoreload
%autoreload 2

from pathlib import Path
import sys

from dotenv import load_dotenv

# climb up until we hit the repo root, then add src
here = Path.cwd().resolve()
while here.name != "over-intra-news" and here.parent != here:
    here = here.parent

src_path = here / "src"
if str(src_path) not in sys.path:
    sys.path.insert(0, str(src_path))

load_dotenv()
```

[2]: True

1 Glasserman-style news regressions and topic persistence

This notebook takes the fixed LDA topic model trained on CC-NEWS articles and links its firm-level topic exposure vectors to equity returns in a **Glasserman-style** framework. Conceptually we follow Glasserman–Krstovski–Laliberte–Mamaysky: topics are estimated once, exposure vectors are aggregated to the firm–period level, and regressions map lagged exposures and firm characteristics into intraday and overnight returns.

Relative to the original paper, we make four deliberate changes:

1. **Different sample and rolling window.**
   4 different LDA models are trained once on CC-NEWS from 2016–2022 and then used for inference on 2022–2025 to create a fully OOS time period. Return regressions use a shorter equity sample than the original paper, so we work with **one-year exposure windows** ($n = 1$) rather than four-year windows. With $n = 1$ the "rolling window" becomes a single lag, which makes the panel explicitly dynamic and preserves effective sample length.
2. **Elastic Net instead of pure lasso.**

Glasserman uses lasso to select a sparse set of predictive topics. Here we use an **Elastic Net (EN) penalty** with mixing parameter α_{EN} close to one:

- the ℓ_1 component keeps the number of active topics manageable, and
- the small ℓ_2 component stabilizes coefficients when topics are highly collinear.

3. **Dynamic panels with GMM and explicit selection correction.**
   Both the topic persistence regressions and the return regressions include **lagged dependent variables** with unobserved firm, topic and/or time heterogeneity. In Wooldridge's language (Chapter 11), this puts us in the world of **unobserved effects models under sequential moment restrictions** rather than strict exogeneity. At the same time, our panel is **unbalanced**: firms enter and exit the S&P 500 and, even for a given firm–topic pair, some years have no relevant articles at all. Because the appearance of a firm–topic cell in the panel is unlikely to be mean independent of the idiosyncratic error, we do not treat missing cells as innocuous. Instead we

   - model the observation indicator with a **first-stage probit selection equation**, and
   - feed the resulting **inverse Mills ratio** into the outcome equation as a control function. We then estimate the augmented dynamic-panel outcome by **Arellano–Bond–style GMM**, using lags of the dependent variable as instruments and treating the selection-correction term as an additional (predetermined) regressor. Fixed effects serve as a benchmark, but our main estimates are GMM-with-selection.

4. **State-space smoothing of forecast coefficients.**
   With annual data we are in a **large-N, small-T** setting, so the year-by-year EN–GMM estimates $\hat{\beta}_t$ can be noisy. To hedge against this small-T instability, we place the coefficient vectors in a simple **state-space model** (e.g. an AR(1) evolution for β_t) and apply **Kalman smoothing**. This produces smoothed paths $\tilde{\beta}_t$ that borrow strength across adjacent years. We then base portfolio construction on the smoothed $\tilde{\beta}_t$, with the explicit goal of reducing forecast noise and **alleviating excessive turnover** while still allowing for gradual structural change in the news–return relationship.

The rest of the notebook is organised as follows:

1. **Topic persistence.** Define firm–period topic exposure vectors and estimate dynamic panel regressions of $t+1$ exposures on lagged exposures, using GMM plus a Heckman-style selection correction to handle lagged dependent variables and non-random observation of firm–topic–year cells.
2. **Annual returns and characteristics.** Build firm-year panels of intraday and overnight returns plus standard characteristics (size, value, momentum, etc.).
3. **Elastic-Net GMM return regressions.** Run Glasserman-style regressions of annual intraday/overnight returns on lagged topic exposures and controls, estimated by EN plus GMM (again with a selection correction), and compare to FE benchmarks.
4. **Forecasts and portfolio inputs.** Store fitted return forecasts in `return_forecasts` for use in the backtesting and portfolio-construction notebooks.

1.1 1. Topic persistence in firm-level news exposures

The first step is to verify that **firm-level topic exposures are persistent over time**. If a firm's news loads heavily on topic k in year t, we want to confirm that it tends to keep loading on the same topic in year $t+1$, separately for intraday and overnight news.

1.1.1 1.1 overview

1.1.1 Document-level topic probabilities Fix a single LDA run and let $k \in \{1, \dots, K\}$ index topics and a index news articles.

For each article a, MALLET produces a document–topic probability vector $\theta^a \in \mathbb{R}^K$ with θ_k^a interpreted as the exposure of article a to topic k:

$$\theta^a = (\theta_1^a, \dots, \theta_K^a), \quad \sum_{k=1}^{K} \theta_k^a = 1 \tag{1}$$

These θ_k^a are the basic building blocks for firm-level topic exposures.

1.1.2 Firm-period exposure vectors Let j index firms and let $s \in \{i, o\}$ denote the session: $s = i$ for intraday news and $s = o$ for overnight news.

For a given firm j, period t, and session s, define the set of relevant articles:

$$A_{j,t}^s = \{\text{articles } a \text{ in period } t \text{ that mention firm } j \text{ in session } s\} \tag{2}$$

The **firm-level exposure of company j to topic k in period t and session s** is then:

$$z_{j,k,t}^s = \sum_{a \in A_{j,t}^s} \theta_k^a \tag{3}$$

When t is a trading day, $z_{j,k,t}^s$ is the total exposure of firm j to topic k in that day and session. When t is a calendar year, the same definition applied to all trading days in the year yields **annual** exposures.

We also define an "all new" version that aggregates intraday and overnight exposures:

$$z_{j,k,t}^{\text{all}} = z_{j,k,t}^i + z_{j,k,t}^o \tag{4}$$

For each firm–year (j, t) we therefore have three K-dimensional exposure vectors $\{z_{j,\cdot,t}^i, z_{j,\cdot,t}^o, z_{j,\cdot,t}^{\text{all}}\}$.

In what follows we work at the **yearly** level for persistence: t indexes calendar years, and all $z_{j,k,t}^s$ are constructed from full-year news.

1.1.3 One-year "window" and dynamic structure Glasserman's persistence regressions use **multi-year averages** of past exposures. For a generic window length $n \geq 1$, define:

$$\bar{z}^s_{j,k,t+1;n} = \frac{1}{n} \sum_{r=0}^{n-1} z^s_{j,k,t-r} \tag{5}$$

Their baseline specification uses $n = 4$. In this project we set:

$$n = 1, \tag{6}$$

to conserve effective sample length. With $n = 1$ the rolling average collapses to:

$$\bar{z}^s_{j,k,t;1} = z^s_{j,k,t} \tag{7}$$

so the persistence regressions become **dynamic panels with a single lag** rather than moving averages of past exposures. It is important to stress that with $n = 1$ we are *not* smoothing over multiple years: we genuinely use the previous year's exposure as a regressor.

1.1.4 Dynamic-panel specification, attrition, and selection For each session $s \in \{i, o, \text{all}\}$ we would like to estimate the persistence regression:

$$z^s_{j,k,t+1} = \alpha_j + \alpha_k + \rho^s z^s_{j,k,t} + u^s_{j,k,t+1} \tag{8}$$

where:

- α_j is a firm fixed effect,
- α_k is a topic fixed effect,
- ρ^s is the **persistence parameter** for session s, and
- $u^s_{j,k,t+1}$ is an idiosyncratic error.

This is Wooldridge's dynamic unobserved-effects model (Chapter 11) with $y_{it} = z^s_{j,k,t}$ and $c_i = \alpha_j + \alpha_k$. The panel is **unbalanced**: firms enter and exit the S&P 500 and, for a given (j, k), some years have no relevant news at all. Define the observation indicator:

$$I^s_{j,k,t} = \mathbf{1}\{z^s_{j,k,t} \text{ is observed}\} \tag{9}$$

so that the outcome equation is only observed when $I^s_{j,k,t} = 1$ and $I^s_{j,k,t+1} = 1$. We do not want to assume that this "attrition" is mean independent of $u^s_{j,k,t+1}$. Instead we model it explicitly via a selection equation.

1.1.5 Selection equation and inverse Mills ratio Let $w^s_{j,k,t}$ collect variables that are plausibly important for whether we observe a valid data point for firm j and topic k in year t and session s.

Crucially, our observation process is a **composite selection mechanism**: 1. **Index Survival:** The firm must be in the S&P 500. This is our **base universe**. 2. **News Existence:** The firm must generate news articles with non-zero exposure to topic k. This is the **conditional outcome**.

To account for both, we model the probability of *news observation conditional on index membership*. We include the following variables in the selection equation: * A lagged selection indicator $I^s_{j,k,t-1}$ (topic stickiness), capturing the persistence of specific news themes. * A firm-level news intensity estimator $\widehat{\lambda}^s_{j,t-1}$, capturing the general propensity of the firm to generate news. * **Lagged Log Market Capitalization** $\ln(\text{MarketCap}_{j,t-1})$. Since size is the primary determinant of S&P 500 inclusion, this control effectively proxies for the "Index Survival" probability, correcting for the bias arising from firms dropping out of the sample.

We then estimate, for each session s, the probit selection equation:

$$\mathbb{P}(I^s_{j,k,t} = 1 | w^s_{j,k,t}) = \Phi(\gamma_s^\top w^s_{j,k,t})$$

where Φ is the standard normal cdf and γ is estimated by maximum likelihood. The "zeros" in this model ($I = 0$) are firms that were in the S&P 500 but had no significant news coverage on topic k.

1.1.6 GMM estimation and choice of instruments We still have a dynamic-panel problem: $z^s_{j,k,t}$ appears on the right-hand side, so fixed effects alone would suffer from Nickell bias. Following Wooldridge's discussion of Arellano–Bond estimators, we work with the first-differenced equation:

$$\Delta z^s_{j,k,t+1} = \rho^s \Delta z^s_{j,k,t} + \delta^s \Delta \hat{m}^s_{j,k,t} + \Delta \varepsilon^s_{j,k,t+1}, \quad t = 2, \dots, T-1 \tag{10}$$

Under sequential exogeneity of the shocks this yields moment conditions of the form:

$$E\Big(z^s_{j,k,t-\ell}\, \Delta \varepsilon^s_{j,k,t+1}\Big) = 0, \quad \ell \geq 2 \tag{11}$$

so earlier lags of $z^s_{j,k,t-l},\ l > 0$ serve as **internal instruments** for $\Delta z^s_{j,k,t}$. The selection-correction term $\hat{m}^s_{j,k,t}$ is constructed from lagged data and the first-stage probit, so we treat $\Delta \hat{m}^s_{j,k,t}$ as predetermined/strictly exogenous in the GMM step.

In practice we:

- build the **difference-GMM instrument matrix** using a limited set of lags of $z^s_{j,k,t-l}$ to avoid weak instruments and "too many instruments" issues when T is small;
- include $\Delta \hat{m}^s_{j,k,t}$ directly as a regressor in the differenced equation; and
- use standard diagnostics (Hansen J-test, tests for serial correlation in $\Delta \hat{\varepsilon}^s_{j,k,t}$) to assess instrument validity.

The resulting estimator is our main topic-persistence estimator. We keep the within-FE estimates (with and without the selection term) as benchmarks:

- If GMM and FE agree, Nickell bias and selection effects are small in practice.

- If they differ, we rely on the GMM-with-selection estimates, subject to the diagnostics above.

The remainder of this section constructs the annual exposure vectors $z^s_{j,k,t}$, estimates the FE and GMM versions of the persistence regression with the selection correction for $s \in \{i, o, \text{all}\}$, and compares the resulting $\hat{\rho}^s$'s to the values reported by Glasserman.

Sample restriction. Throughout this notebook we restrict attention to firm–year cells in which the firm is an S&P 500 constituent. For notational brevity we suppress this conditioning event and write the regressions as if they were estimated on the full universe.

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[3]:
```
import pandas as pd

from notebooks_utils.modeling_notebooks_utils.regression_utils.regression_utils␣
↪import (
    extract_topic_persistence_selection_data, compute_firm_year_intensity
)

article_duration_df: pd.DataFrame = extract_topic_persistence_selection_data()
```

1.1.2 1.2 Selection estimation

1.2.1 ACD-based news intensity To construct a firm–year–session news–intensity estimator we model the **inter-arrival durations** between news days for each firm with an exponential ACD(1,1) process (EACD(1,1)).

For firm j, session $s \in \{\text{intraday}, \text{overnight}\}$ and duration series $\{\tau_t\}_{t=1}^{T}$ (trading days between consecutive news days), the EACD(1,1) model specifies the **conditional mean duration** $\psi_t = \mathbb{E}[\tau_t \mid \mathcal{F}_{t-1}]$ as

$$\psi_t = \omega + \alpha\tau_{t-1} + \beta\psi_{t-1}, \qquad \omega > 0,\ \alpha, \beta \geq 0,\ \alpha + \beta < 1 \tag{12}$$

Durations are modeled as

$$\tau_t = \psi_t \cdot \varepsilon_t, \qquad \varepsilon_t \mid \mathcal{F}_{t-1} \sim \text{Exp}(1) \tag{13}$$

By the change-of-variables theorem1, conditional on $\mathcal{F}_{t-1}$ we have
$\tau_t \sim \text{Exp}(1/\psi_t)$ with density

$$f_{\tau_t|\mathcal{F}_{t-1}}(x) = \frac{1}{\psi_t}\exp\left(-\frac{x}{\psi_t}\right), \qquad x > 0 \tag{14}$$

so the **conditional news arrival intensity** is

$$\lambda_t = \frac{1}{\psi_t} \tag{15}$$

We estimate (ω, α, β) by (quasi) maximum likelihood separately for each firm–session. The ACD recursion captures key features of the news flow:

- **Clustering / persistence** – bursts of intense news flow followed by quieter periods, via the feedback terms in α and β.

- **Firm heterogeneity** – each firm–session obtains its own (ω, α, β), so high-visibility names can have structurally higher news intensity than thinly covered ones.

Given fitted parameters $(\hat{\omega}, \hat{\alpha}, \hat{\beta})$ we recover the fitted conditional mean durations $\hat{\psi}_t$ and define the **instantaneous news intensity** as

$$\hat{\lambda}_t = \frac{1}{\hat{\psi}_t} \tag{16}$$

For the selection equation we aggregate this to a **firm–year–session intensity proxy** by averaging over all events in year y and session s:

$$\hat{\lambda}^s_{j,y} = \frac{1}{T^s_{j,y}} \sum_{t \in \mathcal{T}^s_{j,y}} \hat{\lambda}^s_{j,t} \tag{17}$$

where $\mathcal{T}^s_{j,y}$ is the set of news events for firm j, session s, in calendar year y, and $T^s_{j,y}$ is the number of trading days in that firm–year–session.

Handling Low-Information Firms ("Phantom Firms"): A subset of S&P 500 firms may generate zero or very few news articles in a given year. For these firms, the inter-arrival times are undefined or too sparse to estimate an ACD model. * For these observations, we impute a **zero intensity** ($\hat{\lambda}^s_{j,y} = 0$). * Crucially, these firms are **retained** in the selection dataset. They serve as the necessary "zeros" for the first-stage Probit, allowing us to model the extensive margin of news coverage (the probability of going from "quiet" to "noisy").

1.2.2 Practical estimation and identification strategy In practice, the ACD parameters $(\omega^s_j, \alpha^s_j, \beta^s_j)$ are only well identified when a firm–session has a non-trivial number of observed durations. Small-sample bias in Maximum Likelihood Estimation can lead to spurious parameter estimates even if the optimizer technically converges.

We therefore use a nested estimation rule that targets EACD(1,1) but falls back to more parsimonious specifications when the data do not support a full model.

Our estimation rule:

1. **Minimum Observation Threshold (Identification).** To estimate the dynamic parameters, we restrict the *fitting sample* to firm–sessions with at least **50 distinct news days** over the sample.
   - Firms **above** this threshold get a dynamic intensity estimate $\hat{\lambda}_t$.
   - Firms **below** this threshold (including "Phantom Firms" with zero news) are assigned a static intensity of zero ($\hat{\lambda} = 0$). Crucially, they are **retained** in the panel for the selection equation to prevent selection bias, but they do not pass through the ACD optimizer.
2. **Primary fit: EACD(1,1).** For eligible firm–sessions (events ≥ 50), we estimate an EACD(1,1) on the full duration series by quasi-MLE, imposing non-negativity and a stationarity margin on α^s_j and β^s_j so that $\hat{\alpha}^s_j + \hat{\beta}^s_j < 0.99$.

3. **Fallback fit: EACD(0,1) when needed.** If the EACD(1,1) optimizer does not converge, or the implied persistence $\hat{\alpha}_j^s + \hat{\beta}_j^s$ is too close to the unit-root boundary, we refit a more parsimonious EACD(0,1) model,

$$\psi_{j,t}^s = \omega_j^s + \beta_j^s \psi_{j,t-1}^s$$

   which preserves a slowly time-varying latent level but removes direct feedback from the most recent duration. We retain the EACD(0,1) fit if it converges and satisfies $\hat{\beta}_j^s < 0.99$.

4. **Trimming pathological series.** If neither EACD(1,1) nor EACD(0,1) yields a converged, strictly stationary fit, we revert the firm–session to the static low-intensity proxy ($\hat{\lambda} = 0$) rather than allowing explosive parameters to contaminate the selection regression.

The logic is:

- We assume news arrivals follow some stationary point process with finite intensity.
- EACD(1,1) provides a flexible parametric proxy for time-variation when the data support it.
- When the data do **not** support a full EACD(1,1), forcing a three-parameter model would inject noise; the nested EACD(0, 1) restriction is a way to shrink toward a simpler dynamic structure.
- Only in the small set of truly pathological cases do we exclude the dynamic component entirely.

Thus the firm–year–session intensity proxy $\hat{\lambda}_{j,y}^s$ used in the selection equation is:

- rich and dynamic for high-activity firm–sessions,
- more parsimonious but still time-varying for low-information series, and
- based uniformly on duration-driven ACD models, with static imputations used only where dynamic identification is impossible.

---

1 Since $\tau_t = g(\varepsilon_t)$ where $g(x) = \psi_t \cdot x$ and ψ_t is constant given $\mathcal{F}_{t-1}$, the conditional distribution of τ_t follows from the standard change-of-variables result; see Casella & Berger, Theorem 2.1.5.

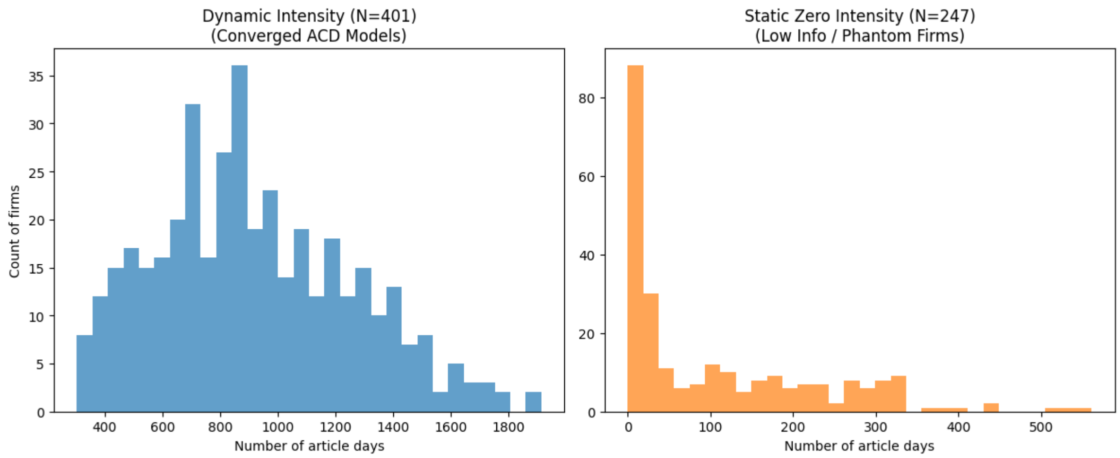
[10]:
```
from notebooks_utils.modeling_notebooks_utils.regression_utils.
  ↪regression_plotting import summarize_dropped_firms
intensity_df: pd.DataFrame = compute_firm_year_intensity(article_duration_df)
summarize_dropped_firms(article_duration_df, intensity_df)
```

```
Total firms in universe: 648
Firms with Dynamic ACD Model (Tier 1/2): 401
Firms with Static Zero Intensity (Tier 3): 247

Article-day counts by Model Type:

                   count        mean         std    min    25%    50%     75%  \
has_dynamic_model
False              247.0  106.716599  123.158173    0.0    3.0   49.0   181.5
True               401.0  916.421446  339.697453  304.0  672.0  874.0  1152.0
```

```
                     max
has_dynamic_model
False              561.0
True              1913.0
```



1.2.3 Selection equation and probit specification Having constructed the news-intensity estimator, we formally specify the selection vector. Let $I^s_{j,k,y}$ be an indicator that firm j and topic k appear in the outcome panel in year y.

The selection covariates vector $w^s_{j,k,y-1}$ is defined as:

$$w^s_{j,k,y-1} = \begin{pmatrix} 1 \\ I^s_{j,k,y-1} \\ \lambda^s_{j,y-1} \\ \ln(\text{MarketCap}_{j,y-1}) \end{pmatrix}$$

where: * $I^s_{j,k,y-1}$ is the lagged selection indicator (topic "stickiness"). * $\lambda^s_{j,y-1}$ is the lagged firm-year-session news intensity from the ACD model. * $\ln(\text{MarketCap}_{j,y-1})$ is the lagged natural log of firm market capitalization, sourced from our equity panel (`equity_regression_panel`).

We use a standard probit specification with a latent selection index:

$$J^s_{j,k,y} = \gamma_s' w^s_{j,k,y-1} + v^s_{j,k,y}, \quad v^s_{j,k,y} \sim \mathcal{N}(0,1)$$

$$I^s_{j,k,y} = \mathbb{1}\{J^s_{j,k,y} > 0\}$$

By including Market Cap, we explicitly model the "Index Survival" constraint. A firm with low market cap in $y-1$ has a higher probability of dropping out of the S&P 500 (and thus our dataset) in year y, regardless of its news intensity. The probit allows these two forces—news generation and index survival—to jointly determine observability.

1.2.4 Inverse Mills ratio and selection correction Under the usual Heckman-style assumptions (joint normality of the selection error $v^s_{j,k,y}$ and the outcome error, and mean independence of $u^s_{j,k,y}$ given $w^s_{j,k,y-1}$), the selection bias can be summarised by an inverse Mills ratio term.

For observed cells with $I^s_{j,k,y} = 1$ we form

$$\hat{m}^s_{j,k,y} = \frac{\varphi\left(\hat{\gamma}_s^\top w^s_{j,k,y-1}\right)}{\Phi\left(\hat{\gamma}_s^\top w^s_{j,k,y-1}\right)}, \tag{18}$$

where $\varphi(\cdot)$ is the standard normal PDF. Intuitively, $\hat{m}^s_{j,k,y}$ measures how "surprising" it is that the cell remains selected, given its lagged inclusion status and lagged news intensity.

In the second-stage topic-persistence regression we will include $\hat{m}^s_{j,k,y}$ as an additional regressor. Under the Heckman framework, this removes the component of the outcome error that is correlated with the selection process.

1.2.5 Sample Attrition and Exogeneity Assumptions To ensure data quality, we filter the raw universe of S&P 500 firms. We distinguish between attrition mechanisms that are plausibly orthogonal to the news-return process (safe to drop) and those that are endogenous (required for the selection correction).

1. Exogenous Attrition (Listwise Deletion) We exclude specific observations where data quality compromises the entity resolution or return calculation. We contend that these exclusion criteria satisfy the condition of mean independence with respect to the outcome error term:

- **Entity Resolution Ambiguity:** Firms with names acting as common nouns (e.g., "Target", "News Corp", "Best Buy") are excluded if they generate excessive false positives in the news collection pipeline. We assume the linguistic properties of a firm's name are orthogonal to its fundamental news-return dynamics.
- **Vendor Data Gaps:** Firm-days with missing pricing data from the vendor (EODHD) are excluded. Given that we condition on S&P 500 constituency (active, solvent firms), we assume these sporadic gaps represent random technical ingestion errors rather than informative signals of financial distress (e.g., trading halts).

2. Endogenous Attrition (Imputation and Modeling) Attrition mechanisms plausibly correlated with firm fundamentals are handled explicitly to avoid selection bias:

- **Missing Market Capitalization:** Occasional gaps in the market capitalization record (e.g., due to vendor feed interruptions) are **not** dropped, as listwise deletion here could correlate with corporate actions or volatility. We impute these values via forward-filling (carrying forward the last known market cap), relying on the high persistence of firm size.
- **Zero-News Firms ("The Zeros"):** Firm-years with zero identified news articles are **retained** in the first-stage probit estimation. These observations constitute the $I^s_{j,k,t} = 0$ category. Excluding them would truncate the dependent variable of the selection equation, rendering the Heckman correction impossible. These firms are only excluded from the second-stage (persistence) regression *after* their contribution to the Inverse Mills Ratio has been calculated.

3. Universe Conditioning Throughout, we restrict attention to the S&P 500 universe. The selection process is therefore defined as the joint probability of S&P 500 inclusion (proxied by Market Cap) and news existence (proxied by News Intensity).