Stress Testing an Economic Literature*

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Abstract

Researcher degrees of freedom in the evidence-generating process, together with publication incentives to report statistically significant findings, can generate substantial uncertainty and systematic skewness in the significance of reported coefficient estimates. To identify the mechanisms of and address these challenges, we utilize a new method for stress testing an economic literature via a novel declarative econometric language that combines techniques from replication and meta-study approaches. Applying this approach to the M&A literature, we find that within-literature variation in dependent variable (cumulative abnormal returns) and control variables (leverage and Tobin's Q) definitions creates significant dispersion in the actual significance of the variables of interest. Reported/published results tend to be more significant than unreported alternatives. Taken together, our publicly available approach will allow researchers to succinctly demonstrate the robustness of individual papers and stress test economic literatures.

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1. Introduction

Economists recognize that empirical design choices can significantly shape research findings. For a given research question, empiricists face a myriad of economically defensible yet potentially arbitrary choices. Leamer (1983) contends that econometric studies rest on "whimsical" assumptions, producing "fragile" results that shift with empirical design choices. Defensible but discretionary empirical design decisions — what Simmons, Nelson, and Simonsohn (2011) term "researcher degrees of freedom" — introduce uncertainty into reported empirical estimates (Menkveld et al. 2024). However, the nature of the publication (and grant) process also creates strong incentives for researchers to utilize their degrees of freedom non-randomly. Instead, researchers are incentivized to report results significantly consistent with their predictions. This creates a potential "publication bias" identified by (Sterling 1959).

Traditionally, empirical papers report a series of robustness tests in the body of a paper, in untabulated results, or in internet appendices. However, these sections are necessarily idiosyncratic and do not remove the ability or incentives of researchers to choose robustness tests that yield results consistent with their baseline analysis. An alternate approach, through pre-registered reports, helps researchers avoid some of these issues by committing to specific empirical analysis. However, the significant number of researcher degrees of freedom in the empirical process makes pre-registering each unique decision potentially cumbersome and unrealistic. It also does not preclude reseachers from finding significant specifications prior to the pre-registered report.

The literature has taken two primary approaches to quantify and address these important issues. First, studies across multiple disciplines have utilized multiple analytical teams to perform the same empirical task. These studies typically, but not always, involve replicating existing findings. This "many-researchers, one-dataset" literature provides compelling evidence on the replicability of, and that degrees of freedom shape, research.[1] This literature demonstrates poor replicability and that research teams analyzing similar data can arrive at opposing conclusions.

Utilizing the many-researcher framework in replicating published results poses a significant, and potentially costly, bottleneck. Successfully replicating an existing paper establishes the necessary baseline for investigating how research design affects findings. Without this, it is impossible to assess whether variations in results stem from different empirical designs or from failures to reproduce the original finding. Yet replication is difficult: it is time-consuming and resource-intensive, particularly when papers use multiple datasets (Whited 2023), and some researchers report difficulty recreating results even when the original study's authors assist and provide code

[1] This literature spans multiple disciplines and includes studies in psychology (Silberzahn and Uhlmann 2015; Silberzahn, Uhlmann, and Martin 2018), neuroscience (Botvinik-Nezer et al. 2020), social and behavioral sciences (Tyner et al. 2026; Miske et al. 2026; Aczel et al. 2026), economics and political science (Huntington-Klein et al. 2021; Breznau 2022; Brodeur et al. 2026), and finance (Menkveld et al. 2024)

(Chang and Li 2022; Tyner et al. 2026; Miske et al. 2026; Aczel et al. 2026). Given these challenges, many branches of academic research lack a culture of replication (Harvey 2017).

To circumvent these costs, the second approach involves meta analysis, sometimes supplemented with real or simulated data, but avoids replication. By studying published results and the specifications used to generate them, researchers have quantified the degree of potential "publication bias" and proposed several solutions, including robustness checks, adjustments to hurdle rates, or specification curves.[2] However, by its nature, this literature cannot identify biases specific to a single study or literature. Rather, it identifies the opportunity for bias across all studies, rather than the existence of bias in a single study. Additionally, since by not replicating the underlying results first, its ability to evaluate the potential importance of a particular methodology or reject the potential appropriateness of a given specification is limited.

In this paper, we combine, and build on the existing literature within, these two approaches by utilizing a newly-developed novel declarative econometric technique from Tumarkin (2026) to stress test an economic literature. This scalable technique allows us to first replicate existing empirical studies without the need for multi-team replication projects, often relying on hundreds of researchers. We then use this technique to implement analysis similar to the specification check and the specification curve of Brodeur, Cook, and Heyes (2020b) and Simonsohn, Simmons, and Nelson (2020), respectively. By combining these two strands of literature, we can compare what how variation in specification choice impacts the significance of specific coefficients in an empirical paper (and across a literature).

Combining these literatures requires overcoming the replication bottleneck. To alleviate this, Tumarkin (2026) introduces a declarative econometric language, called *Foghorn*, that allows researchers to express their empirical designs directly. In traditional research, a researcher conceives an empirical approach, but what gets coded, whether manually or with AI assistance, is a step-by-step data manipulation and estimation procedure that implements that approach. *Foghorn* allows the empirical design itself to be formally written as code, with the corresponding implementation generated automatically.

Encoding designs rather than procedures makes replication more tractable. A declarative specification is deterministic (identical inputs produce identical outputs) and requires the researcher

[2]For example, Brodeur et al. (2016) identifies a "two-humped" pattern in published p-values that suggests authors systematically inflate marginally insignificant results to marginally significant; Brodeur, Cook, and Heyes (2020a) finds evidence of p-hacking in the use of causal inference methodologies; Andrews and Kasy (2019) propose adjusting estimates and confidence intervals for the estimated degrees of selection; Brodeur, Cook, and Heyes (2020b) and Simonsohn, Simmons, and Nelson (2020) propose analysis that plots the distribution of estimates and p-values generated by potential control variable inclusion or variable measurement; Chen and Zimmermann (2020) develops an estimator of publication bias; and Mitton (2022) documents significant variation in empirical methodologies within corporate finance, and discusses potential solutions proposed by the literature above.

to state assumptions explicitly rather than embed them in procedural code. Published papers may elide standard practices that can affect results. Because *Foghorn* specifications make all assumptions explicit, a researcher can efficiently search over plausible alternatives when a paper's description is incomplete.

Stress testing — systematically assessing how sensitive findings are to researcher degrees of freedom — is nearly impossible with traditional bottom-up code: modifying a variable definition requires identifying and altering every relevant procedural step in each paper's unique codebase. Because *Foghorn* encodes designs directly, a design change is a targeted modification to the specification; *Foghorn* generates the corresponding altered implementation automatically, making systematic variation tractable across an entire literature.

We apply *Foghorn* to the mergers and acquisitions (M&A) literature. M&A provides an ideal setting: the literature is mature, with established results across numerous papers sharing a common event-study framework, similar outcome variables, and a standard set of databases that makes cross-paper specification modification tractable. Consistent with Mitton (2022), the implementation of these choices nonetheless vary considerably: 80% of papers in our replicated sample use a unique construction of cumulative abnormal returns (CARs), the market-based measure of announcement effects on shareholder value, differing in announcement windows, expected-return models, and estimation periods. This combination of methodological commonality and within-literature variation makes M&A well suited for both replication and stress testing.

We focus on papers from the four leading finance journals that analyze CARs around M&A announcements. For each paper, we identify the key result as stated by the authors and encode the corresponding estimator, variable definitions, and sample selection directly from the published description, imposing no editorial judgment as to what constitutes the best methodology (for example, Kolari, Pynnonen, and Tuncez (2021); Hou, Xue, and Zhang (2020)). This declarative baseline serves as the starting point for both replication and stress testing.

Replication itself is not a precisely defined concept. Achieving results identical to those published may be impossible, for example, due to changes in the source databases or assumptions elided from the published description. We consider a paper replicated when (i) key variables have point estimates and statistical significance comparable to the published results, (ii) the replicated sample size is similar to the published size, and (iii) most control variables have point estimates similar to those published. Importantly, we replicate from raw data without author-provided code, providing independent verification.

We find that the papers in our sample are, in general, replicable. Using *Foghorn*, we replicate approximately 79% of the papers in our sample. In our experience, replication does not come easily, which may explain the mixed findings in the existing literature.[3] Given the limited space allocated to describing the data manipulation process in research papers, authors may elide assumptions, particularly those that qualify as standard practices or that, prima facie, appear to be of minor relevance to the final results.[4] Because *Foghorn* specifications must be written explicitly, a researcher can search exhaustively over plausible assumptions to find a combination consistent with the published result. This makes implicit assumptions visible from both the top-down specification and the bottom-up implementation, what we call bi-directional transparency.

While replication is necessary, it represents a relatively low bar. A replicable result demonstrates that no coding errors were made but remains silent on the sensitivity of results to the myriad assumptions and empirical designs found in the literature. Therefore, we stress test the replicated M&A studies along two dimensions: the construction of the dependent variable (CARs) and the definitions of the most commonly used control variables in these studies (market-to-book and leverage). We choose these because they are utilized across the M&A literature but demonstrate significant variability in how they are constructed within the same literature. We allow definitions to vary within the literature, that is, according to how they are defined within the sample of replicated papers. However, we take a more conservative approach than suggested by Brodeur, Cook, and Heyes (2020b). Specifically, we only vary the definition of one dimension (CAR or control variables) at a time. Further, we do not include variation as generated by the inclusion or exclusion of control variables. This allows us to study the impact that plausible and defensible alternate definitions of CARs and control variables have on the significance of each replicated paper's variable of interest in isolation. We are thus able to stress test these specifications to determine the actual, and not potential, benefit of the reported specification on the significance of variable of interest in these publish papers.

Varying CAR windows, expected-return models, and estimation periods produces more than 4,500 alternative specifications. We find substantial dispersion in t-statistics, providing evidence that researcher degrees of freedom materially affect the significance of published coefficients. This dispersion is not symmetric: published t-statistics exceed those of stressed alternatives in 80% of tests. Unlike Menkveld et al. (2024), whose design eliminates publication incentives, our setting reveals skewness that favors published specifications. More than half of stress tests result in a drop in significance level, and more than one-third lose significance entirely. We observe similar patterns

[3]Ioannidis (2005) and Chang and Li (2022) document significant replication challenges in science and economics, respectively — only 49% of economics papers in the latter study could be replicated even with author-provided code and author assistance. In contrast, Jensen, Kelly, and Pedersen (2023) find stronger evidence of replicability in the finance asset pricing literature.

[4]For example, it is common practice in corporate finance research to substitute zero for missing values of capital expenditures, deferred taxes, research and development, and other fiscal variables (for example, Bryzgalova et al. (2024); Koh and Reeb (2015)). Yet, not all authors may mention that missing values have been replaced with zeros in their paper.

in the subsample of papers where t-statistics are less than three, where a decline in significance is potentially more meaningful.

Consistent with the presence of publication bias, we also document significant skewness toward published results. Specifically, we find that the t-statistics for the variables of interest from the replicated (published) specifications in our sample are larger than those of the stressed alternatives in over 80% of stress tests. Economically, we observe an average decline of nearly 0.8 in the magnitude of the t-statistics due to stress tests. Further, over half of the t-statistics from stress tests are at a lower significance level (e.g., 10% versus 1%) than the relevant published/replicated t-statistic. Finally, we find that results become insignificant in more than one-third of stress tests. We observe similar results in stress tests on a subsample of papers with t-statistics less than 3 (and therefore a decline in significance is potentially more meaningful). In specification curve analysis similar to Simonsohn, Simmons, and Nelson (2020), we do not find that specific stress-test specifications drive the variability or bias in the results. Instead, they are generally present across all types of stress tests.

To assess whether this skewness reflects publication incentives rather than mechanical dispersion, we perform two additional analyses. First, we examine control variable t-statistics under the same CAR stress tests. We find similar dispersion but significantly less skewness: control variable t-statistics do not systematically favor the published specification. Second, we vary definitions of commonly used control variables (market-to-book and leverage). These tests produce smaller but still meaningful shifts that tend to benefit the significance of the variable of interest in the published specification. Together, these findings show that choices in variable definition (whether for outcomes or controls) can materially affect significance, and that published M&A results often occupy the more favorable end of this distribution.

Advances in artificial intelligence have made implementing empirical research easier, but faster production of bottom-up code does not resolve its fundamental limitations. Language design determines what is achievable; it is not merely a choice of syntax. A language's design constrains which solutions are expressible and encodes what matters, making assumptions explicit or hiding them. When AI generates bottom-up procedural code (whether in SAS, Stata, or Python), the resulting output embeds assumptions implicitly, varies across runs, and produces bespoke implementations for each paper. AI can assist in writing declarative specifications just as it assists in writing procedural code, but the result is verifiable, deterministic, and systematically modifiable in ways that procedural code is not. These limitations make bottom-up code difficult to replicate and impractical to stress test systematically, regardless of whether a human or an AI writes it.

The acceleration of research through AI makes systematic stress testing more urgent than ever. As empirical output grows in volume and speed, the risk of knife-edge results entering the literature increases. Independent, arms-length replication and stress testing require tools that are deterministic, verifiable, and scalable. Declarative econometrics meets this need. A *Foghorn* specification makes all assumptions explicit by construction, is directly inspectable, and can be systematically varied across an entire literature through targeted modifications to formal specifications.

Our empirical findings contribute to the growing literature on research reliability discussed above, by combining the replication and meta-study results to stress test papers and study publication bias. Given our focus on the corporate finance literature, our work is particularly related to Mitton (2022). We build on this literature by first documenting that the M&A literature is broadly replicable, but that the actual replicated results are sensitive to seemingly innocuous specification choices. This demonstrates the significant impact of researcher degrees of freedom on published findings, rather than simply their potential to do so. The skewness we observe — published results systematically occupying the more favorable end of the distribution — goes beyond dispersion and is consistent with specification choices shaped by publication incentives. Stress testing a literature is fundamentally different from performing robustness tests on an individual paper. A robustness test examines a paper's assumptions that differ from common practice; literature-level stress testing examines the assumptions that underlie common practice itself.

Declarative econometrics is not intended to replace existing techniques. Writing bottom-up code builds invaluable knowledge of the nuances and idiosyncrasies in the data, and there will always be a role for it. Rather, declarative methods complement traditional approaches by providing a scalable and systematic way to encode, replicate, and stress test empirical analyses. While we apply this framework to the M&A literature, it is not tied to any research area. Once modules are developed for additional data sources and methodologies, the same approach can be extended to other areas of finance and the social sciences more broadly. The goal is not to undermine published findings but to make empirical literatures more resilient.

The remainder of this paper is organized as follows. Section 2 provides an illustrative example of declarative econometrics. Section 3 develops a formal definition of a declarative econometric language. Section 4 discusses the implementation of such a language. Section 5 describes our sample, defines replication success, and presents replication results for the M&A literature. Section 6 presents stress testing results. We conclude in Section 7.

2. Illustrative Declarative Econometrics

Declarative econometrics takes a novel approach to empirical research. We begin by analyzing a sample statement to introduce the concept before working through a specification. The examples below are intentionally minimal to highlight the differences from a traditional bottom-up approach. While they may not fully showcase the potential of working declaratively or the variety of tools currently available in *Foghorn*, they still offer valuable insights. We remind readers that, although these examples focus on corporate finance, declarative econometrics is a general framework applicable across all areas of the social sciences. We provide a more formal definition of declarative econometrics in Section 3.

2.1. An Illustrative Declarative Econometric Statement

Assume that a researcher wants to compute a market-to-book ratio for research on financial markets. The ratio requires two variables from the Center for Research in Security Prices (CRSP) monthly stock data, shares outstanding (`Crsp.shrout`) and share price (`Crsp.prc`), both of which are indexed by a permno cross-sectional firm identifier and a trading-date time-series identifier.[5] It also requires the book value of total assets variable (`Comp.at`) as of the fiscal year-end from the Compustat Fundamentals Annual data, which is indexed by a gvkey cross-sectional identifier and a datadate fiscal-year-end time-series identifier. Computing a market-to-book ratio in a bottom-up data manipulation language requires writing code to convert gvkey – datadate assets to a corresponding permno – trading-date asset time series. Then, an algebraic step does the actual calculation. The resulting code emphasizes the steps, rather than the algebraic relationship. It would generally be verbose, requiring many lines of precise table joins to transform the underlying data indices before the final algebraic step that computes the market-to-book ratio.

In a declarative language, the index conversion and calculation may be written in a single step. This calculation in *Foghorn* is coded as

$$\texttt{Crsp.shrout} \times \texttt{Crsp.prc} \;/\; \texttt{reindex}(\texttt{Comp.at}). \tag{1}$$

This top-down calculation emphasizes the underlying economic meaning by using a simple reindex function to tag which panel variable should have its indexes converted. The benefits of such succinct coding syntax grow substantially with variable complexity.

Foghorn can convert this top-level equation into bottom-up data manipulation code because it knows the indices of each variable (i.e., cross-sectional, time-series, or panel) at the language level, a feature known as static typing in programming language design. In the expression above, *Foghorn* identifies that `Crsp.shrout` and `Crsp.prc` are both indexed by permno-trading-date. Thus, their product is also indexed by permno-trading-date. *Foghorn* also knows `Comp.at` is indexed by gvkey-datadate. Therefore, because `Comp.at` divides `Crsp.shrout` × `Crsp.prc`, *Foghorn* infers that the `reindex` function must convert `Comp.at` from gvkey-datadate to permno-trading-date using a programming language feature known as type-inference.

[5]The term "indexing" refers to index variables, unique identifiers for individual observations within a dataset. These identifiers may be cross-sectional and/or time-series units. The term "reindexing" describes the procedure of aligning identifiers across different datasets, accurately matching an observation from a source dataset with its corresponding observation in a target dataset.

2.2. An Illustrative Declarative Econometric Specification

Consider a research project to analyze the effect of entrenched corporate boards on stock returns around acquisition announcements. The study will control for both the acquirer's and the target's Tobin's q. To keep this example concise, we will not include additional controls, time-constant or firm-constant fixed effects, or sample selection criteria. We will also not adjust or cluster standard errors. All these features are available in *Foghorn*, which also allows for organizing empirical datasets by any cross-sectional and/or time-series indices.

Example 1 shows the complete econometric code for implementing this empirical study in *Foghorn*. For brevity, we have omitted boilerplate statements that import *Foghorn* libraries.

Example 1: Declarative Econometric Specification

```
study = estimate
  [regHdFe| car ~ bcfIndex + acquirerTobinsQ + targetTobinsQ |]

-- Cumulative abnormal returns
car = acquirer $ cumulativeAbnormalReturn (-2, 2)
        `overModel` singleIndexModel (-210, -11) CrspEqualWeighted

-- Entrenchment index (Bebchuk, Cohen, and Ferrell (2009))
bcfIndex = acquirer
  (Risk.cboard + Risk.labylw + Risk.lachtr + Risk.gparachute + Risk.supermajor + Risk.ppill)

-- Firm value
acquirerTobinsQ = acquirer tobinsQ
targetTobinsQ = target tobinsQ
tobinsQ = (Funda.at - Funda.ceq + reindex (Msf.shrout * Msf.prc)) / Funda.at
```

The sample code in Example 1 differs noticeably from traditional bottom-up data management and econometric estimation techniques. Perhaps most strikingly, it is concise and direct. The code comprises only nine lines of statements; the remaining six lines consist of white space and comments. The specification requires only variable definitions, a functional form between dependent and independent variables, and the estimation technique. This code emphasizes the "what" of this empirical study, providing only the econometric definitions required to describe the specification.

Unlike traditional bottom-up research techniques, the declarative specification is reasonably self-evident.[6] An interested third party does not need to review a step-by-step data manipulation

[6] We recognize that the language has some notational idiosyncracies (e.g., the dollar signs and back ticks), which arise from our decision to implement *Foghorn* as an embedded domain specific language. More information is provided in Section 4, with further details in the companion technical paper (Tumarkin 2026).

process to understand the econometric methodology. Instead, this declarative specification begins with a top-down statement indicating that this study estimates a single regression model. The model's functional form specifies that observed cumulative abnormal returns are related to a hypothesized linear relationship among the acquiring firm's corporate board entrenchment index, the acquiring firm's market-to-book value ratio, and the target firm's market-to-book value ratio.[7]

The code then defines the variables in the model. The acquirer's cumulative abnormal return (CAR) is calculated over a five-day window, starting two days before and ending two days following the announcement. This calculation utilizes the CRSP Equally Weighted Index as a single index market model, with parameters estimated over a window beginning 210 days before and ending 11 days before the announcement. The Entrenchment Index (Bebchuk, Cohen, and Ferrell 2008) for the acquirer is the total of six indices from RiskMetrics (`Risk`): classified boards (`cboard`), limited ability to amend bylaws (`labylw`), limited ability to amend charter (`lachtr`), golden parachutes (`gparachute`), supermajority requirements (`supermajor`), and poison pills (`ppill`). Finally, the acquirer's and target's Tobin's q (lines 10 and 11, respectively) are built upon a general definition in line 12. This uses the book values of assets (`at`) and common equity (`ceq`) from Compustat Fundamentals Annual (`Funda`) data as well as stock price (`prc`) and shares outstanding (`shrout`) from the CRSP Monthly Stock File (`Msf`).

The specification's required data sources, including Compustat, CRSP, RiskMetrics, and SDC, are prominent in the specification.[8] Each of these employs different indexing variables to uniquely identify observations. While verbose data manipulation steps that convert variables across indices often comprise a substantial portion of code in traditional econometric work, they are noticeably concise in Example 1. The `acquirer` and `target` functions attribute data to the respective parties of an acquisition.

2.3. Declarative Econometrics and the Bottom-Up Process

High-level declarative code, such as in this section, may seem insufficient for implementing an econometric study, particularly because there does not appear to be any bottom-up steps. Recall that in declarative econometrics, the researcher defines the empirical specification, with the language determining the implementation. Thus, an econometric study is well-defined provided the language has sufficient information to convert the specification into a database construction process. *Foghorn* translates top-down specifications into standard database code, a process known as transpiling.[9]

[7] We have borrowed notation from *R* for estimators as we believe the use of algebraic operators makes the functional form clear.

[8] Unlike Compustat, CRSP, and RiskMetrics which have the explicit prefixes `Comp`, `CRSP`, and Risk, respectively, SDC data is referenced implicity by the `cumulativeAbnormalReturn`, `acquirer`, and `target` functions.

[9] Transpiling is a new concept to econometrics, but is an established technique in programming languages to add static type constraints to non-statically typed languages. For example, JavaScript is a weakly typed language, making it relatively easy for programmers to include bugs in web applications. Languages such as TypeScript and PureScript

Foghorn analyzes the specification, determines the order in which to perform algebraic, aggregating, reindexing, time-shifting, and other calculations, and generates all the necessary database code for the researcher. For example, in Equation 1, *Foghorn* checks if this conversion is allowed (user-defined permissible index conversions through modules), and, upon execution, generates the appropriate bottom-up code in SQL or SAS, for instance.[10] Transpilation converts functions in *Foghorn* into their data manipulation equivalents. As will be discussed later, the design decision to provide transpiling has numerous benefits, particularly in terms of transparency.

We anticipate that many readers will understand the main ideas behind writing top-down specifications, but be curious about the mechanics underlying how declarative code operates. How can a declarative econometric language conduct an econometric test without bottom-up data manipulation steps? How can the specification work without explicitly describing how observations are matched between datasets? Does the brevity of declarative code limit its applicability across the social sciences? We will address these questions and explore how declarative econometrics can enhance replication, transparency, and stress testing in Section 4. Before doing so, we first develop a formal definition of declarative econometrics.

3. A Declarative Language for Econometrics

A declarative econometric language enables researchers to write high-level, top-down specifications and convert them into data manipulation processes and estimation procedures. For our purposes, an econometric specification, $\mathcal{S}$, fully defines an empirical methodology, including variable definitions, the modeled function form, and the estimation technique. Notably, our definition of a specification does not include the steps required to transform raw data into a dataset used for estimation, which we collectively refer to as an empirical procedure, $\mathcal{P}$.

Formally, a declarative econometric language $\mathcal{L}$ consists of two components. First, the language has a notation system $\mathcal{N}$ that provides syntax and semantics for describing high-level econometric specifications. Second, an implementation $\mathcal{I}$ exists that algorithmically converts a specification into an empirical procedure (i.e., the data processing and estimation procedure):

$$\mathcal{I} : \mathcal{S}^{\mathcal{N}} \longrightarrow \mathcal{P}, \tag{2}$$

where $\mathcal{S}^{\mathcal{N}}$ denotes a specification $\mathcal{S}$ written in notation system $\mathcal{N}$. Thus, a declarative econometric language $\mathcal{L}$ is the pair of the notation and the implementation:

provide type safe languages for web development. These languages transpile to JavaScript, eliminating many classes of errors. *Foghorn* employs transpilation in a similar fashion, eliminating many types of errors in econometric coding. *Foghorn* has a plug-in architecture for transpiling, allowing it target different data manipulation languages. It currently has a SQL and STATA transpiler. SAS transpiler is under development.

[10] We note that, while it would be labor-intesive to convert the the market-to-book ratio into a panel variable indexed by *gvkey-datadate* in a standard data manipulation language, it is trivial to do so in a declarative language. One simply applyies the reindex function to the CRSP variables instead: `reindex` $($`shrout` $\times$ `prc`$)/$ `at`.

$$\mathcal{L} = \{\mathcal{N}, \mathcal{I}\}.$$

For example, consider an ordinary least squares regression where the researcher wishes to examine how cumulative abnormal stock returns relate to the market capitalization of the acquiring firm. The specification $\mathcal{S}$ consists only of the variable definitions, the linear functional form, the choice of OLS as the estimator, the sample selection criteria, and the choice of standard errors. The corresponding procedure $\mathcal{P}$, by contrast, must define the steps that construct cumulative abnormal returns, market capitalization, and other control variables from raw data. The empirical procedure links observations across datasets, combining the data into a final dataset, and estimating the parameter vector on that dataset.

In standard research, the specification consists of the information described in the research paper. The procedure is the complete implementation code from raw data. Due to commercial and proprietary data restrictions, authors may not be able to provide the whole procedure to other researchers, even in online form. Instead, code may start with pre-processed data to satisfy licensing restrictions.

While the specification and procedure are related, they have traditionally been expressed in fundamentally different formats. Specifications are described qualitatively in a paper's text, whereas procedures are implemented in code, leaving no formal link between the two. As a result, errors in the procedure are not visible in the specification. The absence of a programming language for specifications underlies this disconnect. A declarative econometric language resolves the problem by allowing the researcher to state the specification directly, with the implementation translating this high-level description into the complete empirical procedure.

3.1. Declarative econometrics notation

The notation system $\mathcal{N}$ needs to allow researchers to describe a specification's variables, functional form, and estimation technique. It should form a complete algebra whereby different types of operations may be composed transparently through a uniform syntax. Consider, for example, the computation for the acquirer's Tobin's q from Example 1. We could combine the acquirer function (line 13) with the Tobin's q formula (line 15), yielding:

```
acquirer $ (Funda.at - Funda.ceq + reindex (Msf.shrout * Msf.prc)) / Funda.at.
```

This single statement exemplifies the concept of a complete algebra, where different types of operations are composed through a uniform syntax, and it is valid *Foghorn* code. This statement instructs the language to reindex the CRSP data (prefixed by `Msf`) to work with Compustat data (prefixed by `Funda`), perform algebraic operations with the reindexed CRSP data and Compustat data, and match the result with the acquiring firm in SDC. We could even aggregate Tobin's q across the acquirer's peer firms or compute lagged annual averages, for example, in a single statement.

This complete algebra is a key feature of a declarative econometric language's notation system, providing succinct, top-down semantics to define variables. Operations such as arithmetic, data aggregation, index conversion, data merging, time transformations, and other necessary data manipulation tasks work in harmony. Whereas existing packages let researchers manipulate data through a series of steps, they isolate different types of operations. Index conversion semantics may differ from those used in data aggregation. And, it is generally not possible to chain index operations of various types together. By contrast, a declarative language provides a way to compose such operations, compactly describing every test variable in terms of raw data.

The notation system also provides semantics to describe estimators. Most software packages already use declarative syntax to define estimators. For example, in SAS, Stata, or R, the researcher uses a command to describe the specification but does not instruct the package on how to perform the required computations. Researchers, for example, generally do not concern themselves with the matrix inversion algorithms needed for most econometric models. A declarative econometric language's notation system should be no different. The estimator description parameterizes the estimation method, such as the technique (e.g., OLS, GMM), dependent variables, explanatory variables, and standard error calculations.

While the estimator description in a declarative language is syntactically similar to that in standard econometrics packages, it is functionally more powerful. A declarative language enforces a *whole-specification* approach to writing econometric tests. As detailed in Section 4, declarative econometrics elevates econometric information from the data to the language. The language's compiler can then reason about a specification logically as a whole, rather than evaluating a specification simply as a sequence of programming steps. Compiler reasoning is one factor behind the validity of the code in Figure 1, even though the functional form appears before the variable definitions. A declarative econometric language validates that a specification is internally consistent before execution. A functional form is not valid unless the variables it requires are defined and have identical indexing. The language ensures that all operations that comprise variable definitions are correct, and it can infer desired data transformations (as described in the introduction). The language's ability to ensure specification integrity has clear benefits for writing econometric tests, in general. However, the power of language-level integrity checking is particularly evident in stress testing.

3.2. Empirical Procedure

The declarative language implementation $\mathcal{I}$ converts the empirical specification $\mathcal{S}^{\mathcal{N}}$ into the empirical procedure $\mathcal{P}$. The empirical procedure can be seen as a mapping from the universe of raw data, $\mathcal{D}_0$, to an estimated parameter vector, $\hat{\theta}$:

$$\mathcal{P} : \mathcal{D}_0 \longrightarrow \hat{\theta}.$$

Without loss of generality, we consider the implementation of empirical specification to consist of two broadly defined steps. First, a data manipulation (generation) process, $\mathcal{M}$, transforms raw data into the processed data required for estimation. Second, an estimation procedure, $\mathcal{E}$, computes the coefficient vector, standard errors, and other statistics of interest from the processed data.

Let the data manipulation process $\mathcal{M}$ have n steps. Notate the data after i steps as $\mathcal{D}_i$. An individual step, $\mathcal{M}_i$, in that data process transforms the data from $\mathcal{D}_{i-1}$ to $\mathcal{D}_i$,

$$\mathcal{M}_i : \mathcal{D}_{i-1} \longrightarrow \mathcal{D}_i.$$

The cumulative process $\mathcal{M} : \mathcal{D}_0 \longrightarrow \mathcal{D}_n$, which converts the raw data into the final data needed for estimation, is the sequential composition of the individual steps:

$$\mathcal{M} = \mathcal{M}_n \circ \mathcal{M}_{n-1} \circ \ldots \circ \mathcal{M}_2 \circ \mathcal{M}_1.$$

We note that mathematical composition associates to the right – the rightmost transformation is applied first, followed by those to its left.

Finally, the estimation procedure $\mathcal{E}$ maps the final data into the coefficient vector:

$$\mathcal{E} : \mathcal{D}_n \longrightarrow \hat{\theta}.$$

Thus, we can view the empirical procedure $\mathcal{P}$ as the composition of the estimation procedure and the data manipulation process:

$$\mathcal{P} = \mathcal{E} \circ \mathcal{M}. \tag{3}$$

3.3. Stress testing

Stress testing an economic literature is a principal innovation from declarative econometrics. Stress testing a literature is fundamentally different than performing robustness tests on an individual paper. While a robustness test typically examines a paper's assumptions that differ from common practice, literature-level stress testing examines the assumptions that underlie common practice. A stress test $\mathcal{T}$ may be considered a transformation of a base empirical specification $\mathcal{S}$ to a new one, $\mathcal{S}'$:

$$\mathcal{T} : \mathcal{S} \longrightarrow \mathcal{S}'. \tag{4}$$

Researchers have not yet developed a systematic approach for literature-wide stress testing. Such stress tests must be scalable both in the range of tests they can accommodate and in their ability to apply those tests consistently across specifications. Equally important, they must ensure correctness, regardless of stress-test complexity.

3.3.1. *Stress Testing with Existing Technologies*

With existing technologies, researchers cannot manipulate the specification directly as per Equation 4. Instead, they must work with the data manipulation and estimation procedures that together comprise the empirical method.

A manual approach follows traditional economic practice: the researcher applies a stress test transformation to an original procedure $\mathcal{P}$, derives the stressed procedure $\mathcal{P}'$, and constructs the corresponding data-management process $\mathcal{M}'$ and estimation procedure $\mathcal{E}'$. While feasible for a few stress data-generating and estimation processes, this strategy does not scale; the effort required to stress test a literature increases multiplicatively with both the number of tests and the number of projects, and remains vulnerable to human error.

Alternatively, a researcher may pursue a procedural approach, directly modifying the data-manipulation process and estimation procedures:

$$\mathcal{T}^{\mathcal{E},\mathcal{P}} : \mathcal{E} \circ \mathcal{M} \longrightarrow \mathcal{E}' \circ \mathcal{M}'.$$

This strategy will not be effective across empirical procedures. Procedures are typically implemented as bespoke data-manipulation processes and estimation procedures, with coding choices varying across papers. A modification that applies to one implementation is unlikely to translate to another.

Furthermore, this process is unlikely to succeed even when procedural implementations share steps. Consider two procedures $\mathcal{P}_{\mathcal{A}}$ and $\mathcal{P}_{\mathcal{B}}$, with corresponding data manipulation processes $\mathcal{M}_{\mathcal{A}}$ and $\mathcal{M}_{\mathcal{B}}$. Suppose both data manipulation processes contain a common step $\mathcal{R}$ that appears somewhere in the data manipulation pipelines: $R \coloneqq \mathcal{M}_{\mathcal{A},i} = \mathcal{M}_{\mathcal{B},j}$. Function composition, however, suggests that the role of $\mathcal{R}$ within procedure $\mathcal{A}$ need not match its role with procedure $\mathcal{B}$. Consequently, knowing that a stress test $\mathcal{T}^{\mathcal{E},\mathcal{P}}$ correctly transforms $\mathcal{P}_{\mathcal{A}}$ into $\mathcal{P}_{\mathcal{A}'}$ does not imply that it will do the same for $\mathcal{P}_{\mathcal{B}}$, even if the two procedures share steps:

$$\mathcal{T}^{\mathcal{E},\mathcal{P}} : \mathcal{P}_{\mathcal{A}} \to \mathcal{P}'_{\mathcal{A}} \nRightarrow \mathcal{T}^{\mathcal{E},\mathcal{P}} : \mathcal{P}_{\mathcal{B}} \to \mathcal{P}'_{\mathcal{B}}.$$

Like manual stress testing, the procedural approach is neither scalable nor reliable, underscoring the need for a systematic framework.

3.3.2. *Declarative Stress Testing*

Declarative econometrics offers an alternative, scalable approach to creating correct stress tests. Recall that in declarative econometrics, a researcher is working with specification descriptions, not the data manipulation process and estimation procedure. A declarative language can permit direct specification manipulation, providing a way to write stress tests in terms of modified specifications directly:

$$\mathcal{T}^{\mathcal{S}} : \mathcal{S} \to \mathcal{S}'.$$

The ability to transform specifications retains the descriptive style of the declarative econometrics, focusing on variable and estimator definitions, and occurring within the standard language without the need to resort to macro-programming or similar techniques.

Recall that the language implementation converts a declarative stress test into our desired modified data manipulation process and estimation procedure. Thus, an implementation can take the specification that arises from a stress test and determine the correct procedure:

$$\mathcal{I} \circ \mathcal{T}^{\mathcal{S}} : \mathcal{S}^{\mathcal{N}} \to \mathcal{P}' = \mathcal{E}' \circ \mathcal{M}' \quad \text{for all } \mathcal{S}^{\mathcal{N}}.$$

This approach has numerous benefits. First, it is straightforward to conceptualize stress tests based on specifications. The researcher needs only to consider the econometrics of the test, determining the necessary changes to variable definitions and the estimator required for the stress test. By contrast, a stress test that manipulates bottom-up data processes and estimation procedures is more complicated to write, as one needs to consider the role of each step in the data pipeline.

Second, declarative stress testing emphasizes correctness of transformations, avoiding the function composition and bespoke code pitfalls associated with traditional methods. The whole-specification approach embedded within declarative econometrics means that, not only can the language reason about specifications, but it can also reason about stress test transformations. As a consequence, it can ensure that, given any declarative specification, the stress test transformation will return a valid modified version of the specification. Such transformations are called *total* mapping, also known as *total* function, and the language itself checks to ensure that all stress test transformations meet this criterion.[11]

Finally, scalability is a natural consequence of declarative stress testing. Total functions ensure that a declarative stress test can be applied across specifications. The implementation can transform any stressed specification into the corresponding stressed data manipulation process and estimation procedure. The stress tests themselves are scalable. As transformation functions, stress tests can be combined through functional composition. Thus, it is possible to build a complicated stress test from multiple simple tests. The language itself will guarantee that the derived, stressed specification is valid, and it will provide the corresponding bottom-up data processing process and estimation procedure.

[11]A stress test may be inherently incompatible in certain empirical settings. For example, a stress that lags explanatory variable by a year would be incompatible with a cross-sectional dataset lacking a time dimension. Such incompatibility can be handled elegantly by total functions within a declarative language. Details are provided in the companion paper (Tumarkin 2026).

4. Implementing a Declarative Econometric Language

Traditional econometric code requires the researcher to specify each step of data manipulation explicitly. The researcher knows, for instance, that share prices are numbers and ticker symbols are text, but the programming language does not. A statement adding the two is syntactically valid in SQL, SAS, and other data manipulation languages; the error surfaces only at runtime. This disconnect between what the researcher knows and what the language knows limits how concise and expressive econometric code can be.

Declarative econometrics closes this gap. Instead of writing step-by-step instructions, the researcher writes a specification that describes the analysis: variable definitions and an estimator. The language itself determines the necessary data manipulation steps. This is possible because a declarative language can reason about the specification before execution, validating relationships among variables and inferring how to combine data from different sources.

4.1. Core design principles

Foghorn, our implementation of a declarative econometric language, rests on three design principles: separation of logic from implementation, modularity, and transparency through transpilation.

Separation of logic from implementation. A *Foghorn* specification encodes econometric logic directly. When a researcher defines a variable, *Foghorn* tracks what that variable represents: its indices (cross-sectional and time-series identifiers) and its data type (such as a number or text). The language uses this information to validate operations and infer necessary transformations. For example, *Foghorn* will not allow a researcher to combine CRSP return data with Compustat financial data without explicit reindexing, because the two datasets use different identifiers. Once the researcher specifies the reindexing, *Foghorn* determines the necessary steps automatically. This approach catches errors at specification time rather than runtime and produces code that is an order of magnitude shorter than equivalent procedural code.

Modularity. *Foghorn* separates its core language from dataset-specific information. The core defines general rules for specification design, algebraic operations, data aggregation, and merging. Dataset-specific information enters through plug-in modules. For example, the corporate finance module, *Coficat*, provides information about common finance databases and the relationships among them.[12] This modular design means the language is not tied to any particular research area. Researchers can write modules for new datasets, methodologies, or both, extending the language to any area of econometric research.

Transparency through transpilation. *Foghorn* translates specifications into standard database code, a process called transpilation. While new to econometrics, transpilation is an established tech-

[12] *Coficat* is tortured wordplay for a *co*-rporate *fi*-nance research copy-*cat* tool.

nique in computer science for adding safeguards that enhance reasoning while targeting widely-used languages. The specification serves as an auditable, top-level description of the analysis; the transpiled code provides the step-by-step implementation. This creates bi-directional transparency: reviewers can examine either the concise specification or the detailed implementation. *Foghorn* currently transpiles to SQL and Stata, with a SAS transpiler under development.

4.2. The transpilation process

Given a specification, *Foghorn* analyzes the required variables, determines the necessary transformations and then the order of operations, and generates all necessary data manipulation code. The transpiled output includes data retrieval, variable construction, index transformations, and sample selection. Because the specification is deterministic, identical specifications produce identical implementations.

Transpilation allows *Foghorn* to leverage existing tools. Any data process or estimator from any software package can be incorporated by defining a declarative syntax and writing a corresponding transpiler. This means declarative econometrics does not constitute a closed system; it builds on established data manipulation and estimation methods.

4.3. Benefits and limitations

Declarative econometrics offers several benefits for empirical research. First, it makes assumptions explicit. A specification must state variable definitions, index relationships, and sample selection criteria directly; nothing is buried in procedural code. Second, it enables systematic modification. Because specifications are formal objects, they can be programmatically varied to conduct stress tests across an entire literature. Third, it improves verifiability. The specification is concise enough to review directly, while the transpiled code provides complete implementation details.

These benefits come with limitations. *Foghorn* requires modules for specific research areas, and creating a module requires building a standardized database and encoding its logic. This upfront cost is best amortized across multiple papers, making declarative econometrics most suitable for established literatures. For unique empirical questions or novel datasets, traditional bottom-up techniques may be more appropriate.

Foghorn is also not optimized for computational efficiency. It applies sample selection as a final step, meaning the transpiled code computes variables over entire datasets before filtering. This design ensures correctness and reproducibility but may be slower than hand-optimized code.

Declarative econometrics complements rather than replaces traditional methods. Working directly with data builds invaluable knowledge of its nuances and idiosyncrasies. However, for replication and stress testing at the literature level, a declarative approach provides capabilities that procedural code cannot match.

Foghorn will be publicly available for use by researchers. Technical details on the language design, including its type system and implementation in Haskell, are provided in Appendix A and the companion paper (Tumarkin 2026).

5. Replicating the M&A Literature

We employ our declarative econometric technique to stress test the merger and acquisition (M&A) literature. M&A provides an ideal setting for stress testing, given the importance of M&A to corporations. The literature is mature, having been extensively studied over an extended period, and has established results across numerous papers. Papers draw information from a common set of databases, and, although the event study methodology is an accepted framework, critical assumptions vary across papers.

5.1. Sample selection

Our sample selection process begins with papers published in the four journals with arguably the highest impact factors in academic finance: *The Journal of Finance*, the *Journal of Financial Economics*, *The Review of Financial Studies*, and the *Journal of Financial and Quantitative Analysis*. We identify those papers that analyze returns around M&A announcements, yielding 207 candidates for replication published between 1983 and 2023. The early 1980s start of this period coincides with the nascent academic empirical research into M&A documented by (Mulherin, Netter, and Poulsen 2017). We eliminate studies with purely theoretical contributions and those whose analysis is primarily descriptive.

The inclusion criteria derive from both our replication and stress testing objectives. We first impose a data requirement; we must have access to a paper's data to replicate its results. The candidate paper must use publicly available data, such as that from the Bureau of Labor Statistics and academic websites, or commercially available data to which we have access. As a result, we restrict our sample to papers that use the following commercial data providers: S&P Compustat, Center for Research in Security Prices, Refinitiv Thomson, MSCI RiskMetrics, and SDC Platinum.

Stress testing at the literature-level is the examination of assumptions that underlie common practice. Therefore, we select those papers that exemplify typical empirical specification design and methodology. We limit our sample to those papers where (1) the benchmark analysis, as stated in each paper, uses Cumulative Abnormal Returns (CARs) as the dependent variable and (2) the primary estimation technique involves ordinary least squares or panel regressions. As we cannot stress test null results, we examine only those benchmark analyses that find a statistically significant result with a coefficient in the direction hypothesized.

Finally, we have practical considerations that eliminate some papers from our sample. The paper must describe the methodology well enough for us to replicate the key findings. In some cases, the paper may not adequately define a variable, requiring that we make assumptions to replicate the result. Examples include financial variable definitions and industry classification levels. In such cases, we revert to definitions used by other authors in the literature. These replication assumptions are documented in the online replication code.

After applying these criteria, our sample consists of 47 candidate papers. This dataset requirement restricts the candidate studies to those that examine M&A within the United States. It also eliminates those studies that use proprietary or hand-collected datasets in their baseline findings. The earliest papers in our sample use hand-collected data from the Wall Street Journal, Grimm's Mergerstat Review, and other sources. Thus, our candidate papers begin with those published after 2000, when data sources became more standardized.

5.2. Defining Replication Success

Academics currently lack consensus on what defines successful replication. We consider replication to be the recreation of published results starting from raw data using a process derived from the description in the published article. This process excludes code provided by the author, as independent verification is necessary to ensure the accuracy of author-provided code.

It is probably not possible to replicate papers exactly. Data providers update information, often restating historic data to improve accuracy (Ljungqvist, Malloy, and Marston 2009). Lyle, Siano, and Yohn (2025) find that Compustat's periodic "standardizations significantly alter key financial figures such as sales and earnings, among many others, leading to material differences in research findings." Researchers also may elide essential steps in their data manipulation process, making precise replication difficult. For example, authors generally do not precisely describe the process to match observations across databases, especially with text-based matching. Authors may also omit their process for dealing with missing financial data, such as research and development expenses. Lyle, Siano, and Yohn (2025) assert that "precise replication of prior studies using common Compustat products is nearly impossible."

Reproduction, as opposed to replication, is the independent execution of a study performed using data and code provided by the authors. Reproduction should be easier than replication, yet researchers have experienced difficulty reproducing results. Chang and Li (2022) attempt to reproduce 67 macroeconomic papers. Defining success as one that produces the "key qualitative results of the paper," they can reproduce 33% of the sample without contacting the authors. Fišar et al. (2024) assess the reproducibility of nearly 500 articles in *Management Science*. A "fully reproduced" paper is one in which the reproduction generates the exact numerical results as the published article. A "largely reproduced with minor issues" paper is one in which the reproduction has small differences from the published article. They find that only 45% of articles that voluntarily provided data and code were reproducible before the journal's 2019 institution of a data and code disclosure policy.

We use similar qualitative criteria for replication. We consider a paper replicated when (i) the replicated coefficient on the key economic variable examined in the paper has the same sign with similar magnitude and statistical significance to the published result, and (ii) the replicated and the published samples have a similar number of observations. While many of the control variables are similar to those in published results, we do not concern ourselves with discrepancies due to the issues highlighted above.[13]

5.3. Replication Process

We replicate within *foghorn*, focusing on a single result examining cumulative abnormal returns in the target paper. The specifications selected for replication are typically identified by the author as a key result supporting the paper's hypotheses. We use a single, principal result to keep the scope of our replication manageable and to ensure that stress testing is comparable across papers.

We use the empirical methodology and assumptions as described by the authors to reimplement a paper. In some cases, a paper may not provide sufficient detail. Common issues include the handling of missing data, variable definitions, and sample selection. For example, many well-known financial variables are missing from Compustat (e.g., research and development expenses (Koh and Reeb 2015)), and the authors may not indicate if they drop observations or replace missing values with zero or industry averages. In other cases, a paper may not provide the individual variables used to create a composite financial control (e.g., the components used to create a total debt control variable). Papers may also not include the market index or model estimation window used when computing cumulative abnormal returns. Papers may also cite other research as a methodology source without clarifying whether sample selection and other decisions from the source apply.

Fortunately, these elided assumptions generally have precedent in the literature. We use common missing variable treatments, common variable definitions, sample selection, and other criteria as necessary, selecting the assumptions that yield the replication closest to the published result. Declarative econometrics is very helpful in efficiently systematizing this search process. For example, acquirer market capitalization is a common control in the M&A literature and may be sourced from Compustat, CRSP, and SDC in our sample of papers. If not specified, we can quickly switch the source for market capitalization without having to worry about integrating the data into

[13]Our inability to replicate a result does not prove that it is not replicable. Rather, it suggests that our interpretation of the empirical approach did not yield similar results. Consequently, we do not list those papers whose results we were unable to replicate.

the overall data management process.[14]

5.4. Results

Table 1 summarizes the results for the papers that were successfully replicated. For each study, it lists the key economic variable of interest and identifies the table and column of the replicated specification. The table reports both the published and replicated coefficients, with significance levels indicated by stars at the 1%, 5%, and 10% levels, and compares the number of observations in the published and replicated tests.

Because we replicate a number of papers, we also provide a separate section, "Replication Tables," located after the standard tables, that presents direct comparisons of all explanatory variables between the published and replicated results. Within each table, coefficients are reported in the same order as tabulated in the original publication, with the primary economic variable highlighted in bold. We also include t-statistics, p-values, or standard errors as appropriate, consistent with the original study.

Finally, many of these papers employ fixed-effect indicator variables, which require omitting one unspecified category to estimate a constant. Consequently, published and replicated constants are not directly comparable, and we do not report constants even when they appear in the original tables.

The findings in Table 1 suggest that key results in published papers are generally replicable. In 16 of the 20 papers we have attempted to date, we generate coefficients on key economic variables with comparable economic and statistical magnitudes.[15] These replications suggest that important findings in the literature exist in a common data-processing framework. Thus, the results can be generated simultaneously; researchers do not need to impose paper-specific methodologies and assumptions to reproduce each result.

We do not tabulate papers for which replication was unsuccessful. Failure to replicate does not imply that the original results are not replicable. By applying a declarative approach to economics, we aim to make all assumptions explicit, but the possibility of misinterpreting a paper's methodology remains.

Literature-level replications can significantly enhance transparency. Beyond offering bi-directional transparency for individual papers, generating results within a shared data-processing framework clarifies the empirical practices and assumptions applied across the literature. We now assess the robustness of these results to variations in standard practice through stress testing.

[14] In *foghorn*, the `acquirer` function links source data to deal observations. Thus, we can simply slot in `acquirer Sdc.market_cap`, `acquirer (Crsp.prc * Crsp.shrout)`, and `acquirer (Comp.prccF * Comp.csho)` and the transpiler creates the correct empirical procedure across database sources.

[15] We continue to work on replication and expand our sample of papers.

6. Stress Testing the M&A Literature

We now build off of the work of Mitton (2022) and utilize a methodology similar to that suggested by Brodeur, Cook, and Heyes (2020b) and Simonsohn, Simmons, and Nelson (2020) and perform two types of within-literature stress tests on the replicated results presented in the previous section. These tests examine the robustness of each replicated paper's coefficient of interest by varying (1) the dependent variable definition and (2) definitions of control variables common across most of the papers. We utilize the fact that, consistent with the findings of Mitton (2022), the definitions of the dependent variable and common control variables vary significantly within the M&A literature. This allows us to study how potentially arbitrary differences in variable definitions impact the significance of published papers' reported findings. We ask two questions: first, do seemingly innocuous specification choices lead to significant variation in the significance of coefficient estimates? Second, does this variation tend to favor the published specification? In other words, does the significance of the published results tend to be greater than when using plausible alternative definitions.

For all stress tests, we study how the significance (t-statistics) of the variables of interest in each paper vary across these stress tests. We define our primary measure, *tstat_diff* for each stress test as the following:

$$tstat\_diff_{i,j,k} = \begin{cases} base\_tstat_{i,j} - stress\_tstat_{i,j,k} & \text{if} \quad base\_tstat_i > 0 \\ stress\_tstat_{i,j,k} - base\_tstat_{i,j} & \text{if} \quad base\_tstat_i < 0 \end{cases}$$

where $base\_tstat_{i,j}$ is the replicated t-statistic for variable *i* in paper specification *j*, and $stress\_tstat_{i,j,k}$ is the t-statistic for variable *i* in paper specification *j* and stress *k*. *tstat_diff* will be positive when the magnitude of the replicated t-statistic is greater than the magnitude of the t-statistic of the same variable in the stress test (i.e. the replicated t-statistic is more significant than the stress test's t-statistic). *tstat_diff* less than zero can be thought of as conservative (the alternative definition in the stress test produces a larger, or more significant t-statistic than the replicated t-statistic of the specification found in the published paper) and *tstat_diff* greater than zero can be thought of as aggressive (the replicated t-statistic of the reported specification in the published paper produces a larger, more significant t-statistic than the stress test).

6.1. Dependent variable stress testing

To perform stress testing on dependent variable definitions we rely on the chosen sample of papers outlined in the section above and allow the definition and estimation of CARs to vary along three dimensions. First, we vary the size of the CAR announcement window for each test along the following dimensions relative to the announcement day: [−1, +1], [−2, +2], [−3, +3], [−5, +5], [−1, +5], [−5, +1], [0, +5], and [−5, 0]. Second, we vary how abnormal returns are estimated:

subtracting the expected return from the daily raw return utilizing a single-index model (SIM) with equally weighted returns, an SIM with value weighted returns, a Fama-French 3-factor model (FF3), a Fama-French 4-factor model (FF4), and the equally weighted (OEW) and value weighted (OVW) market return (i.e. assuming the beta of the single-index model is equal to one following Brown and Warner (1980)). Third, we vary the expected return estimation period (for tests estimating the market return using the SIM, FF3, and FF4) along the following daily windows relative to the announcement day: [−205, −6], [−210, −11], [−245, −45], [−252, −20], [−272, −20], [−300, −91], and [−370, −253]. These variations generate 238 to 336 stress tests per replicated paper, depending on the specification.

6.1.1. Impact on the significance of variables of interest

We complete the stress tests described in Section 6.1 and compute the *tstat_diff* for each stress test on each paper specification variable of interest. We focus on baseline replicated results from our sample of published papers where the coefficient on the variable of interest was predicted to be significant. From our sample, this yields 15 specifications and 4,543 stress tests for variables of interest. We report the results of these tests in Figure 1 and Table 7.

Figure 1 shows that even slight within-literature variations in how the dependent variable (*CAR*) is defined produce significant dispersion in the t-statistics of variables of interest in the replicated papers. A positive *tstat_diff* indicates the reported/replicated t-statistic is larger in magnitude than the corresponding t-statistic for a given stress test. Table 7, Panel A reports a *tstat_diff* standard deviation of 1.05. Figure 1 also shows that this distribution is significantly skewed in favor of the published specification. As reported in Panel A of Table 7, the reported t-statistic is 0.67 larger than the median stress test t-statistic (i.e. this is consistent with the reported t-statistic being a significant 2.20, while the stress test t-statistic is an insignificant 1.53). This evidence is consistent with the exploratory findings of Menkveld et al. (2024).

As reported in Table 7, Panel C, we find the replicated/reported t-statistic is larger in magnitude than the stress test t-statistic (*tstat_diff* was positive) in 80% of stress tests (3,642 of 4,543). As further reported in the panel, 53% of stress tests result in a drop in significance (i.e. moving from one conventional significance level to a lower one) and 37% of stress tests lose significance (a t-statistic of less than 1.65). Finally, only 5% of stress tests increase in significance.

It is possible that these findings are centered in highly significant results where the dispersion will not impact the overall significance of the results. For example, a *tstat_diff* of 1.0 is less meaningful when both replicated and stress test t-statistics are above 5.0. The evidence in Panel C does not suggest this is the case, given the high proportion of tests that drop or lose significance. In Panel B of Figure 1, we restrict our analysis to replicated t-statistics that are less than 3 (where a reduction of 1.05 would reduce the significance of an estimate from 1% significance to 10% significance at best). Panel B of the figure shows similar evidence of dispersion and loss of significance in stress tests where the baseline reported t-statistic is less than 3. Table 7, Panels A and B, reports the summary statistics of *tstat_diff* in this subsample, with a median of 0.56, a mean of 0.60, and standard deviation of 0.76. Given the proximity to cutoffs for significance we see an even greater proportion of stress tests with lower significance in Panel C. While 78% of stress tests are smaller in magnitude than the replicated/reported t-statistic, 64% of stress tests dropped significance, 46% lost significance, and only 6% increased in significance. Thus, it does not appear that our findings are only found among highly significant results.

In untabulated robustness tests, we do not find that these results are driven by a specific stress test or specific type of stress test. We find consistent evidence when we drop any specific stress test (i.e. no stress tests have a $[-5, 0]$ announcement window) or stress test type (i.e. do not allow stress test CAR windows to vary but allow the estimation period or method to vary). We explicitly plot the impact of the individual stress tests in the section below.

6.1.2. Impact on the significance of control variables

The higher significance we find in published specifications relative to corresponding stress tests that we document above may be an artifact of our methodology, or simply reflect the randomness induced by non-standard errors (Menkveld et al. 2024). To test this, we calculate *tstat_diff* for control variables rather than variables of interest using the same stress tests. If our methodology is driving the results, we would expect that the significance of published control variables would behave similar to the variables of interest, relative to their stress test alternatives. However, if these results are instead driven by publication incentives, we expect the significance of control variables will not exhibit the same tendency towards using definitions of the dependent variable that yield more significant coefficients on the variable of interest. We report these results in Figure 2 and Table 10.

Figure 2 and Panels A and B of Table 10 show significant variation in the t-statistics of control variables in stress tests relative to the replicated t-statistics. Table 10, Panel A shows that the standard deviation of *tstat_diff* remains large (1.39) and the skewness (1.35 vs. 1.26) and kurtosis (16.59 vs. 7.80) are even larger. This supports the notion that the choice of dependent variable definition can introduce significant variation in estimated coefficients on all variables. This is consistent with the work of Mitton (2022) and Menkveld et al. (2024). However, we no longer observe the degree of aggressiveness with control variables that we observed with variables of interest. As reported in Panel B of Table 10, the median difference between a replicated/reported t-statistic of a control variable and the corresponding t-statistic from a stress test is 0.22 (relative to 0.67 for variables of interest). We find that 61% of stress tests of control variables (versus 80% of variables of interest) were lower than the replicated/reported t-statistic. Only 16% of stress tests result in a drop in significance (relative to 53% of stress tests for variables of interest) and 12% of stress tests lose significance (relative to 37% of stress tests for variables of interest). Finally, 11% of stress tests for control variables increase in significance (relative to 5% of stress tests for variables of interest).

A t-test comparing the mean *tstat_diff* between variables of interest (0.775) and control variables (0.336) is highly significant (*t-statistic* of -20.720) and as reported in Table 13, a two-sample Kolmogorov-Smirnov test for the equality of distributions shows that the distribution for *tstat_diff* is significantly smaller for the control variables than for variables of interest. Taken together, these results document evidence of significant sensitivity of variables of interest to within-literature variation in CAR definitions. We document that t-statistics are significantly more skewed towards significance in the published results relative to corresponding stress tests, where incentives for significant results in publication are the strongest. We do not observe this same behavior (in terms of skewness favoring published results) in the significance of control variable estimates, where these publication incentives are less severe.

We have reported stress tests thus far in aggregate across all of the replicated studies. However, a natural question is how much variation occurs within each study. To report this variation, we randomly order the individual paper specifications and report histograms of *tstat_diff* for each specification individually in Figure 3. The figure shows that some paper specifications are significantly skewed right, while others are rather centered around zero. Importantly, we observe significant variation in t-statistics for all specifications. Thus, while the selection of dependent variables tends to favor the published version of specifications more in some papers than others, all exhibit significant variation and suggest that our evidence is not being driven by one outlying paper-specification.

Finally, we study whether the skewness or dispersion we observe in the reported significance of variables of interest is determined by specific stress tests. To do so we employ a specification curve methodology similar to Simonsohn, Simmons, and Nelson (2020) in Figure 4. Specifically, we report the *tstat_diff* of stress tests between the 1st and 99th percentile. Additionally, we also include vertically aligned horizontal rows below the figure designating whether a given empirical choice was included in a given stress test. As can be seen in the figure, we observe that no single specification type tends to explain large (or small) *tstat_diff*. In other words, it does not appear that papers avoid a specific definition literature-wide. Rather, we observe consistent results across all specification choices. We now turn to studying whether and how the definitions of independent control variables materially impact the significance of variables of interest.

6.2. Independent (control) variable stress testing

To perform stress testing on independent variable definitions we rely on the chosen sample of papers outlined in the section above and allow the definition and estimation of two controls common to the majority of the published studies in our sample: (1) market-to-book (Tobin's Q) and (2) leverage. As identified by Mitton (2022), both of these measures vary significantly across the general corporate finance literature. Similar to our analysis in Section 6.1, we vary the definition of these control variables only within the more narrow M&A literature, since these represent defensible alternative definitions of these variables. We then study the impact that varying only these definitions has on the significance of the variables of interest. We utilize the nine alternative definitions of market-to-book provided, along with references, in Table 5. These definitions are used within the literature as controls from both acquirers and targets. We also utilize the nine definitions of leverage provided, along with references to the appropriate literature, in Table 6.[16] We allow these variables to vary for those specifications in our sample in which they appear. These variations generate 80 to 96 stress tests per specification, dependent on the specification. Unlike varying the dependent variable, changing a control variable definition does not mechanically alter the left-hand side of the regression and can only affect the coefficient on the variable of interest through correlation.

6.2.1. Independent (control) variable stress test results

From our sample, 12 of the 15 specifications contain either market-to-book or leverage, yielding 1,136 stress tests for variables of interest. As we are not stress testing the inclusion/exclusion of variables, if a given control variable does not appear in a specification, we do not vary the definition of that variable for stress tests of the specification. We report the results of these tests in Figure 5 and Table 14. Figure 5 shows that, while dispersion in *tstat_diff* persists, there is much larger clustering around zero. Table 14, Panels A and B confirm this. The mean, median, and standard deviation of *tstat_diff* is smaller than what we observed in the dependent variable stress tests, at 0.13, 0.03, and 0.53, respectively. However, we see even higher skewness and kurtosis, 2.34 and 11.69, respectively.

Importantly, we continue to see a slight skewness favoring the published specifications in Table 14, Panel C. Specifically, 63% of stress tests were lower than the reported/replicated t-statistic. 19% of stress tests resulted in a drop in significance, 11% resulted in a loss in significance, and only 3% resulted in an increase in significance. These results are roughly consistent when we

[16]We conservatively rely on the variation of definitions of these variables that occurs only within the replicated M&A literature. However, Mitton (2022) identifies 25 unique definitions of Tobin's Q and 96 unique definitions of leverage across all areas of corporate finance within his sample.

restrict the sample to those reported/replicated results with t-statistics less than 3, as reported in Panel B of Figure 5 and Table 14. In these cases we see roughly similar summary statistics, and slightly higher proportion of stress tests leading to a drop in significance (25%) and a loss in significance (14%).

To fully ascertain whether these results may be an artifact of our methodology, we again compare the results to the variation in t-statistics for control variables. Importantly, since we are varying control market-to-book and leverage, we exclude these variables from this sample when they are varied (to avoid creating a direct effect on the t-statistics). We present these results in Figure 6 and Table 17.

The figure shows even higher clustering of stress tests near a *tstat_diff* of zero. Table 17, Panel A shows that the average *tstat_diff* for control variables (excluding market-to-book or leverage when these are allowed to vary in a given stress test) is 0.04 (compared with 0.13). This difference is similarly significant with a t-statistic of -3.45 and a p-value of 0.0006. Further, as reported in Table 20, a two-sample Kolmogorov-Smirnov test for the equality of distributions shows that the distribution for *tstat_diff* is significantly smaller for the control variables than for variables of interest when we vary market-to-book and/or leverage definitions. Similar to the CAR analysis, we also report specification curve analysis on *tstat_diff* for these control variables in Figure 7. Similar to our CAR results, we do not find evidence that the skewness (or dispersion) of reported t-statistics (relative to their within-literature alternatives) are driven by particular stress test definitions.

Taken together, these findings suggest that, while variation in control variables does not have the same size of impact on the significance of variables of interest, it still generates a meaningful effect. This is unsurprising given its indirect influence on the estimation of the coefficients of interest. However, again we find evidence that the definitions chosen for control variables tend to favor the significance of the variable of interest in published results.

7. Conclusion

This paper utilizes a newly-developed novel declarative econometric technique from Tumarkin (2026). This scalable technique allows us to build on the existing literature by combining the replication and meta-study approaches to stress test an economic literature. Specifically, applying this framework to the mergers and acquisitions literature, we show the actual, rather than potential, impacts that seemingly innocuous empirical decisions, or “researcher degrees of freedom”, have on the significance (and publishability) of coefficient estimates.

We show that most published results in this literature are replicable once implicit assumptions are made explicit. However, we find that within-literature stress testing reveals significant sensitivity to specification choices. By utilizing the same dataset used to replicate the original results, we vary the definitions of dependent variables (cumulative abnormal returns) and common independent control variables (Tobin's Q and leverage) only within the replicated M&A literature. This creates a series of conservative stress tests using plausible and defensible alternative definitions that could have been used during when designing the empirical specifications of the paper. We find that even among these conservative stress tests, reported results are significantly more likely to be above standard thresholds for statistical significance (e.g., 10%, 5%, and 1%) than stressed alternatives. This suggests that researcher discretion, as well as the incentives of the publication process, plays a meaningful role in shaping published findings. At the same time, the framework highlights that many conclusions remain robust under alternative specifications, reinforcing the value of accumulated knowledge in this field.

More broadly, our results contribute to the literature by illustrate how the declarative econometric technique of Tumarkin (2026) can complement existing empirical practices by providing a scalable and systematic way to encode, replicate, and stress test empirical analyses. The promise of this approach extends beyond M&A research: once modules are developed, it can be applied to other areas of finance and the social sciences more generally. In doing so, declarative econometrics provides a path toward more resilient empirical literatures.

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Appendix

A Technical Implementation Details

Traditional econometric code embodies a form of dramatic irony; the researcher has information about the data that the programming language does not. For example, a researcher will know that share prices are represented as floating-point numbers, while ticker symbols are represented as text. However, a statement adding the two (i.e., `price + ticker`) is syntactically valid in SQL, SAS, and other data manipulation languages. The language will only recognize the error when the code is executed against the data. This inability of traditional data manipulation languages to reason about the data before execution significantly inhibits their ability to write expressive, succinct econometric specifications.

Declarative econometrics bridges the knowledge gap between the researcher and the computer by enabling the language to reason about a specification before execution, that is, as the researcher develops the specification. The *Foghorn* source code defines all functions and operations at two levels. The "type level" describes rules that the variables involved in a function must satisfy. These rules can embed logic using cross-sectional indices, time-series indices, data types, and other variable-specific information. The "term level" implements the actual function or operation. For instance, *Foghorn* implements algebraic addition similarly to most programming languages at the term level. However, its type-level rule stipulates that the operands must have identical cross-sectional and/or time-series indices and be of numeric data types (i.e., information that can be added). Thus, adding a numeric share price to a textual ticker symbol is forbidden.

It is the ability to encode logic about the data that makes declarative econometrics powerful, expressive, and succinct. Returning to Example 1, verbose data manipulation steps to convert variables from one set of indices to another are noticeably absent. However, while some programming languages achieve syntactical succinctness by ignoring information about the data, this declarative econometric code achieves simplicity for the opposite reason: it can reason about the data. *Foghorn* would not let a researcher combine CRSP data with Compustat data to compute Tobin's q without explicit reindexing. Moreover, the `reindex` function does not require detailed instructions, as the language can determine and validate the necessary conversions.

Declarative econometrics offers a general framework applicable across all social science disciplines. At its core, declarative econometrics elevates econometric information from the data to the language. However, the approach does not achieve this by restricting the datasets with which it can work. *Foghorn*'s core is database-agnostic, defining general rules that validate relationships among specifications and variables. Dataset-specific information enters the language through topic modules. For example, the corporate finance module, *Coficat*, provides information about many finance datasets.[17] Users may write modules targeting specific research areas and extend the language's capabilities.

Foghorn will be publicly available for use by econometric researchers. However, we recognize that other researchers may write new modules for *Foghorn* or create other declarative econometric languages. Therefore, when describing how *Foghorn* operates, we emphasize those features that make a declarative econometric approach viable. A complete technical discussion on the design and implementation of the language is beyond the scope of this paper. Details are provided in the companion paper (Tumarkin 2026).

A.1 Embedded domain-specific language

Instead of writing a declarative language from scratch, we believe it is best to leverage existing technology with an embedded domain-specific language (EDSL). An EDSL operates within a host language, serving as a dialect that facilitates specific tasks. The EDSL allows a programmer to revert to the host language when necessary. Therefore, a declarative econometric EDSL can offer data manipulation and estimation tools based on a precise top-down specification while preserving the full capabilities of the host general-purpose programming language.

We implement *Foghorn* as an EDSL within Haskell, a language that has strong support for declarative programming. *Foghorn* is designed for social science researchers to use without requiring knowledge of Haskell. As exemplified by the sample code in Example 1, most specifications can be written in a syntax similar to existing econometric packages with the addition of algebraic constructs to define variables.[18]

Haskell's many unique features make it a desirable host for a declarative econometric EDSL. These include, but are not limited to, lazy evaluation, general algebraic data types, recursive data types, higher-order functions, abstract type classes, and dependent types. However, a technical discussion of the advantages these features provide for a declarative econometric language is deferred to the companion paper (Tumarkin 2026).

Most notably, for this discussion, Haskell code exists at both the term level and the type level. This separation is a key aspect of Haskell's powerful and expressive type system. Most people are familiar with what Haskell considers the term-level, which, in traditional languages, is where the steps of a function are performed. The type-level in Haskell is a unique environment that can be

[17] *Coficat* is tortured wordplay for a *co*-rporate *fi*-nance research copy-*cat* tool.

[18] *Foghorn* is an open-source programming language that accepts contributions that identify issues, fix bugs, and expand its scope. While *Foghorn* is intended to be used for econometric research without learning Haskell, understanding the source code of the core language requires intermediate to advanced Haskell. This is not uncommon in programming languages where the language's source code is often far more complicated than programs written in the language. For example, many Python users would have trouble working through the source to Python's most popular implementation, CPython, which is not written in Python but C.

extended to embed logic. Working at the type-level, one can describe intricate relationships among the inputs to and the output from functions. *Foghorn* uses this to analyze, validate, and infer critical aspects of econometric specifications.

A.2 Encoding econometric logic (Database agnostic reasoning in the core language)

Foghorn is designed to be usable across the social sciences. Thus, it contains a "core" language that emphasizes general econometric logic, lacking information about a specific data set or research area. *Foghorn*'s core provides the building blocks of econometric analysis, including specification design, algebraic calculations, data aggregation, data merging, and other common operations. By tracking index and data type information, the core can achieve a level of concision that is not possible when a language lacks such information.

A declarative econometric language like *Foghorn* needs to reason about the data. In programming language design, this ability is most powerfully expressed through type-level logic. In *Foghorn*, each variable is declared with type-level information about its indexing variables i (i.e., cross-sectional and/or time-series indices) and data type d (e.g., integer, floating-point number, text). We notate a variable as `Var i d`, where, for example, CRSP stock share price would be declared at the type-level as `Var (Permno, TradingDate) Float`. Variables carry this type-level information around in the code, with the language tracking and reasoning about types throughout the specification.

All operations and functions in *Foghorn* contain "type signatures" that define rules about the relationships among input variables and output at the type level. Type signatures are declared as

```
Constraints => Input 1 -> Input 2 -> … -> Input N -> Output.
```

Functions may include any number of constraints and inputs, with only the output being mandatory. For example, the type signature for addition, subtraction, and multiplication is written as:

$$\underbrace{\texttt{Numeric d}}_{\text{Constraint}} \texttt{ => } \underbrace{\texttt{Var i d}}_{\text{Input 1}} \texttt{ -> } \underbrace{\texttt{Var i d}}_{\text{Input 2}} \texttt{ -> } \underbrace{\texttt{Var i d}}_{\text{Output}}.$$

The type constraint, `Numeric d`, is left of the double-arrow and indicates that the data type `d` must be numerical. On the right-hand side, there are two input variables and an output variable, each of type `Var i d`. *Foghorn* can reason that these operations are valid only when the input share indexing identifiers `i` and a numeric data type `d` are used, and the result is a new variable of the same indexing and data type.

Rules in *Foghorn* are often written using type-level variables (a language feature called parametric polymorphism) instead of specific indices or data types.[19] The above example has two type-level variables, `i` and `d`. Type-level variables ensure that rules are as general as possible, and *Foghorn* can

[19] Type-level variables are distinct from term-level variables. Term-level variables express values, permitting the language to manipulate values. Type-level variables express types, permitting the language to reason about type information.

apply them to any dataset. *Foghorn* has a rich, extendable list of data types that enable it to precisely reason about econometric specifications. For example, many kinds of economic data are stored as integers. These include standard industry classification (SIC) codes, fiscal years, calendar years, many identifiers (e.g., CIK, permno, and gvkey), and actual integer numbers. *Foghorn* separates these into separate types. The function to compute Fama-French industry classifications (Fama and French 1992) will only work with SIC codes. Arithmetic operations are only supported for types where the operations make sense (e.g., addition of SIC codes is not permitted).

Type constraints may be of arbitrary complexity due to Haskell's support for advanced programming at the type level. Yet, *Foghorn* does not require that users worry about type-level programming. *Foghorn* inherits Haskell's ability to infer types. For example, consider the reindexing function which has the type signature:

```
Reindexable i i' => Var i d -> Var i' d
```

The type constraint `Reindexable i i'` defines a type class. A source index variable set `i` is paired with a target one `i'` in `Reindexable` only when a variable indexed by observation identifier `i` can be transformed into one indexed by identifier `i'`. Type inference means that *Foghorn* can contextually determine the target indexing variables from reindexing. For example, assume we have variables `a` and `b` indexed by `i` and `i'`, respectively. Type-inference ensures that the expression `reindex a + b` is fully defined. *Foghorn* knows the source indexing for `a` (each variable carries information about index type), and it can infer the target indexing from `b` on the other side of the addition operand. This expression is validated provided that the index type pair `i` and `i'` are an instance of `Reindexable` (and that the underlying data types permit addition).

A.3 Modularity (Database specific information through topic modules)

Foghorn uses a plug-in module system to target different branches of econometric literature. In *Foghorn*, modules must define the data sets available for a literature and the conversions among variable indices.[20] This approach ensures that a declarative econometric language is not tied down to any specific econometric methodology. For example, one module may link firm financial data to stock return data based on what data was publicly known to the market (i.e., the firm's financial data relevant to a specific market observation is from the most recent data published by the company). Another module may use contemporaneous data (i.e., the firm financial data is linked to any return data that occurs during the corresponding fiscal year). A third module may provide both options, requiring the econometrician to specify the linking method explicitly. A fourth module may not allow such index conversions to occur directly.

[20]Common data sets used in finance are already in *Foghorn*. Additional types of data sets, both within Finance and in other areas of the social sciences, will be added to the core distribution over time. However, users are not restricted to the core datasets and may implement their own.

A module consists of two pieces: a standardized database and its *Foghorn* code. The database is topic-specific, providing a standard against which empirical specifications may be executed. It contains the datasets commonly used in the research area and tables, or other rules, to link those datasets. A module's database serves as a foundation; it does not contain processed data, leaving calculations to the transpiled code generated by *Foghorn*.

The *Foghorn* code serves as the second piece of the module. The code provides information about the database, such as the data sources, variables, index information, and permissible index transformations. This information is used by the core language when analyzing specifications and transpiling. Modules can provide topic specific functionality. *Foghorn* provides a clean way to compose base-level functions into succinct module-level ones. Haskell is a functional programming language, meaning that functions, not objects, are the primary units of programs. Functions are composed simply by using a "dot" operator (i.e., the mathematical definition of composition $h = f \circ g$ is translated literally yielding `h = f . g`. Thus, it is simple to write module-level functions that address common problems in a specific economic literature by composing the building blocks provided by the core.

A.4 Transpiling

Foghorn translates top-down specifications into standard database code, a process known as transpiling. While new to econometrics, transpilation is an established technique in programming languages to add type-safety, enhance abstraction, and add concision to non-statically-typed languages. For example, there are many web-development languages for type-safe, high-level web development that transpile to Javascript, thereby preventing errors and making it easier to write modular code. *Foghorn* similarly employs transpilation, eliminating many types of mistakes in econometric coding.

Transpilation ensures that a declarative econometric language does not constitute a closed system. Having another tool for bottom-up data manipulation would not achieve our objectives for literature-level stress-testing and bi-directional transparency. There are numerous established methods for manipulating data and estimating econometric models. *Foghorn* uses a plug-in architecture for transpiling, allowing it to target various data manipulation languages. Users can pick the transpiler needed for their preferred target language. *Foghorn* currently has SQL and Stata transpilers, with a SAS transpiler under development.

Foghorn uses a simple approach to transpilation. *Foghorn* analyzes a specification and determines the basis set of variables underlying the required estimation panel. This basis set includes final variables used in estimation, intermediate variables needed for calculations, and source variables. It then categorizes the variables into two groups based on whether the variable has been computed. Source variables are placed into the computed group; intermediate variables and final variables are placed into the uncomputed group. For each uncomputed variable, it checks if all its basis variables are in the computed set. If so, that variable is calculated and placed into the computed group. On iteration, all variables are eventually moved from the uncomputed group to the computed group. In summary, *foghorn* analyzes the specification, determines the order in which to perform algebraic, aggregating, reindexing, time-shifting, and other calculations, and generates all the necessary database code for the researcher. In other words, transpilation converts functions in *Foghorn* into their data manipulation equivalents.

Transpilation provides several benefits. The most clear advantage of transpilation is leveraging existing tools. Thus, a declarative approach can incorporate any data process or econometric estimator from any software package. One only needs to define a declarative syntax for a new process or estimator and then write a corresponding transpiler. Declarative econometrics is unique in that it defines the complete estimator at the specification level. By creating a direct link between specification and implementation, and then allowing researchers to manipulate specifications, new types of economic research become possible.

Transpilation greatly improves econometric transparency. Data manipulation languages are generally verbose, requiring hundreds if not thousands of lines of code to implement a standard economic paper. A person reviewing such code may suffer from information overload, failing to identify critical assumptions. A declarative specification, on the other hand, is concise and emphasizes the logic of any empirical study. Key assumptions form the basis of the declarative code, with implementation details provided in the transpiled, step-by-step data manipulation code. For example, *Foghorn* has an SQL transpiler that exports a specification into the step-by-step data generating-process.

A.5 Whole-specification coding (Benefits and disadvantages)

Declarative econometrics promotes a whole-specification approach to econometrics. As the language can reason about a specification through type-level logic, the estimator definition is intertwined with the variable definitions. There are several benefits of an approach where an empirical researcher can focus on specification design instead of implementation. Declarative econometrics makes key assumptions explicit, improving empirical clarity and transparency.

Declarative econometrics is not intended to, nor should it, replace standard techniques. Datasets are idiosyncratic and intimate knowledge is required for convincing empirical research. Thus, there are significant advantages to researchers working directly with data from the bottom-up. However, declarative econometrics makes new types of literature-level analysis possible, improving our critical understanding of standard practices through stress testing and replication.

Finally, we note that declarative econometrics has some disadvantages. *Foghorn* requires modules for specific topics. Creating a module requires building a standard database for the topic and encoding the logic into a *Foghorn* library. Thus, declarative econometrics is best suited to established topics where the upfront cost of writing a module can be amortized across paper replication, stress testing, and new research questions. For a unique empirical question, standard bottom-up techniques are better suited.

Moreover, declarative econometrics is not intrinsically designed to be efficient. *Foghorn* applies sample selection as a last step. As a result, the transpiled code will perform computations over an entire source dataset as it implements a study. It will compute variables that do not ultimately meet sample selection criteria. This inefficiency is by design. Computing variables over an entire dataset guarantees that the transpiled code will execute without crashing and generate the correct final sample for estimation.

Foghorn is just one possible implementation of a declarative econometric language. Other notation systems and implementations are possible. However, we believe the features highlighted above are critical to enabling new types of research, particularly in the areas of stress testing. Further details about the notation system and implementation are in the technical companion paper (Tumarkin 2026).

B Glossary

This glossary provides definitions of programming and econometric terms as used throughout the paper.

B.1 Programming Terms

Declarative language A programming language in which the programmer specifies what the program should accomplish, rather than detailing how to perform each step. Programs written in declarative languages emphasize logic and relationships, often leading to more concise code, leaving the system to work out the control flow and implementation details needed to accomplish the task. In *foghorn*, researchers write declarative econometric specifications, with the transpiler determining the steps necessary for implementation.

Embedded Domain-Specific Language (EDSL) A specialized programming language built within a general-purpose language, designed to express solutions in a specific domain (e.g., econometrics) more naturally and concisely. EDSLs leverage the host language's syntax and features while providing domain-specific tools and constructs. Developers commonly use EDSLs to express logic specific to a domain, benefiting from enhanced type safety and improved tooling support. Haskell is well-suited for EDSLs because of its strong abstractions and type safety. *foghorn* is an EDSL of Haskell, providing concise, type-safe econometric logic.

Function composition The process of combining two or more functions to create a new function, where the output of one serves as the input of the next. Function composition allows programmers to build complex operations from simple, reusable parts in a concise, declarative manner. In *foghorn*, the composition of econometric functions improves modularity, readability, and code reuse.

Higher-order function A function that takes other functions as arguments, returns a function as its result, or both. Higher-order functions are central to expressing abstract computation succinctly and avoiding repetitive code. *foghorn* employs higher-order functions to improve modularity and reduce boilerplate.

Imperative language A programming language in which programs are written as sequences of explicit instructions that specify how a computer should perform tasks. These languages focus on describing the control flow and individual steps needed to manipulate program state, often using variables, loops, and conditional statements. Imperative programming contrasts with declarative styles, where the focus is on desired outcomes rather than step-by-step procedures. Existing econometric languages are either imperative or used in an imperative style (e.g., SAS, SQL).

Module A self-contained unit of code that groups related functions, types, and definitions under a common namespace. Modules promote code organization, reuse, and abstraction by allowing programmers to separate and isolate components within a program. *foghorn* uses modules for its core language and for working in specific areas of empirical research (e.g., corporate finance).

Static typing A system in which the types of variables and functions are evaluated at compile time rather than at runtime. Static typing allows many errors — such as type mismatches or invalid operations — to be caught early, improving reliability and program safety. *foghorn* variables carry type information, including the cross-sectional and/or time-series indexing dimensions, allowing the language to validate that operations make sense automatically. *foghorn* uses static typing alongside type-level programming and type inference to encode and enforce econometric logic in specifications.

Term-level The "usual" layer of programming and code execution where values are defined, manipulated, and passed to functions. Unlike type-level programming, term-level programming focuses on concrete computations and data transformations. Most everyday programming tasks — such as arithmetic, data processing, and control flow — occur at the term level. In *foghorn*, the term-level defines the actual operations.

Transpiling The process of converting source code written in one programming language into source code of another language, while preserving program behavior. Unlike compiling, which often targets low-level machine code, transpiling typically produces human-readable code in another high-level language. *foghorn* allows econometricians to write specifications with enhanced features and stronger guarantees — such as improved type safety — while producing output in established data and econometric software.

Type A type is an abstract classification that specifies the kind of values a variable, expression, or function can take and the operations that may be performed on them. Types provide a framework for reasoning about program behavior, ensuring consistency and preventing invalid operations. *foghorn* variables carry type information on their index variables (i.e., the cross-sectional and/or time-series dimensions) and information type (e.g., numeric, SIC code, text). This, combined with static typing, type inference, and type-level programming lets the language reason about econometric specifications.

Type checking Type checking is the process by which a compiler or interpreter verifies that program constructs are used consistently with their declared or inferred types. It ensures, for example, that operations are applied to compatible data types and that functions receive valid arguments. *foghorn* uses type checking to ensure that econometric specifications, and the variables within them, are consistent.

Type inference Type inference is the process by which a compiler automatically determines the types of expressions without requiring explicit type annotations from the programmer. This enables concise code while retaining the benefits of static typing, since the compiler can still catch type errors at compile time. *foghorn* leverages Haskell's type inference to achieve strong econometric type safety with reduced syntactic overhead, as an econometrician does not need to label a variable's index or informational types.

Type signature A formal declaration of the inputs and output of a function, along with any constraints. *foghorn* uses type signatures to define econometric logic.

Type-level A layer above the term-level where logic about types is encoded. In strongly typed functional languages like Haskell, type-level programming allows developers to encode invariants, perform compile-time checks, and enforce constraints through types themselves. Type-level programming is the practice of writing programs that use a language's type system to encode logic, perform computations, and write expressions and abstractions that occur within a language's type system rather than at the term-level. This approach can enforce complex invariants, guarantee program properties at compile time, and eliminate certain classes of runtime errors. In *foghorn*, type-level programming defines econometric operations, and specifications.

B.2 Econometric & Research Terms

Bi-directional transparency Transparency in both directions: top-down (explicit specifications and assumptions) and bottom-up (generated data-manipulation code). Ensures hidden assumptions are revealed.

Empirical specification A formal, high-level description of the econometric model being estimated, consisting of: the dependent variable, explanatory variables, the functional form of the relationship, and the chosen estimator. In this paper, the specification is written at a high level and does not include step-by-step data manipulation.

Empirical procedure The complete process of estimating a model from raw data. It consists of the complete data manipulation process that transforms raw data into the final dataset and the econometric estimation procedure.

Indexing variables Identifiers that uniquely label dataset observations, which may be cross-sectional or time-series.

Reindexing Reindexing is the process of aligning data across datasets with different indexing systems.

Replication Re-implementing a paper's empirical specification to see if results can be reproduced with comparable magnitude, significance, and sample size. In this paper, replication is the process of independently coding an empirical specification as described within a paper. The replication is conducted from raw data, limiting author-provided information to proprietary data. Replication in this context is judged successful when: (i) coefficient estimates and significance are similar, (ii) sample sizes align, and (iii) control variables behave similarly.

Reproduction Obtaining exact results, or results with minor variations, to a published paper's empirical specification using data and code provided by the authors.

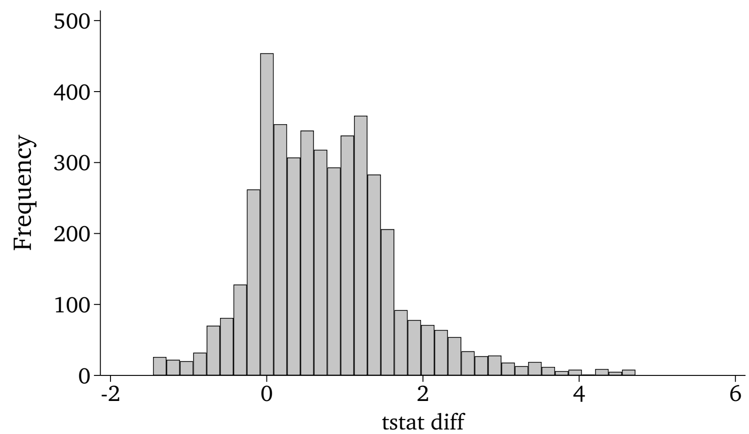
Robustness test A paper-level sensitivity check in which the authors vary aspects of their own methodology to show that results are not overly sensitive to small changes. These tests are typically idiosyncratic, tied to one paper's assumptions

Stress test A literature-level test that systematically varies common assumptions or practices across multiple papers.

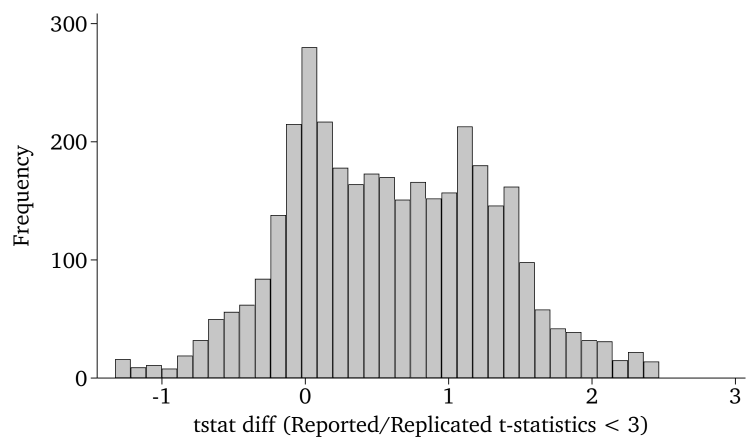
Figure 1

CAR Stress Tests: Histogram of the Change in t-statistics of Variables of Interest

This histogram plots *tstat_diff* for stress tests on the significance of the coefficient on the variable of interest by varying the definition of Cumulative Abnormal Returns (CARs) performed on 15 specifications from replicated papers. Stress tests allow for within-literature variation on (1) the CAR announcement window ([−1, +1], [−2, +2], [−3, +3], [−5, +5], [−1, +5], [−5, +1], [0, +5], and [−5, 0]), (2) abnormal return calculation (equally and value weighted single-index model (SIM), a Fama-French 3-factor (FF3) and 4-factor (FF4) model, and the equally weighted (OEW) and value weighted (OVW) market return). (3) the expected return estimation period for tests estimating the market return using the SIM, FF3, and FF4 ([−205, −6], [−210, −11], [−245, −45], [−252, −20], [−272, −20], [−300, −91], and [−370, −253]). *tstat_diff* defined as the reported/replicated t-statistic less the stress test t-statistic (for reported/replicated t-statistics > 0) and the stress test t-statistic less the reported/replicated t-statistic (for reported/replicated t-statistics < 0). Panel A plots the 1st through 99th percentiles of all stress tests resulting in 4,543 stress tests. Panel B plots the 1st through 99th percentiles of a subsample of 3,633 stress tests where the reported/replicated t-statistic is < 3.



Panel A: All original specifications



Panel B: Original specifications with t-statistic < 3

Figure 2

CAR Stress Tests: Histogram of the Change in t-statistics of Control Variables

This histogram plots *tstat_diff* for stress tests on the significance of the coefficients on control variables by varying the definition of Cumulative Abnormal Returns (CARs) performed on 15 specifications from replicated papers. Stress tests allow for within-literature variation on (1) the CAR announcement window ([−1, +1], [−2, +2], [−3, +3], [−5, +5], [−1, +5], [−5, +1], [0, +5], and [−5, 0]), (2) abnormal return calculation (equally and value weighted single-index model (SIM), a Fama-French 3-factor (FF3) and 4-factor (FF4) model, and the equally weighted (OEW) and value weighted (OVW) market return). (3) the expected return estimation period for tests estimating the market return using the SIM, FF3, and FF4 ([−205, −6], [−210, −11], [−245, −45], [−252, −20], [−272, −20], [−300, −91], and [−370, −253]). *tstat_diff* defined as the reported/replicated t-statistic less the stress test t-statistic (for reported/replicated t-statistics > 0) and the stress test t-statistic less the reported/replicated t-statistic (for reported/replicated t-statistics < 0). The figure plots the 1st through 99th percentiles of all stress tests resulting in 52,234 stress tests (one *tstat_diff* for each control variable-specification-stress test).

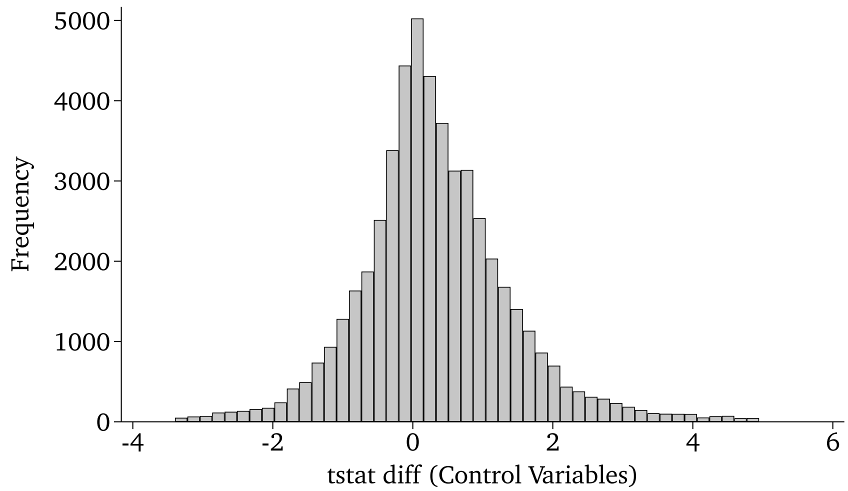


Figure 3

CAR Stress Tests: Histograms Individual Paper Specifications for Variables of Interest

This figure plots the histogram of *tstat_diff* by specification for each of the 15 specifications from replicated papers. Each histogram presents stress tests on the significance of the coefficient on the variable of interest by varying the definition of Cumulative Abnormal Returns (CARs). Stress tests allow for within-literature variation on (1) the CAR announcement window ([−1, +1], [−2, +2], [−3, +3], [−5, +5], [−1, +5], [−5, +1], [0, +5], and [−5, 0]), (2) abnormal return calculation (equally and value weighted single-index model (SIM), a Fama-French 3-factor (FF3) and 4-factor (FF4) model, and the equally weighted (OEW) and value weighted (OVW) market return). (3) the expected return estimation period for tests estimating the market return using the SIM, FF3, and FF4 ([−205, −6], [−210, −11], [−245, −45], [−252, −20], [−272, −20], [−300, −91], and [−370, −253]). *tstat_diff* defined as the reported/replicated t-statistic less the stress test t-statistic (for reported/replicated t-statistics $>$ 0) and the stress test t-statistic less the reported/replicated t-statistic (for reported/replicated t-statistics $<$ 0). Specification numbers are assigned randomly to each specification. Each histogram plots the *tstat_diff* for all stress tests for that specification.

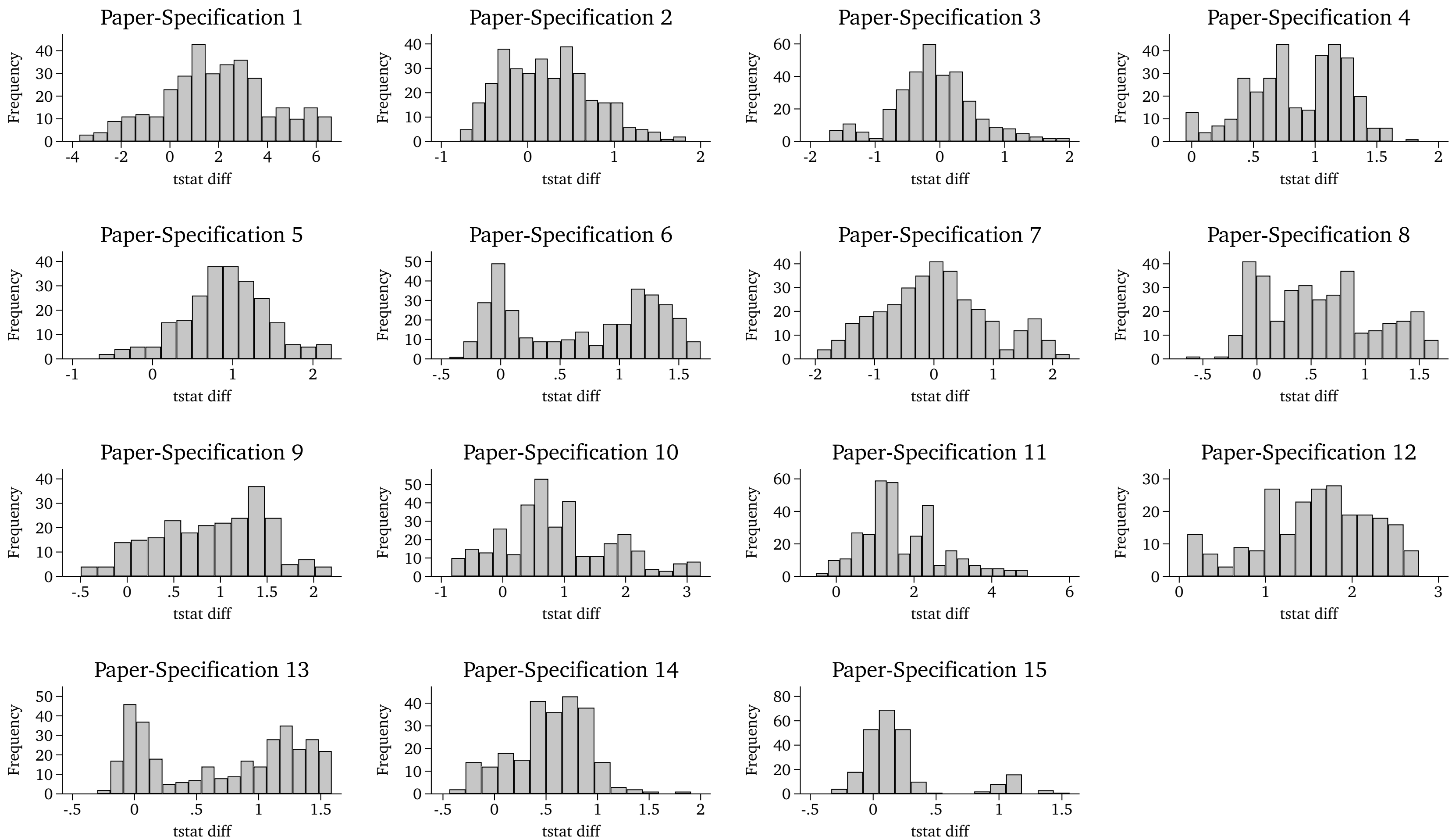

Paper-Specification 1
Paper-Specification 2
Paper-Specification 3
Paper-Specification 4
Paper-Specification 5
Paper-Specification 6
Paper-Specification 7
Paper-Specification 8
Paper-Specification 9
Paper-Specification 10
Paper-Specification 11
Paper-Specification 12
Paper-Specification 13
Paper-Specification 14
Paper-Specification 15
Frequency
tstat diff

Figure 4

CAR Stress Test Specification Curve

Each dot in the top portion of the figure depicts the *tstat_diff* for stress tests on the significance of the coefficient on the variable of interest by varying the definition of Cumulative Abnormal Returns (CARs) performed on 15 specifications from replicated papers, matching the sample reported in Figure 1, Panel A. The figure also reports a dashed line representing where *tstat_diff* is equal to zero. The vertically aligned dots below this plot indicate the combination of specifications within the given stress test used to compute *tstat_diff*. Thus, a positive *tstat_diff* (to the right of the figure) shows that the stress test, including the combination of specifications reported, yields a lower t-statistic than the t-statistic reported in a given replicated paper.

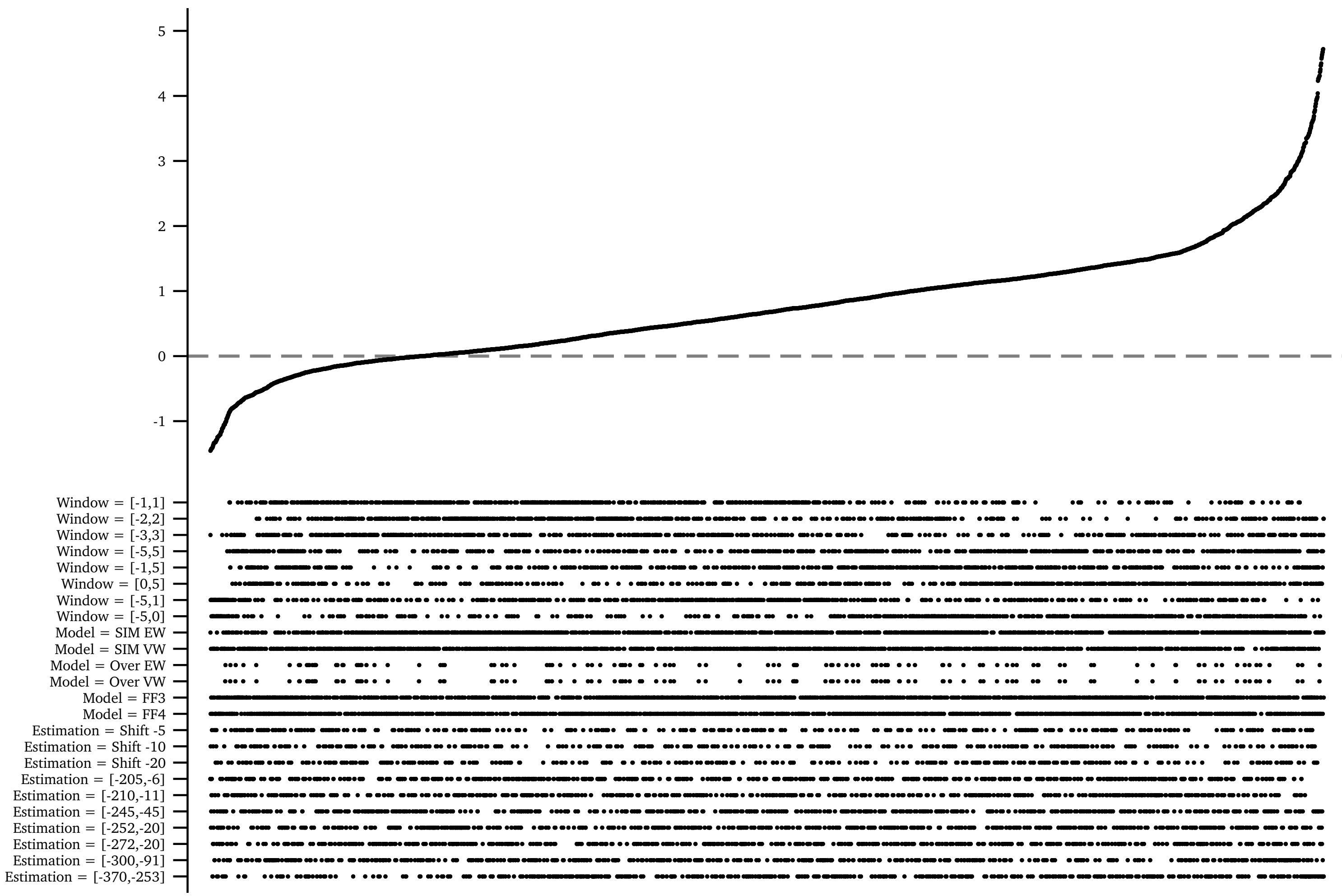
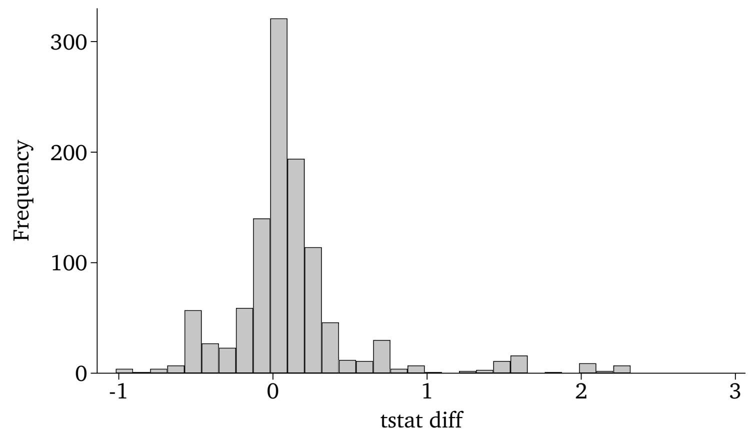


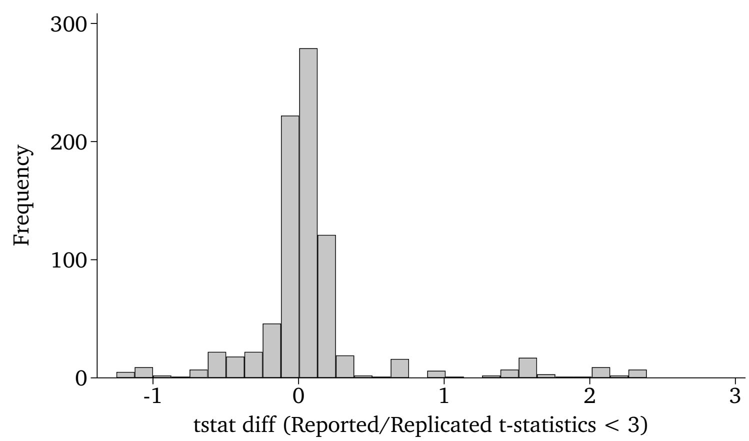
Figure 5

Control Variable Stress Tests: Histogram of the Change in t-statistics of Variables of Interest

This histogram plots *tstat_diff* for stress tests on the significance of the coefficient on the variable of interest by varying the definition of two independent control variables common across the majority of replicated specifications: market-to-book (Tobin's Q) and leverage. These are performed on all specifications that contain these variables (12) from replicated papers. Stress tests allow for within-literature variation based on the definitions presented in Table 2. *tstat_diff* defined as the reported/replicated t-statistic less the stress test t-statistic (for reported/replicated t-statistics > 0) and the stress test t-statistic less the reported/replicated t-statistic (for reported/replicated t-statistics < 0). Panel A plots the 1^{st} through 99^{th} percentiles of all stress tests resulting in 1,136 stress tests. Panel B plots the 1^{st} through 99^{th} percentiles of a subsample of 848 stress tests where the reported/replicated t-statistic is < 3.



Panel A: All original specifications



Panel B: Original specifications with t-statistic < 3

Figure 6

Control Variable Stress Tests: Histogram of the Change in t-statistics of Control Variables

This histogram plots *tstat_diff* for stress tests on the significance of the coefficients on control variables by varying the definition of two independent control variables common across the majority of replicated specifications: market-to-book (Tobin's Q) and leverage. These are performed on all specifications that contain these variables (12) from replicated papers. Stress tests allow for within-literature variation based on the definitions presented in Table 2. *tstat_diff* defined as the reported/replicated t-statistic less the stress test t-statistic (for reported/replicated t-statistics > 0) and the stress test t-statistic less the reported/replicated t-statistic (for reported/replicated t-statistics < 0). The figure plots the 1st through 99th percentiles of all stress tests resulting in 12,374 stress tests (one *tstat_diff* for each control variable-specification-stress test).

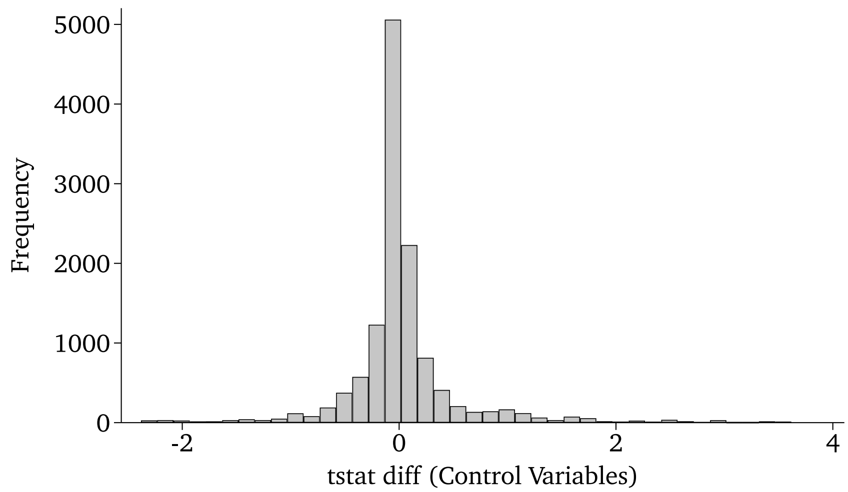


Figure 7

Control Variable Stress Test Specification Curve

Each dot in the top portion of the figure depicts the *tstat_diff* for stress tests on the significance of the coefficient on the variable of interest by varying the definition of two independent control variables common across the majority of replicated specifications: market-to-book (Tobin's Q) and leverage. These are performed on all specifications that contain these variables (12) from replicated papers, matching the sample reported in Figure 5, Panel A. The figure also reports a dashed line representing where *tstat_diff* is equal to zero. The vertically aligned dots below this plot indicate the combination of specifications within the given stress test used to compute *tstat_diff*. Thus, a positive *tstat_diff* (to the right of the figure) shows that the stress test, including the combination of specifications reported, yields a lower t-statistic than the t-statistic reported in a given replicated paper.

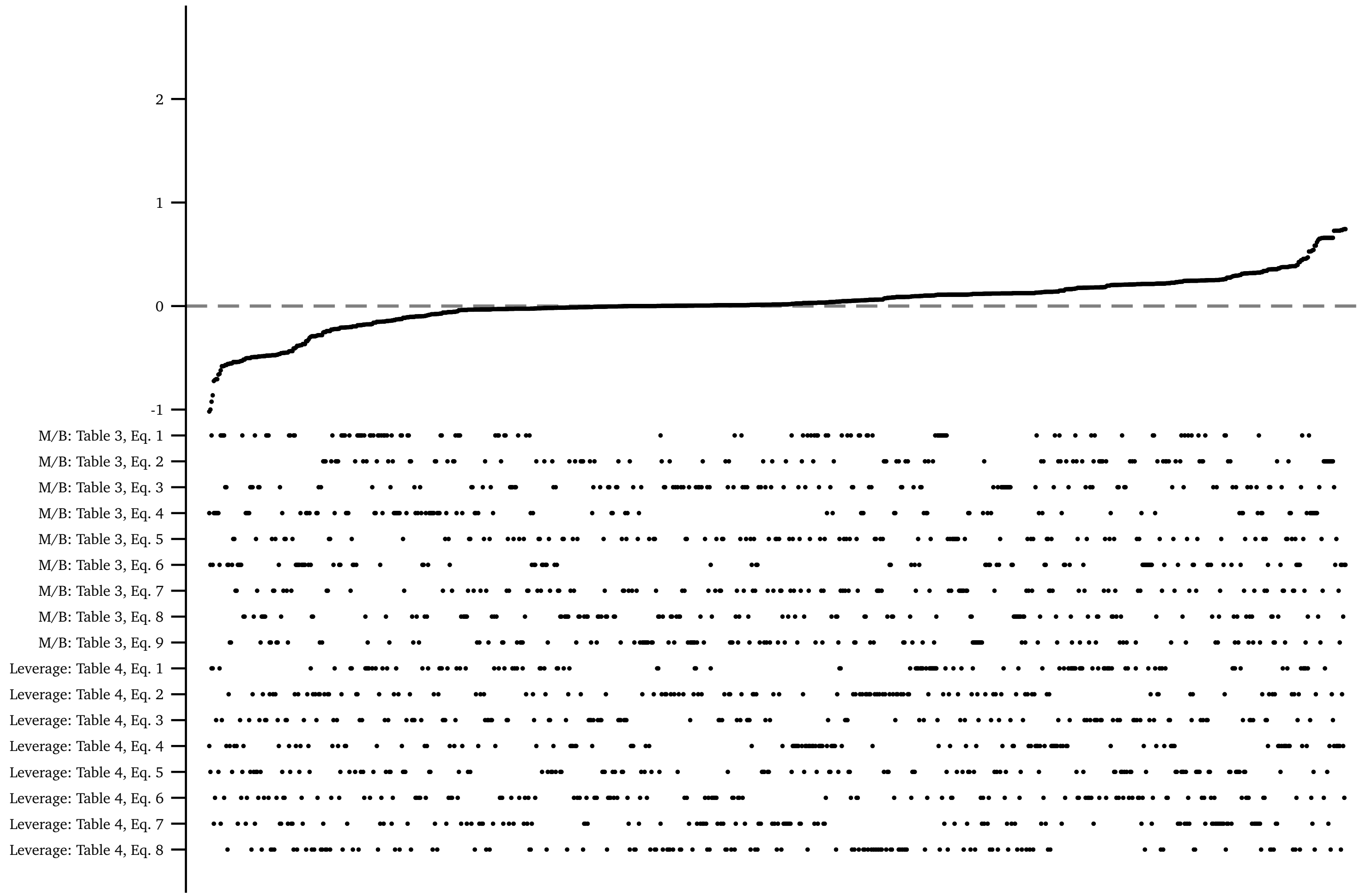


Table 1
Replication summary.

The table reports estimation results from linear regression models examining the relation between the market reaction to acquisition announcements and target lockup options. Replication code written in the foghorn declarative econometric language and the transpiled SQL data manipulation code are available on Github. *t*-statistics are reported in parentheses. Coefficients marked with ***, **, and * are significant at the 1%, 5% and 10% level, respectively.

Paper	Key Economic Variable, Table, and Column	Coefficient		Observations	
		Published	Replicated	Published	Replicated
Bates and Lemmon (2003)	Bidder Termination Fee Indicator Table 8, Column (1)	−0.030**	−0.022**	3037	3203
Becher, Griffin, and Nini (2021)	Financial Covenant Violation Table 6, Column (1)	1.860***	1.093**	7191	7299
Burch (2001)	Lockup (0/1) Table 6, Column (6)	−0.012*	−0.017***	744	776
Fuller, Netter, and Stegemoller (2002)	Dummy = 1 if Fifth or Higher Bid Table VII, Column "Private"	−0.019***	−0.018***	2060	1313
Golubov, Yawson, and Zhang (2015)	Ln (Acquirer Size) Table 1, Column "Full Sample"	−0.004***	−0.003***	12 491	14 863
Gorton, Kahl, and Rosen (2009)	Log 123–456 Size Ratio Table V, Column "Harford Waves (4)"	0.029***	0.041**	1334	1141
Harford, Humphery-Jenner, and Powell (2012)	Dictator Dummy Table 5, Column (1)	−0.524**	−0.594**	3934	3258
John, Knyazeva, and Knyazeva (2015)	Acquirer—Weak Labor Rights Table V, Column (3)	0.494***	0.267**	13 838	13 846

Continued

Table 1
Continued.

Paper	Key Economic Variable, Table, and Column	Coefficient		Observations	
		Published	Replicated	Published	Replicated
Li, Qiu, and Shen (2018)	OC *(Organizational Capital)* Table 2, Column 1	0.250***	0.306**	17 910	17 609
Ma, Whidbee, and Zhang (2019)	RPR *(Relative Price Ratio)* Table 3, Column “All”	−5.487***	−8.878***	19 119	16 014
Masulis, Wang, and Xie (2007)	GIM Index Table VI, Column (1)	−0.107**	−0.083**	3333	3380
Moeller, Schlingemann, and Stulz (2004)	Small *(Market Capitalization Acquirers)* Table 5, Column 1	0.016***	0.015***	9712	10 796
Nguyen and Phan (2017)	PU_Announcement *(Political Uncertainty)* Table 7, Column (3)	0.007**	0.010**	6376	6674
Roosenboom, Schlingemann, and Vasconcelos (2013)	Stock Liquidity Table 2, Column (3)	−0.038***	−0.006***	3815	4189
Wang and Xie (2009)	Shareholder-Rights Difference Table 5, Column “TCAR”	0.836***	0.594**	396	378

Table 2

Cumulative Abnormal Return Definitions in the M&A Literature.

The table presents the definitions of cumulative abnormal returns (CAR) used in the replicated papers. Panel A lists papers that use excess return models, where the daily abnormal return is the stock return less the market index. Panel B lists papers that use abnormal return models, where the daily abnormal return is the stock return less the return predicted by an empirical model. Event windows, *[start, end]*, indicate the start and end days use to sum abnormal returns. Both *start* and *end* are given in trading days relative to the announcement date. The market model include single index models, *SIM*, and the Fama-French 4 factor model, *FF4*. Estimation periods, *[start, end]*, list the start and end days used to estimate the model parameters. Both days are trading days relative to the announcement date.

#	References	Event Window	Market Index/Model	Model Estimation Period
Panel A: Excess Return Models				
1	Bates and Lemmon (2003), Gorton, Kahl, and Rosen (2009), Li, Qiu, and Shen (2018)	[−1, 1]	CRSP Value Weighted	N/A
2	Burch (2001)	[−1, 2]	CRSP Value Weighted	N/A
3	Fuller, Netter, and Stegemoller (2002)	[−2, 2]	CRSP Value Weighted	N/A
Panel B: Abnormal Return Models				
4	Becher, Griffin, and Nini (2021)	[−1, 1]	SIM CRSP Equal Weighted	[−271, −20]
5	Moeller, Schlingemann, and Stulz (2004)	[−1, 1]	SIM CRSP Equal Weighted	[−205, −6]
6	Nguyen and Phan (2017)	[−1, 1]	SIM CRSP Value Weighted	[−210, −11]
7	Harford, Humphery-Jenner, and Powell (2012), Masulis, Wang, and Xie (2007)	[−2, 2]	SIM CRSP Equal Weighted	[−210, −11]
8	Roosenboom, Schlingemann, and Vasconcelos (2013)	[−2, 2]	SIM CRSP Value Weighted	[−245, −46]
9	John, Knyazeva, and Knyazeva (2015)	[−2, 2]	SIM CRSP Value Weighted	[−210, −11]

Continued

Table 2
Continued.

#	References	Event Window	Market Index/Model	Model Estimation Period
10	Golubov, Yawson, and Zhang (2015)	[−2, 2]	SIM CRSP Value Weighted	[−300, −91]
11	Ma, Whidbee, and Zhang (2019)	[−5, 1]	SIM CRSP Equal Weighted	[−370, −253]
12	Wang and Xie (2009)	[−5, 5]	SIM CRSP Value Weighted	[−210, −11]

Table 3

Market-to-book ratio (Tobin's q) control variable alternative definitions used for stress testing.

The table presents the various definitions of market-to-book ratio used in the literature. This ratio is also referred to as Tobin's q in the literature. For each definition, the table lists the formula as `datasource.variable`. `Funda` indicates a variable sourced from Compustat Fundamentals Annual Data, and `Fundq` indicates a variable sourced from Compustat Fundamentals Quarterly data. `at` is the total book value of assets, `ceq` is the total book value of common/ordinary equity, `csho` is the total number of shares of common/ordinary equity as of the fiscal year end, `dlc` is the total book value of debt in current liabilities, `dltt` is the total book value of long-term debt, `lt` is the total book value of liabilities, `prccF` is the closed sharing price at the end of the fiscal year, `txdb` is the balance sheet value of deferred taxes, and `txditc` is the value of deferred taxes and investment tax credit. Missing values of `txdb` and `txditc` are treated as zeros. `preferred` is the liquidating value of preferred stock (`Funda. pstkl`) if it is available, otherwise it is the redemption value (`Funda. pstkrv`).

#	Formula References
1	`(Fundq.at - Fundq.ceq + Fundq.csho × Fundq.prccF) / Fundq.at` Becher, Griffin, and Nini (2021)
2	`(Funda.at - Funda.ceq + Funda.csho × Funda.prccF) / Funda.at` Burch (2001), Harford, Humphery-Jenner, and Powell (2012), Masulis, Wang, and Xie (2007), Moeller, Schlingemann, and Stulz (2004)
3	`(Funda.at + (Funda.prccF × Funda.csho) - Funda.ceq - Funda.txdb) / Funda.at` Golubov, Yawson, and Zhang (2015)
4	`Funda.at + (Funda.prccF × Funda.csho) - Funda.ceq - Funda.txdb / Funda.ceq` Gorton, Kahl, and Rosen (2009)
5	`Funda.csho × Funda.prccF / Funda.at` Li, Qiu, and Shen (2018)
6	`ln (Funda.csho × Funda.prccF / Funda.ceq)` Ma, Whidbee, and Zhang (2019)
7	`ln (Funda.csho × Funda.prccF / Funda.ceq)` Nguyen and Phan (2017)
8	`(Funda.lt - txditc + preferred + Funda.csho × Funda.prccF) / Funda.at` Roosenboom, Schlingemann, and Vasconcelos (2013)
9	`(Funda.at - Funda.ceq + Funda.csho × Funda.prccF) / Funda.at` Wang and Xie (2009)

Table 4

Leverage control variable alternative definitions used for stress testing.

The table presents the various definitions of leverage ratios used in the literature. For each definition, the table lists the formula as `datasource.variable`. `Funda` indicates a variable sourced from Compustat Fundamentals Annual Data, and `Fundq` indicates a variable sourced from Compustat Fundamentals Quarterly data. `Funda.at` (`Funda.atq`) is the annual (quarterly) total book value of assets, `Funda.ceq` is the total annual book value of common/ordinary equity, `Funda.csho` is the total annual number of shares of common/ordinary equity as of the fiscal year end, `Funda.dlc` (`Funda.dlcq`) is the total annual (quarterly) book value of debt in current liabilities, `Funda.dltt` (`Funda.dlttq`) is the total annual (quarterly) book value of long-term debt, `Funda.lt` is the total annual book value of liabilities, `Funda.prccF` is the closed sharing price at the end of the fiscal year, `Funda.txditc` is the annual value of deferred taxes and investment tax credit. Missing values of `Funda.txditc` are treated as zeros. `preferred` is the liquidating value of preferred stock (`Funda.pstkl`) if it is available, otherwise it is the redemption value (`Funda.pstkrv`).

#	Formula References
1	`(Fundq.dlttq + Fundq.dlcq) / Fundq.atq` Becher, Griffin, and Nini (2021)
2	`(Funda.dlc + Funda.dltt) / Funda.at` Burch (2001), Harford, Humphery-Jenner, and Powell (2012), Nguyen and Phan (2017)
3	`(Funda.dltt + Funda.dlc) / (Funda.lt - txditc + preferred + Funda.csho × Funda.prccF)` Golubov, Yawson, and Zhang (2015), Roosenboom, Schlingemann, and Vasconcelos (2013)
4	`(Funda.at - Funda.ceq) / Funda.at` Ma, Whidbee, and Zhang (2019)
5	`(Funda.dlc + Funda.dltt) / (Funda.at + Funda.csho × Funda.prccF)` Masulis, Wang, and Xie (2007)
6	`(Funda.dltt + Funda.dlc) / (Funda.at - Funda.ceq + Funda.csho × Funda.prccF)` Moeller, Schlingemann, and Stulz (2004)
7	`Funda.dlc + Funda.dltt / (Funda.dlc + Funda.dltt + Funda.csho × Funda.prccF)` Li, Qiu, and Shen (2018)
8	`(Funda.dlc + Funda.dltt) / Funda.at` Wang and Xie (2009)

Table 5
CAR Stress Tests: Variables of Interest

size: 9pt, { par(justify: true, leading: 0.2em,)[This table reports summary statistics on stress tests on the significance of the coefficient on the variable of interest by varying the definition of Cumulative Abnormal Returns (CARs) performed on 15 specifications from replicated papers. Stress tests allow for within-literature variation on (1) the CAR announcement window ([−1, +1], [−2, +2], [−3, +3], [−5, +5], [−1, +5], [−5, +1], [0, +5], and [−5, 0]), (2) abnormal return calculation (equally and value weighted single-index model (SIM), a Fama-French 3-factor (FF3) and 4-factor (FF4) model, and the equally weighted (OEW) and value weighted (OVW) market return). (3) the expected return estimation period for tests estimating the market return using the SIM, FF3, and FF4 ([−205, −6], [−210, −11], [−245, −45], [−252, −20], [−272, −20], [−300, −91], and [−370, −253]). Panel A reports summary statistics for *tstat_diff*. *tstat_diff* is defined as the reported/replicated t-statistic less the stress test t-statistic (for reported/replicated t-statistics > 0) and the stress test t-statistic less the reported/replicated t-statistic (for reported/replicated t-statistics < 0). Panel B reports distribution statistics for *tstat_diff*. Panel C reports summary statistics on the proportion of stress tests resulting in lower significance (*tstat_diff*<0), a reduction in the level of significance (i.e. moving from 1% significance to 5% significance), a loss of significance, and an increase in the level of significance.] },)

	N	Mean	Std. Dev.	Skewness	Kurtosis
Panel A: Summary statistics					
All specifications	4543	0.774	1.052	1.257	7.802
<3	3633	0.597	0.762	0.089	3.156

	Min	1%	5%	10%	25%	50%	75%	90%	95%	99%	Max
Panel B: Distribution											
All specifications	−3.711	−1.475	−0.560	−0.228	0.087	0.674	1.261	1.888	2.512	4.720	6.634
<3	−1.966	−1.327	−0.564	−0.265	0.040	0.560	1.154	1.527	1.830	2.486	3.220

	Increase in tstat_diff	Drop in Significance	Loss of Significance	Increase in Significance
Panel C: Changes in statistical significance thresholds (%)				
All specifications	80.176	52.651	36.897	4.708
<3	77.744	63.603	46.052	5.887

Table 6

CAR Stress Tests: Control Variables

This table reports summary statistics on stress tests on the significance of coefficients on control variables by varying the definition of Cumulative Abnormal Returns (CARs) performed on 15 specifications from replicated papers. Stress tests allow for within-literature variation on (1) the CAR announcement window ([−1, +1], [−2, +2], [−3, +3], [−5, +5], [−1, +5], [−5, +1], [0, +5], and [−5, 0]), (2) abnormal return calculation (equally and value weighted single-index model (SIM), a Fama-French 3-factor (FF3) and 4-factor (FF4) model, and the equally weighted (OEW) and value weighted (OVW) market return). (3) the expected return estimation period for tests estimating the market return using the SIM, FF3, and FF4 ([−205, −6], [−210, −11], [−245, −45], [−252, −20], [−272, −20], [−300, −91], and [−370, −253]). Panel A reports summary statistics for *tstat_diff*. *tstat_diff* is defined as the reported/replicated t-statistic less the stress test t-statistic (for reported/replicated t-statistics > 0) and the stress test t-statistic less the reported/replicated t-statistic (for reported/replicated t-statistics < 0). Panel B reports distribution statistics for *tstat_diff*. Panel C reports summary statistics on the proportion of stress tests resulting in lower significance (*tstat_diff* < 0), a reduction in the level of significance (i.e. moving from 1% significance to 5% significance), a loss of significance, and an increase in the level of significance.

	N	Mean	Std. Dev.	Skewness	Kurtosis
Panel A: Summary statistics					
All specifications	52 234	0.336	1.390	1.347	16.592

	Min	1%	5%	10%	25%	50%	75%	90%	95%	99%	Max
Panel B: Distribution											
All specifications	−14.243	−3.397	−1.430	−0.948	−0.291	0.222	0.893	1.675	2.352	4.946	15.480

	Increase in tstat_diff	Drop in Significance	Loss of Significance	Increase in Significance
Panel C: Changes in statistical significance thresholds (%)				
All specifications	61.418	15.985	11.496	11.250

Table 7

Comparing the Distributions of Variables of Interest and Control Variables in CAR Stress Tests

This table reports a two-sample Kolmogorov-Smirnov test for the equality of distributions between the distribution of *tstat_diff* on variables of interest (corresponding to those described in Table 7) and the distribution of *tstat_diff* on control variables (corresponding to those described in Table 10).

Group	D	p-value
Controls	0.197	$<$0.001
Variables of Interest	−0.004	0.816
Combined K-S	0.197	$<$0.001

Table 8

Control Variable Definition Stress Tests: Variables of Interest

This table reports summary statistics on stress tests on the significance of the coefficient on the variable of interest by varying the definition of two independent control variables common across the majority of replicated specifications: market-to-book (Tobin's Q) and leverage. These are performed on all specifications that contain these variables (12) from replicated papers. Stress tests allow for within-literature variation based on the definitions presented in Table 2. Panel A reports summary statistics for *tstat_diff*. *tstat_diff* is defined as the reported/replicated t-statistic less the stress test t-statistic (for reported/replicated t-statistics > 0) and the stress test t-statistic less the reported/replicated t-statistic (for reported/replicated t-statistics < 0). Panel B reports distribution statistics for *tstat_diff*. Panel C reports summary statistics on the proportion of stress tests resulting in lower significance (*tstat_diff*<0), a reduction in the level of significance (i.e. moving from 1% significance to 5% significance), a loss of significance, and an increase in the level of significance.

	N	Mean	Std. Dev.	Skewness	Kurtosis
Panel A: Summary statistics					
All specifications	1136	0.132	0.533	2.336	11.693
<3	848	0.106	0.499	2.068	9.994

	Min	1%	5%	10%	25%	50%	75%	90%	95%	99%	Max
Panel B: Distribution											
All specifications	−1.251	−1.047	−0.501	−0.338	−0.029	0.032	0.207	0.546	1.446	2.320	3.473
<3	−1.251	−1.088	−0.506	−0.251	−0.029	0.025	0.135	0.323	1.502	2.145	2.391

	Increase in tstat_diff	Drop in Significance	Loss of Significance	Increase in Significance
Panel C: Changes in statistical significance thresholds (%)				
All specifications	62.676	18.661	10.651	2.464
<3	61.320	24.764	14.268	3.301

Table 9

Control Variable Definition Stress Tests: Control Variables

This table reports summary statistics on stress tests on the significance of coefficients on control variables by varying the definition of two independent control variables common across the majority of replicated specifications: market-to-book (Tobin's Q) and leverage. These are performed on all specifications that contain these variables (12) from replicated papers. Stress tests allow for within-literature variation based on the definitions presented in Table 2. Panel A reports summary statistics for *tstat_diff*. *tstat_diff* is defined as the reported/replicated t-statistic less the stress test t-statistic (for reported/replicated t-statistics > 0) and the stress test t-statistic less the reported/replicated t-statistic (for reported/replicated t-statistics < 0). Panel B reports distribution statistics for *tstat_diff*. Panel C reports summary statistics on the proportion of stress tests resulting in lower significance (*tstat_diff*<0), a reduction in the level of significance (i.e. moving from 1% significance to 5% significance), a loss of significance, and an increase in the level of significance.

	N	Mean	Std. Dev.	Skewness	Kurtosis
Panel A: Summary statistics					
All specifications	12 784	0.044	0.836	1.021	31.564

	Min	1%	5%	10%	25%	50%	75%	90%	95%	99%	Max
Panel B: Distribution											
All specifications	−9.492	−2.381	−0.696	−0.386	−0.111	−0.001	0.086	0.484	1.097	3.618	11.730

	Increase in tstat_diff	Drop in Significance	Loss of Significance	Increase in Significance
Panel C: Changes in statistical significance thresholds (%)				
All specifications	46.127	4.458	2.933	4.497

Table 10

Comparing the Distributions of Variables of Interest and Control Variables in Control Variable Stress Tests

This table reports a two-sample Kolmogorov-Smirnov test for the equality of distributions between the distribution of *tstat_diff* on variables of interest (corresponding to those described in Table 14) and the distribution of *tstat_diff* on control variables (corresponding to those described in Table 17).

Group	D	p-value
Controls	0.190	<0.001
Variables of Interest	−0.014	0.661
Combined K-S	0.190	<0.001

Stress Testing an Economic Literature

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Replication Table IA1

Replication of Bates and Lemmon (2003), Table 8, Column (1).

The table reports estimation results from linear regression models examining the relation between the market reaction to acquisition announcements and target and bidder termination fees. The dependent variable is the acquiring firm's cumulative abnormal return, which is aggregated over the 3-day trading window beginning 1 trading days prior to and ending 1 trading days following the merger announcement. All variables are as defined in Bates and Lemmon (2003). Replication code written in the foghorn declarative econometric language and the transpiled SQL data manipulation code are available on Github. t-statistics are reported in parentheses. Coefficients displayed in bold represent the key economic variable of interest in the paper. Coefficients marked with ***, **, and * are significant at the 1%, 5% and 10% level, respectively.

	Column (1)	
	Published	Replicated
Target termination fee indicator	0.010 (0.960)	0.014* (1.703)
Bidder termination fee indicator	-0.030** **(-2.340)**	-0.022** **(-2.009)**
Deal includes a lockup of target shares	0.002 (0.820)	0.002 (0.286)
Deal status (1=completed 0=withdrawn)	0.039*** (3.440)	0.018** (1.978)
Prior bidding indicator	-0.063*** (-6.120)	-0.057*** (-5.959)
Stock offer	-0.025*** (-2.540)	-0.034*** (-4.145)
Tender offer	0.091*** (7.530)	0.080*** (7.366)
Bidder toehold	-0.063*** (-4.320)	-0.001** (-2.434)
Deal attitude (1=hostile 0=friendly or unsolicited)	0.040** (2.260)	0.032** (2.206)
Log marketvalue of equity	-0.012*** (-4.600)	<0.001*** (-3.521)
Number of observations	3037	3203
Adjusted-R^2	0.067	0.063

Replication Table IA2

Replication of Becher, Griffin, and Nini (2021), Table 6, Column (1).

The table reports estimation results from linear regression models examining the relation between the market reaction to acquisition announcements and financial covenant violations. The dependent variable is the acquiring firm's cumulative abnormal return, which is aggregated over the 3-day trading window beginning 1 trading days prior to and ending 1 trading days following the merger announcement. All variables are as defined in Becher, Griffin, and Nini (2021). Replication code written in the foghorn declarative econometric language and the transpiled SQL data manipulation code are available on Github. Standard errors are reported in cornered parentheses. Coefficients displayed in bold represent the key economic variable of interest in the paper. Coefficients marked with ***, **, and * are significant at the 1%, 5% and 10% level, respectively.

	Column (1)	
	Published	Replicated
Financial covenant violation	1.860***	1.093**
	〔**0.687**〕	〔**0.537**〕
Size	-0.057***	-0.627***
	〔0.007〕	〔0.059〕
Stock price runup	-0.041	-0.003
	〔0.241〕	〔0.002〕
Market-to-book ratio	-0.277**	-0.278**
	〔0.108〕	〔0.118〕
Operating cash flow / assets	-0.711	9.852**
	〔0.933〕	〔3.952〕
Leverage ratio	0.870	0.847
	〔0.556〕	〔0.574〕
Observations	7191	7299
Adjusted R-squared	0.018	0.030

Replication Table IA3

Replication of Burch (2001), Table 6, Column (6).

The table reports estimation results from linear regression models examining the relation between the market reaction to acquisition announcements and target lockup options. The dependent variable is the acquiring firm's cumulative abnormal return, which is aggregated over the 4-day trading window beginning 1 trading days prior to and ending 2 trading days following the merger announcement. All variables are as defined in Burch (2001). Replication code written in the foghorn declarative econometric language and the transpiled SQL data manipulation code are available on Github. *p*-values are reported in brackets. Coefficients displayed in bold represent the key economic variable of interest in the paper. Coefficients marked with ***, **, and * are significant at the 1%, 5% and 10% level, respectively.

	Column (6)	
	Published	Replicated
Lockup (0/1)	-0.012*	-0.017***
	[0.093]	**[0.002]**
Toehold	0.001**	<0.001
	[0.039]	[0.994]
Completed	<0.001	0.002
	[0.945]	[0.820]
Hostile	0.001	0.015
	[0.880]	[0.209]
Free cash flow	-0.002	-0.030
	[0.910]	[0.285]
Instown	-0.023	-0.012
	[0.106]	[0.370]
Litigation	-0.006	-0.002
	[0.427]	[0.804]
Market-to-book	-0.007***	-0.009***
	[0.002]	[<0.001]
Size	-0.002	-0.003*
	[0.289]	[0.086]
Leverage	0.003	0.023*
	[0.833]	[0.060]
Observations	744	776
Adjusted R-squared	0.018	0.043

Replication Table IA4

Replication of Fuller, Netter, and Stegemoller (2002), Table VII, Column "Private".

The table reports estimation results from linear regression models examining the relation between the market reaction to acquisition announcements and bidding firm acquisition frequency. The dependent variable is the acquiring firm's cumulative abnormal return, which is aggregated over the 5-day trading window beginning 2 trading days prior to and ending 2 trading days following the merger announcement. All variables are as defined in Fuller, Netter, and Stegemoller (2002). Replication code written in the foghorn declarative econometric language and the transpiled SQL data manipulation code are available on Github. *p*-values are reported in brackets. Coefficients displayed in bold represent the key economic variable of interest in the paper. Coefficients marked with ***, **, and * are significant at the 1%, 5% and 10% level, respectively.

	Column "Private"	
	Published	Replicated
Dummy = 1 if target is acquired with common stock	0.043*** [0.007]	0.115** [0.025]
Dummy = 1 if target is acquired with combo	0.009 [0.460]	0.032 [0.580]
Dummy = 1 if first bid	-0.003 [0.685]	-0.010 [0.305]
Dummy = 1 if fifth or higher bid	-0.019*** **[<0.001]**	-0.018*** **[0.005]**
Dummy = 1 if target is foreign	-0.012* [0.062]	-0.006 [0.474]
Dummy = 1 if bidder or target is a tech firm	-0.004 [0.431]	-0.002 [0.722]
Dummy = 1 if target and bidder are in same industry	0.004 [0.358]	-0.013** [0.035]
Log of relative size	0.007*** [0.010]	0.001 [0.662]
Log of target size	0.001 [0.442]	0.002 [0.390]
Interaction variable = relative size × stock	0.011** [0.012]	0.011** [0.020]
Interaction variable = relative size × combo	0.003 [0.513]	0.002 [0.739]
N	2060	1313
F-statistic	5.140	6.310
Adjusted R2	0.035	0.042

Replication Table IA5

Replication of Golubov, Yawson, and Zhang (2015), Table 1, Column "Full Sample".

The table reports estimation results from linear regression models examining the relation between the market reaction to acquisition announcements and acquirer size. The dependent variable is the acquiring firm's cumulative abnormal return, which is aggregated over the 5-day trading window beginning 2 trading days prior to and ending 2 trading days following the merger announcement. All variables are as defined in Golubov, Yawson, and Zhang (2015). Replication code written in the foghorn declarative econometric language and the transpiled SQL data manipulation code are available on Github. *t*-statistics are reported in parentheses. Coefficients displayed in bold represent the key economic variable of interest in the paper. Coefficients marked with ***, **, and * are significant at the 1%, 5% and 10% level, respectively.

	Column "Full Sample"	
	Published	Replicated
Intercept	0.032*** (2.941)	0.051*** (3.226)
Ln (acquirer size)	-0.004*** **(5.496)**	-0.003*** **(-2.856)**
Tobin's Q	-0.002*** (2.966)	-0.001* (-1.912)
Run-up	-0.013*** (4.512)	-0.005*** (-3.484)
Free cash flow	-0.012 (1.331)	-0.014* (-1.711)
Leverage	0.017** (2.523)	0.001 (0.087)
Sigma	0.350** (2.306)	0.075 (0.694)
Relative size	0.002 (1.549)	29.263** (2.191)
Relatedness	<-0.001 (0.160)	0.001 (0.683)
Tender offer	0.002 (0.392)	-0.001 (-0.131)
Hostile	0.007 (0.592)	<0.001 (-0.010)
Public × All-cash	-0.003 (0.755)	-0.006 (-1.490)
Public × Stock	-0.032*** (12.268)	-0.042*** (-9.530)
Private × All-cash	-0.004 (1.520)	-0.002 (-0.933)
Private × Stock	-0.001 (0.259)	-0.002 (-0.822)
Subsidiary × All-cash	0.007*** (2.606)	0.005** (2.066)
N	12491	14863
R2	0.057	0.082
Adj. R2	0.055	0.080

Replication Table IA6

Replication of Gorton, Kahl, and Rosen (2009), Table V, Column “Harford Waves (4)”.

The table reports estimation results from linear regression models examining the relation between the market reaction to acquisition announcements and the distribution of firm sizes in the acquired firm’s industry. The dependent variable is the acquiring firm’s cumulative abnormal return, which is aggregated over the 3-day trading window beginning 1 trading days prior to and ending 1 trading days following the merger announcement. All variables are as defined in Gorton, Kahl, and Rosen (2009). Replication code written in the foghorn declarative econometric language and the transpiled SQL data manipulation code are available on Github. *p*-values are reported in brackets. Coefficients displayed in bold represent the key economic variable of interest in the paper. Coefficients marked with ***, **, and * are significant at the 1%, 5% and 10% level, respectively.

	Column “Harford Waves (4)”	
	Published	Replicated
Log 123–456 size ratio	0.029***	0.041**
	[0.007]	**[0.023]**
Cash	0.001	0.004
	[0.881]	[0.520]
Ratio	0.003	0.007
	[0.694]	[0.497]
Log value	-0.006***	-0.004**
	[<0.001]	[0.029]
Tar priv	0.015***	0.024***
	[0.001]	[<0.001]
Tar sub	0.022***	0.020***
	[<0.001]	[0.010]
Cross industry	0.007	0.009
	[0.104]	[0.405]
Competing bid	0.006	-0.036**
	[0.720]	[0.014]
Tender offer	0.017*	0.019*
	[0.056]	[0.086]
Stock market return	-0.001	0.003
	[0.861]	[0.558]
Market/book	0.002*	0.001
	[0.080]	[0.114]
Industry Herfindahl	0.036	0.109**
	[0.720]	[0.032]
Observations	1334	1141
R2	0.113	0.075

Replication Table IA7

Replication of Harford, Humphery-Jenner, and Powell (2012), Table 5, Column (1).

The table reports estimation results from linear regression models examining the relation between the market reaction to acquisition announcements and managerial entrenchment. The dependent variable is the acquiring firm's cumulative abnormal return, which is aggregated over the 5-day trading window beginning 2 trading days prior to and ending 2 trading days following the merger announcement. All variables are as defined in Harford, Humphery-Jenner, and Powell (2012). Replication code written in the foghorn declarative econometric language and the transpiled SQL data manipulation code are available on Github. Standard errors are reported in cornered parentheses. Coefficients displayed in bold represent the key economic variable of interest in the paper. Coefficients marked with ***, **, and * are significant at the 1%, 5% and 10% level, respectively.

	Column (1)	
	Published	Replicated
Dictator dummy	-0.524**	-0.594**
	〔**-0.210**〕	〔**0.243**〕
Subsidiary	2.059***	2.749***
	〔-0.327〕	〔0.385〕
Private	1.495***	2.325***
	〔-0.278〕	〔0.386〕
All cash	0.313	0.286
	〔-0.310〕	〔0.254〕
All stock	-0.813**	-0.498
	〔-0.345〕	〔0.426〕
Log firm age	-0.016	-0.072
	〔-0.152〕	〔0.167〕
Stock run-up	0.977***	-2.037***
	〔-0.340〕	〔0.351〕
PRIV	-0.085***	0.051
	〔-0.019〕	〔0.037〕
Log market value	-0.318***	<0.001
	〔-0.083〕	〔<0.001〕
Tobin's q	0.292**	0.069
	〔-0.117〕	〔0.164〕
Free cash flow	6.625*	-1.796
	〔-3.892〕	〔2.206〕
Leverage	3.187***	-1.182
	〔-1.041〕	〔0.793〕
Industry M&A	-0.156	-2.785**
	〔-6.130〕	〔1.375〕
Relative size	0.146	1.707***
	〔-0.793〕	〔0.614〕

Continued

Replication Table IA7
Continued

	Column (1)	
	Published	Replicated
Tech	0.314	-0.294
	〔-0.248〕	〔0.340〕
Conglomerate	0.038	0.422*
	〔-0.227〕	〔0.238〕
Competed	-0.948	-1.073
	〔-0.701〕	〔0.653〕
Volume	0.124	-0.332*
	〔-0.098〕	〔0.182〕
Cross-border	2.964**	-0.186
	〔-1.160〕	〔0.294〕
Friendly	-2.786***	-2.640***
	〔-0.870〕	〔0.872〕
Serial_3	0.092	-0.154
	〔-0.274〕	〔0.312〕
Number of observations	3934	3258
F-statistic	8.310***	8.804
Adjusted R2	0.073	0.054

Replication Table IA8

Replication of John, Knyazeva, and Knyazeva (2015), Table V, Column (3).

The table reports estimation results from linear regression models examining the relation between the market reaction to acquisition announcements and state-level labor rights. The dependent variable is the acquiring firm's cumulative abnormal return, which is aggregated over the 5-day trading window beginning 2 trading days prior to and ending 2 trading days following the merger announcement. All variables are as defined in John, Knyazeva, and Knyazeva (2015). Replication code written in the foghorn declarative econometric language and the transpiled SQL data manipulation code are available on Github. *t*-statistics are reported in parentheses. Coefficients displayed in bold represent the key economic variable of interest in the paper. Coefficients marked with ***, **, and * are significant at the 1%, 5% and 10% level, respectively.

	Column (3)	
Acquirer—weak labor rights	0.494***	0.267**
	(5.440)	**(2.122)**
Acquirer size	-0.262***	-0.325***
	(-5.250)	(-6.621)
Relative deal size	-0.882***	2.024***
	(-3.530)	(10.551)
Diversifying acquisition	-0.081	-0.447**
	(-0.930)	(-2.115)
Tech indicator	0.276	-0.939***
	(0.590)	(-3.617)
Number of observations	13838	13846
R2	0.010	0.034

Replication Table IA9

Replication of Li, Qiu, and Shen (2018), Table 2, Column 1.

The table reports estimation results from linear regression models examining the relation between the market reaction to acquisition announcements and organizational capital. The dependent variable is the acquiring firm's cumulative abnormal return, which is aggregated over the 3-day trading window beginning 1 trading days prior to and ending 1 trading days following the merger announcement. All variables are as defined in Li, Qiu, and Shen (2018). Replication code written in the foghorn declarative econometric language and the transpiled SQL data manipulation code are available on Github. Standard errors are reported in cornered parentheses. Coefficients displayed in bold represent the key economic variable of interest in the paper. Coefficients marked with ***, **, and * are significant at the 1%, 5% and 10% level, respectively.

	Column 1	
OC	0.250***	0.306**
	〔**0.084**〕	〔**0.125**〕
ROA	-0.007	-0.004
	〔0.008〕	〔0.007〕
M/B	-0.032	-0.083**
	〔0.021〕	〔0.041〕
LEVERAGE	2.921***	3.452***
	〔0.396〕	〔1.061〕
PAST_RETURN	0.002*	0.008***
	〔0.001〕	〔0.002〕
TOP5_INSTITUTIONS	-1.905***	-1.131
	〔0.563〕	〔1.128〕
FIRM_SIZE	-0.405***	-0.513***
	〔0.040〕	〔0.082〕
ALL_CASH	0.536***	0.371**
	〔0.127〕	〔0.157〕
ALL_STOCK	0.023	-0.015
	〔0.196〕	〔0.313〕
DIVERSIFYING	-0.037	-0.069
	〔0.132〕	〔0.179〕
TENDER_OFFER	1.138***	1.272***
	〔0.311〕	〔0.357〕
RELATIVE_SIZE	0.950***	0.175
	〔0.168〕	〔0.127〕
PRIVATE_TARGET	2.270***	2.026***
	〔0.186〕	〔0.251〕
SUBSIDIARY_TARGET	2.758***	2.815***
	〔0.198〕	〔0.279〕
No. of obs.	17910	17609
Adj. R2	0.053	0.035

Replication Table IA10

Replication of Ma, Whidbee, and Zhang (2019), Table 3, Column “All”.

The table reports estimation results from linear regression models examining the relation between the market reaction to acquisition announcements and acquirer stock price relative to its 52-week high. The dependent variable is the acquiring firm’s cumulative abnormal return, which is aggregated over the 7-day trading window beginning 5 trading days prior to and ending 1 trading days following the merger announcement. Reference price ratio (RPR) is the ratio of the acquirer’s preannouncement stock price to its 52-week high price. All variables are as defined in Ma, Whidbee, and Zhang (2019). Replication code written in the foghorn declarative econometric language and the transpiled SQL data manipulation code are available on Github. *t*-statistics are reported in parentheses. Coefficients displayed in bold represent the key economic variable of interest in the paper. Coefficients marked with ***, **, and * are significant at the 1%, 5% and 10% level, respectively.

	Column “All”	
	Published	Replicated
RPR	-5.487***	-8.878***
	(-8.560)	**(-12.977)**
Ln(M/B)	-0.285**	-1.169***
	(-2.140)	(-8.175)
Stock	-1.208***	-1.459***
	(-4.060)	(-4.768)
Cash	0.145	0.453***
	(0.910)	(2.833)
Private	2.321***	1.322***
	(10.600)	(6.228)
Stock × Private	2.125***	2.299***
	(5.040)	(5.178)
Rel. size	2.216***	1.803***
	(8.800)	(6.574)
Size	-0.398***	-0.171***
	(-7.690)	(-3.107)
Leverage	-0.081	0.424
	(-0.210)	(0.964)
Dormant > 1 yr	0.628***	0.695**
	(2.880)	(2.349)
Same industry	0.107	0.237
	(0.670)	(1.437)
Tender offer	1.058**	0.139
	(2.220)	(0.380)
Hostile	-0.759*	-0.826
	(-1.890)	(-1.597)
Toehold	0.047	-0.565**
	(0.100)	(-2.431)
Cross border	-0.187	-0.028
	(-0.770)	(-0.113)
Past return	0.777***	2.943***
	(4.700)	(15.511)
N	19119	16014
Adj. R2	0.064	0.083

Replication Table IA11

Replication of Masulis, Wang, and Xie (2007), Table VI, Column (1).

The table reports estimation results from linear regression models examining the relation between the market reaction to acquisition announcements and corporate governance. The dependent variable is the acquiring firm's cumulative abnormal return, which is aggregated over the 5-day trading window beginning 2 trading days prior to and ending 2 trading days following the merger announcement. All variables are as defined in Masulis, Wang, and Xie (2007). Replication code written in the foghorn declarative econometric language and the transpiled SQL data manipulation code are available on Github. *t*-statistics are reported in parentheses. Coefficients displayed in bold represent the key economic variable of interest in the paper. Coefficients marked with ***, **, and * are significant at the 1%, 5% and 10% level, respectively.

	Column (1)	
	Published	Replicated
Antitakeover Provisions:		
GIM index	-0.107**	-0.083**
	(-2.490)	**(-2.072)**
Bidder Characteristics:		
Log(total assets)	-0.301***	-0.328***
	(-3.590)	(-3.634)
Tobin's q	-0.085	-0.033
	(-0.680)	(-0.227)
Free cash flow	1.902	-0.755
	(0.860)	(-0.335)
Leverage	0.678	-0.284
	(0.640)	(-0.239)
Stock price runup	-0.906**	-1.526***
	(-2.540)	(-4.156)
Deal Characteristics:		
Industry M&A	-1.096	-1.637
	(-0.770)	(-1.110)
Relative deal size	0.209	1.486**
	(0.360)	(2.253)
High tech	0.420	-0.197
	(0.920)	(-0.506)
High tech × relative deal size	-6.078***	-0.824
	(-3.150)	(-0.355)
Diversifying acquisition	-0.269	0.165
	(-0.880)	(0.685)
Public target × stock deal	-3.902***	-2.758***
	(-7.290)	(-7.314)
Public target × all-cash deal	-2.082***	-0.942*
	(-3.340)	(-1.891)
Private target × all-cash deal	-1.969***	-0.685
	(-3.530)	(-1.502)
Private target × stock deal	-1.689***	-0.408
	(-3.100)	(-1.280)
Subsidiary target × all-cash deal	-1.472***	-0.069
	(-2.900)	(-0.190)
Number of obs.	3333	3380
Adjusted-R^2	0.062	0.055

Replication Table IA12

Replication of Moeller, Schlingemann, and Stulz (2004), Table 5, Column (1)

The table reports estimation results from linear regression models examining the relation between the market reaction to acquisition announcements and firm size. The dependent variable is the acquiring firm's cumulative abnormal return, which is aggregated over the 3-day trading window beginning 1 trading days prior to and ending 1 trading days following the merger announcement. All variables are as defined in Moeller, Schlingemann, and Stulz (2004). Replication code written in the foghorn declarative econometric language and the transpiled SQL data manipulation code are available on Github. *p*-values are reported in brackets. Coefficients displayed in bold represent the key economic variable of interest in the paper. Coefficients marked with ***, **, and * are significant at the 1%, 5% and 10% level, respectively.

	Column (1)	
	Published	Replicated
Intercept	0.015*** [<0.001]	0.004 [0.196]
Private	-0.004* [0.085]	-0.007*** [0.004]
Public	-0.032*** [<0.001]	-0.028*** [<0.001]
Small	**0.016*** [<0.001]**	**0.015*** [<0.001]**
Conglomerate	-0.004* [0.051]	0.001 [0.736]
Tender offer	0.015*** [0.001]	0.014*** [0.003]
Hostile	-0.012 [0.195]	0.019* [0.065]
Competed	-0.007 [0.299]	-0.010 [0.234]
All equity	-0.003 [0.341]	0.001 [0.829]
All cash	-0.004** [0.047]	0.002 [0.315]
Relative size	0.012*** [0.001]	<0.001 [0.102]
Tobin's q	-0.001* [0.064]	<0.001 [0.573]
Debt/assets(mkt.)	0.001 [0.876]	-0.012* [0.057]
Liquidity index	-0.009*** [0.003]	-0.001 [0.121]
CF/assets (mkt.)	0.001 [0.811]	0.031*** [0.002]
n	9712	10796
Adjusted-R2	0.052	0.018

Replication Table IA13

Replication of Nguyen and Phan (2017), Table 7, Column (3).

The table reports estimation results from linear regression models examining the relation between the market reaction to acquisition announcements and government policy uncertainty. The dependent variable is the acquiring firm's cumulative abnormal return, which is aggregated over the 3-day trading window beginning 1 trading days prior to and ending 1 trading days following the merger announcement. All variables are as defined in Nguyen and Phan (2017). Replication code written in the foghorn declarative econometric language and the transpiled SQL data manipulation code are available on Github. *t*-statistics are reported in parentheses. Coefficients displayed in bold represent the key economic variable of interest in the paper. Coefficients marked with ***, **, and * are significant at the 1%, 5% and 10% level, respectively.

	Column (3)	
	Published	Replicated
PU_ANNOUNCEMENT	0.007**	0.010**
	(2.040)	**(2.265)**
SIZE	-0.007***	-0.005**
	(8.400)	(-2.451)
MARKET-TO-BOOK_RATIO	-0.003**	-0.001
	(2.570)	(-1.108)
PAST_12_MONTH_RETURNS	-0.003	0.005***
	(1.060)	(2.863)
AVERAGE_SALES_GROWTH	-0.006	<0.001***
	(1.040)	(5.078)
BOOK_LEVERAGE	0.022***	0.005
	(3.940)	(0.678)
NONCASH_WORKING_CAPITAL	0.016	-0.005
	(1.600)	(-0.403)
FIRM_AGE	0.006**	<0.001**
	(2.720)	(2.227)
EXCESS_CASH	0.001***	<0.001
	(4.930)	(-0.437)
DEAL_RATIO	0.001	0.024*
	(1.440)	(1.829)
STOCK_DUMMY	-0.002	-0.006*
	(0.660)	(-1.744)
CASH_DUMMY	0.008***	0.013***
	(4.360)	(5.105)
HIGH_TECH_DUMMY	-0.007**	-0.004
	(2.210)	(-1.484)
DIVERSIFYING_DUMMY	-0.001	-0.003
	(0.440)	(-1.200)

Continued

Replication Table IA13
Continued

	Column (3)	
	Published	Replicated
HOSTILE_DUMMY	-0.020 (1.390)	-0.021 (-1.366)
PUBLIC_TARGET_DUMMY	-0.017*** (4.720)	-0.027*** (-6.401)
CHALLENGE_DUMMY	0.015** (2.300)	-0.009 (-1.345)
TARGET_INDUSTRY_M&A_INTENSITY	0.001 (0.570)	<0.001 (-1.421)
Intercept	0.012 (0.740)	-0.005 (-0.169)
No. of obs.	6376	6674
Adj. R2	0.030	0.113

Replication Table IA14

Replication of Roosenboom, Schlingemann, and Vasconcelos (2013), Table 2, Column (3).

The table reports estimation results from linear regression models examining the relation between the market reaction to acquisition announcements and acquiring firm stock liquidity. The dependent variable is the acquiring firm's cumulative abnormal return, which is aggregated over the 5-day trading window beginning 2 trading days prior to and ending 2 trading days following the merger announcement. All variables are as defined in Roosenboom, Schlingemann, and Vasconcelos (2013). Replication code written in the foghorn declarative econometric language and the transpiled SQL data manipulation code are available on Github. *p*-values are reported in brackets. Coefficients displayed in bold represent the key economic variable of interest in the paper. Coefficients marked with ***, **, and * are significant at the 1%, 5% and 10% level, respectively.

	Column (3)	
	Published	Replicated
Stock Liquidity	-0.038*** **[0.006]**	-0.006*** **[<0.001]**
Payment = Equity	-0.008*** [0.005]	-0.016*** [<0.001]
Target = Public	-0.024*** [<0.001]	-0.026*** [<0.001]
Target = Subsidiary	0.010*** [0.001]	0.006* [0.061]
Relative Size	-0.002 [0.800]	0.005 [0.418]
Total Assets	<0.001 [0.996]	0.001 [0.560]
Leverage	<0.001 [0.997]	0.022* [0.067]
Market to Book	0.001 [0.514]	-0.015 [0.108]
Cash Flow	0.018 [0.401]	-0.003 [0.840]
Observations	3815	4189
Adjusted-R^2	0.057	0.074

Replication Table IA15

Replication of Wang and Xie (2009), Table 5, Column "TCAR".

The table reports estimation results from linear regression models examining the relation between the market reaction to acquisition announcements and shareholder rights. The dependent variable is the acquiring firm's cumulative abnormal return, which is aggregated over the 11-day trading window beginning 5 trading days prior to and ending 5 trading days following the merger announcement. All variables are as defined in Wang and Xie (2009). Replication code written in the foghorn declarative econometric language and the transpiled SQL data manipulation code are available on Github. *t*-statistics are reported in parentheses. Coefficients displayed in bold represent the key economic variable of interest in the paper. Coefficients marked with ***, **, and * are significant at the 1%, 5% and 10% level, respectively.

	Column "TCAR"	
	Published	Replicated
Shareholder-rights difference (Target index - bidder index)	0.836***	0.594**
	(3.480)	**(2.170)**
Bidder Characteristics:		
Log(market cap)	2.084	0.582
	(1.250)	(0.207)
Tobin's Q	-0.543	-0.589
	(-0.570)	(-0.539)
Leverage	-10.512*	-13.799***
	(-1.710)	(-2.590)
Return on assets (ROA)	35.827***	38.425***
	(2.660)	(2.866)
Target Characteristics:		
Log(market cap)	-3.985**	-6.677**
	(-2.480)	(-2.194)
Tobin's Q	-0.114	-0.624
	(-0.100)	(-0.649)
Leverage	-1.101	4.273
	(-0.170)	(0.876)
Return on assets (ROA)	-12.927	-9.049
	(-1.200)	(-0.854)
Deal Characteristics:		
Market cap ratio	-5.770	-8.000***
	(-1.590)	(-2.623)
Tender offer	9.859**	5.007*
	(2.550)	(1.833)
Diversifying acquisition	3.873	3.232
	(1.500)	(1.579)
All cash deal	2.022	2.059
	(0.440)	(0.782)
Merger of equals	-9.446***	-0.385
	(-3.990)	(-0.100)
High-tech combination	0.042	-1.284
	(0.010)	(-0.574)
Number of Obs.	396	378
Adjusted R2	0.216	0.190