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RESEARCH ARTICLE

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Repositioning, audience churn, and identity ambiguity: The external costs of market repositioning

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Abstract

Research Summary: Prior literature has long underscored the importance for market actors to establish clear identities. Extant studies mostly adopt a static view, assessing whether actors adhere to a specific prototype or membership. By stressing a dynamic perspective, we maintain that identities are in flux as actors constantly shift positions. Specifically, we emphasize that repositioning can induce identity ambiguity, undermining the accuracy of audience evaluation. Analyzing market repositioning of US firms, we find that firms with greater repositioning tend to experience a higher degree of churn in their coverage audiences (financial analysts). More importantly, audiences are found to be less accurate in evaluating firms that undertake greater repositioning. These results align with our conjecture about external repositioning costs: Firms risk incurring identity ambiguity when shifting market positions.

Managerial Summary: Firms constantly reposition in the market via adjusting their product portfolios. We maintain that firms with greater repositioning are subject to considerable external costs, because repositioning can breed ambiguity about their market identities. By analyzing product market positioning and repositioning of US public firms, we find that firms' repositioning often leads to an increased turnover of analysts covering them and undermines the accuracy of analysts' forecasts on their earnings. Our extensions also indicate that firms' repositioning efforts may be less ambiguous, when their initial position is more conventional in the product space and/or when analysts have developed greater firm-specific experiences. Together, the findings underscore the importance for firms to consider external costs in their repositioning processes.

KEYWORDS

analyst coverage, competitive repositioning, forecast accuracy, market category, market identity

1 | INTRODUCTION

Prior literature has long established the importance for market actors to establish a clear and coherent identity, which is useful for producers to recognize peers, consumers to compare products, and other audiences to classify firms and products (Durand & Paolella, 2013; Zuckerman, 1999). Otherwise, actors may incur penalties for presenting ambiguous identities if their positions defy prevailing market prototypes or categorical frames (Leung & Sharkey, 2014; Litov et al., 2012; Pontikes, 2012; Zuckerman, 2004). While research on identity ambiguity has proliferated over decades (David & Lee, 2022; Durand & Thornton, 2018), most of current studies conceptualize it from a static perspective, focusing on how actors' extant identities are presented and interpreted by audiences at a given time point (Cutolo & Ferriani, 2024). However, much less attention is paid to the dynamics of market positions and identities, with only a few exceptions (Kovács et al., 2023).

Actors' identities are not fixed, but in flux over time. Individuals may jump from one job category to another (Kovács et al., 2023; Leung, 2014; Zuckerman et al., 2003), and firms may shift between product market categories (Bhaskarabhatla et al., 2021; Pontikes & Barnett, 2015). Such dynamics deserve more attention as they bear importance for understanding market identities. Specifically, we maintain that actors' repositioning is likely to ambiguate their identities as audiences may feel uncertain about what to expect from actors with considerable positional changes (Hsu et al., 2011). While prior research has long emphasized the detrimental effect of repositioning or change (Benner, 2010; Leung, 2014), however, there is a lack of direct evidence regarding whether and how repositioning relates to identity ambiguity (Kovács et al., 2023). To address this important gap, we emphasize the repositioning-induced identity ambiguity, by examining its impact on the accuracy of audience evaluation.

By doing so, this study mainly extends research on market identities. Specifically, moving beyond a static consideration of position-based identities, we highlight the vital implications of dynamic repositioning. While prior work has long posited that actors with ambiguous identities risk ignorance or penalty (Durand & Thornton, 2018), most studies focus on the cross-sectional association between actors' positioning and audiences' evaluation. Some scholars, for instance, examine the implications of firms' positioning that deviate from market prototypes (Litov et al., 2012), some explore how audiences react to offerings that span categories (Leung & Sharkey, 2014; Lo & Kennedy, 2015), and others highlight the fates of firms that fail to secure coherent categorical memberships (Bowers, 2015; Zuckerman, 2004). Despite so, much less attention is paid to the implications of actors' longitudinal changes in market positions. Actors may alter their distance from prototypes, convert from being category-spanners to specialists, or reshuffle their categorical adherence (Kovács et al., 2023; Leung, 2014; Zuckerman, 2000). Repositioning deserves greater emphasis from research on market identities, as identity ambiguity is not only associated with actors' extant positioning, but also with their repositioning—the extent to which their positions have been altered. Although this has been hinted or theorized in some of prior studies (Benner, 2010; Tripsas, 2009), we are among the first to establish how repositioning affects the *accuracy* of audience evaluation, thereby providing more direct evidence on repositioning-induced identity ambiguity.

Our work also builds on and adds to studies on typecasting (Kovács et al., 2023; Zuckerman et al., 2003). Earlier research on typecasting emphasizes that actors with past specialization in one particular category gain less opportunities to reposition into others, because audiences would question their skills to explore distant areas (Ferguson & Hasan, 2013; Leung, 2014; Zuckerman et al., 2003). Recent studies call for attention to examining the consequences after actors have repositioned. Specifically, Kovács et al. (2023) highlight that when book authors change genres in their new publications, readers may be slow in updating their expectations, resulting in categorical "mismatch" and devaluation of the new books. Extending this, we emphasize a potential "self-selection" from the audience side (Feldman, 2016; Theeke et al., 2018), by arguing that the repositioning-led mismatch will foster audience churn. Instead of assuming that audiences are somehow "blind" to actors' repositioning, we conjecture that they may actively respond to the repositioning-led mismatch with their feet. However, the "self-selection" is far from sufficient, such that actors' repositioning will still undermine the evaluation accuracy of market audiences. By doing so, we shift attention from whether audiences accept or penalize the repositioned actors (Kovács et al., 2023; Zuckerman et al., 2003) to whether audiences are capable of accurately evaluating these actors.

Moreover, our study may help extend the literature on competitive repositioning, that is, the extent to which firms change their product portfolios or move between market segments (de Figueiredo & Silverman, 2007; Dobrev & Kim, 2006). While prior work has examined various driving forces for firms' repositioning (Bhaskarabhatla et al., 2021; Wang & Shaver, 2014), recent studies advocate greater recognition of various repositioning costs. Menon and Yao (2017), for instance, underscore the costs associated with repositioning complexity and path dependence, and Argyres et al. (2019) distinguish between adjustment, transaction, and opportunity costs. While important, existing studies focus mostly on the "internal" costs or barriers to changes at the producer side. However, much less is discussed about the costs at the audience side. We highlight that competitive repositioning incurs substantial "external costs" as it breeds identity ambiguity that challenges audience evaluation.

We test our hypotheses in publicly listed US firms between 2001 and 2020. This research context fits well for several reasons. First, prior studies have long established that firms in this setting are largely subject to the influence of market identities (Litov et al., 2012; Wang & Jensen, 2019; Zuckerman, 2000). Second, while it is challenging to develop a general measure of repositioning, the indicator developed by Hoberg et al. (2014) for all of US public firms can more precisely capture the degree of their repositioning in the product space. Finally, whereas prior studies usually use audiences' ignorance or devaluation as indirect evidence for identity ambiguity (Cudennec & Durand, 2023; Hsu et al., 2009; Kovács et al., 2023; Leung &

Sharkey, 2014), this research setting allows a more direct test of ambiguity via analyzing the accuracy of financial analysts' forecasts (Feldman et al., 2014). Our findings suggest that firms with greater repositioning will experience a higher churn in the analysts who cover them, and that analysts are less accurate in forecasting the earnings of the repositioned firms. The evidence together lends support to our claims about external repositioning costs: Firms risk incurring identity ambiguity when shifting market positions.

2 | THEORY

2.1 | Market identities

Market identities denote actors' positions in the market that are used to specify what to expect from them, serving as important interfaces between actors and their external audiences (Kim & Jensen, 2011; Zuckerman, 1999). This stream of literature has long underscored the importance for actors to present a clear, coherent, and robust market identity (Jensen & Kim, 2014). If not, actors presenting ambiguous identities are likely to be ignored or penalized by market audiences (Hsu, 2006; Leung & Sharkey, 2014; Zuckerman et al., 2003). Then, under what conditions are market identities clear or ambiguous? Prior literature has employed different approaches to conceptualize market identities.

First, market identities are often established through a process of categorizing actors, based on how their observable characteristics align with a category's prototype (Litov et al., 2012). For hedge funds, their identities are assigned according to the closeness of each fund's investment distribution to conventional others (Smith, 2011). The closer it is, the less ambiguous a fund's identity becomes. Second, market identities are also based on the extent to which actors exhibit key attributes in the categories. For classic symphony orchestras, their identities are more robust if they focus on a subset of highly salient composers (e.g., Mozart or Beethoven) (Durand & Kremp, 2016). Third, market identities are also related to category spanning (Hsu et al., 2009). When actors straddle multiple categories, their identities become blurry as audiences may find it confusing to interpret and evaluate them. Supporting this, Negro and Leung (2013) show that wines spanning styles get lower ratings, Leung and Sharkey (2014) present that projects with more category labels receive less funding, and Lo and Kennedy (2015) report that patent examiners spend longer time processing inventions that straddle technology classes.[1] See Cutolo and Ferriani (2024) for a thorough review.

While the short review above shows the prevalence of market identities, one commonality of prior studies also looms large. Extant research on market identities focuses mostly on actors' extant category memberships at a given time point (e.g., industries, film genres, wine styles, or status) (Hsu, 2006; Negro & Leung, 2013; Smith, 2011; Wang & Jensen, 2019), but pay less attention to their membership changes or repositioning in the market. Indeed, firms may adjust their industry memberships via divestment or spin-offs (Feldman, 2016; Zuckerman, 2000), universities' status rankings may fluctuate over years (Askin & Bothner, 2016), artists may adjust their distinctiveness from peers in next albums (Negro et al., 2022), and film actors may

[1]Recent work also emphasizes the heterogeneity of categories in their contrast. When a category has low-contrast, blurry boundaries, actors within it may endure ambiguous identities even without spanning categories (Kovács & Hannan, 2010; Ubisch & Wang, 2023). Moreover, Wang and Jensen (2019) highlight that identity ambiguity is associated not only with bridging product categories but also with status inconsistency across status positions.

occasionally try genres new to them (Zuckerman et al., 2003). Such changes deserve attention as they also shape how ambiguous actors' identities are. Specifically, if an actor's categorical positioning serves as an important signal for its market identity that sets audience expectations (Negro et al., 2015), repositioning will lead to temporal inconsistency of signals. This inconsistency can make its identity ambiguous as audiences are confused about what to expect from it (Connelly et al., 2011; Wang, 2022).

2.2 | Repositioning and identity ambiguity

Actors' categorical memberships are never static as they are constantly repositioning. Repositioning here refers to the extent to which actors change their market positions. For example, firms may adjust their product portfolios or alter their submarket participations, individuals may change their occupations or job market categories, and entrepreneurs may change industries in their subsequent venturing (Bigelow et al., 2019; Eggers & Song, 2015; Leung, 2014; Pontikes & Barnett, 2015; Tripsas, 2009; Zuckerman et al., 2003). Repositioning may be driven by different forces. First, external shocks often drive actors to reshuffle their positions (Argyres et al., 2019). TV broadcasting firms, for instance, may abandon their current positions when dominant rivals move closer (Wang & Shaver, 2014); wholesale firms may expand their positions after abrupt exit of major competitors (Ren et al., 2019); pharmaceutical and food producers may reposition away from the submarkets that are constrained by new regulations (Bhaskarabhatla et al., 2021; Hou & Yao, 2022). Second, even without exogenous shocks, firms are found to constantly alter their market positions, entering new segments to pursue opportunities or leaving current segments to reallocate resources (de Figueiredo & Silverman, 2007; Dobrev & Kim, 2006; Pontikes & Barnett, 2015).

Given the ubiquity, it is surprising that repositioning has not been well incorporated into research on market identities. We underscore dynamic repositioning as it complements current literature on cross-sectional categorical positioning. Suppose an actor undergoes constant repositioning, shifting from one crisp category to another every year. If we adopt a static view to consider its membership at each point of time, its categorial identity would be defined as being clear since it does not straddle categories. However, if employing a dynamic perspective, one would perceive a less robust identity because of the categorial shift it has made (Benner, 2010).

Emphasizing the role of repositioning in constructing market identities, our core premise is that actors' repositioning can result in identity ambiguity. As reviewed above, market identities are assigned based on actors' positions, according to their product portfolios, organizational alignments, or category spanning (Cudennec & Durand, 2023; Durand & Kremp, 2016; Jensen & Kim, 2014; Litov et al., 2012; Smith, 2011). If so, actors' repositioning will imply that their identities are in flux. When actors change market positions, their identities are altered. For instance, if firms revise product portfolios (Hou & Yao, 2022; Wang & Shaver, 2014), their adherence to market prototypes is changed; if actors shift affiliations with submarkets or categories (Kovács et al., 2023; Pontikes & Barnett, 2015; Zuckerman, 2000), their categorical memberships are simultaneously modified. This will breed identity ambiguity as audiences are uncertain about what to expect from them. Because of this, we conjecture that repositioning will have two important consequences: audience churn and evaluation inaccuracy.

2.2.1 | Audience churn

Repositioning may lead to a greater degree of audience churn (i.e., the turnover of audiences). Market audiences, particularly those professional intermediaries (e.g., financial analysts or professional critics), tend to specialize in only a few categories that fit well with their technical or cultural knowledge (Sharkey et al., 2022; Zuckerman, 2004). In other words, audiences' expertise, preference, or coverage choices are usually position-based. When an actor changes its position, extant audiences may become mismatched as they may not have the knowledge (or taste) for its new position (Kovács et al., 2023). The mismatch may undermine the ability of these audiences to interpret and evaluate the actor. This will drive these audiences to abandon their coverage because their performance, reputation, and career are likely dependent on the extent to which they can accurately assess the actor and its offerings (Feldman, 2016; Theeke et al., 2018). Meanwhile, after positional changes, the actor may attract a set of new audiences who are more interested in and/or specialized for its new position. As a result, we expect that reposition-led mismatch will lead audiences to "self-select" with their feet: When an actor undertakes a greater level of market positioning, extant audiences are more likely to terminate coverage of the actor and new audiences are more likely to initiate coverage of it.

Hypothesis 1. *The greater the repositioning an actor undertakes, the greater the audience churn it will experience.*

2.2.2 | Evaluation inaccuracy

More importantly, repositioning may also undermine the accuracy of audience evaluation. We maintain that repositioning is associated with identity ambiguity that challenges audience evaluation. When an actor makes distant repositioning, its identity becomes ambiguous. Audiences may feel confused about what to expect from it as they are uncertain about what it can deliver after jumping across positions or categories (Benner, 2010). In other words, in evaluating an actor who shifts between distant market positions, audiences will subject their interpretation to incongruent identity-based expectations (Leung, 2014; Negro et al., 2015; Wang, 2022). As it is cognitively challenging for audiences (both old and new) to integrate inconsistent expectations or signals (Connelly et al., 2011), the accuracy of audience evaluation may suffer.

Moreover, even if audience churn can help accommodate some of the repositioning-led mismatches, it may still be insufficient to fully address the associated identity ambiguity. Audiences are often slow in updating their perceptions of an actor, even though it may have made a significant positional shift (Feldman, 2016; Kovács et al., 2023; Tripsas, 2009). This inertia will impair the efficiency of audience churn, such that the actor may still be covered by many mismatched (old) audiences (Kovács et al., 2023). The mismatch will limit the extent to which audiences can effectively handle the identity ambiguity associated with repositioning.

Meanwhile, although repositioning may attract new audiences who are generally more specialized for an actor's new position, these new audiences may still lack actor-specific experience that is essential for accurate evaluation (Mikhail et al., 2003). For instance, after a firm repositions from hardware production to software development, it may attract new analysts who are experts in software. While these analysts may have a better understanding of the software market, they may have yet to establish a close connection with the firm or gain specific experience about it. This limits the extent to which the analysts understand the firm's management style, operational routines, strategy processes, and specific financial metrics (Clement, 1999). As such, new audiences will still face difficulties in dealing with the repositioning-led identity ambiguity, which undermines the accuracy of their evaluation for the repositioned actors.

Finally, repositioning can also hinder peer learning in audiences' evaluation, which further impedes their ability to interpret firms with ambiguous identities. Evaluation is usually not solely based on audiences' independent analysis, but rather on observational learning among them (Prato & Stark, 2023). Audiences often review and learn from their peers' analyses, which are useful for them to refine methodologies, identify potential oversights, and ultimately generate more informed and accurate evaluations (Merkley et al., 2017). However, the effectiveness of learning may be particularly undermined by repositioning and audience churn. As old audiences of an actor depart and new audiences join, the previously established learning routine of its audiences is disrupted. Peer learning may become less effective because the new composition of audiences has yet to grasp how to effectively leverage each other's analyses. This can hamper the benefits of peer learning among audiences, further limiting their ability to address the repositioning-led identity ambiguity. Based on these, we expect:

Hypothesis 2. *The greater the repositioning an actor undertakes, the less accurate the evaluation its audiences will make.*

3 | EMPIRICS

To test the hypotheses, we analyze a large sample of publicly listed firms in the United States by compiling together several datasets. First, we use the Compustat Fundamentals database to retrieve key accounting information of US firms (e.g., sales, R&D, capital expenses), the Compustat Historical Segments database for information about their business and geographic structure, as well as the Subsidiary data from WRDS. Second, data on securities analysts are coded from the Institutional Brokers' Estimate System (IBES) database, which puts together earnings estimates made by stock analysts in local and global broker firms. We merge data between Compustat and IBES based on firms' CUSIP codes.

Moreover, we also gather data on product positioning and repositioning from the data library established by Hoberg and Phillips. Hoberg and Phillips (2010) conduct a large-scale text analysis of firms' business descriptions from their 10K annual filings on the SEC Edgar website, to create a vector of product words of each firm each year with their text reading algorithms. Based on these product words, two important measures can be built. By calculating the pairwise cosine similarity between any two firms' product words, we can create a more precise measure of their competitive similarity. By calculating the cosine similarity of product words of one firm in two consecutive years, we can capture how firms shift their positions in the product space over time (Hoberg et al., 2014). We merge the Hoberg and Phillips data library with other databases via firms' GVKEY codes. After removing observations with missing values, our final sample includes 42,431 firm-year pairs for the period 2001–2020.

3.1 | Measures

3.1.1 | Repositioning

We measure the degree of firms' repositioning based on product self-fluidity in Hoberg et al. (2014), which captures how a firm changes its own product words in its business description from year $t-1$ to t. Specifically, suppose that there are in total W_t unique product words used by all firms at year t. For each firm f at year t, a unique vector $P_{f,t}$ is generated from text analysis, which includes W_t elements (words), with each being populated by 1 if firm f uses the given word and 0 otherwise. As such, each vector presents a firm's product position at a certain year, and is normalized to have unit length as follows:

$$V_{f,t} = \frac{P_{f,t}}{\sqrt{P_{f,t} \cdot P_{f,t}}}$$

A firm's product self-similarity can then be calculated as the cosine similarity between its normalized product vectors in year $t-1$ and year t as follows:

$$Self - similarity_{f,t} = \left(V_{f,t} \cdot V_{f,t-1}\right)$$

Subtracting the self-similarity score from one will arrive at a firm's repositioning score from $t-1$ to t. That is, the more similar a firm's own product words are between year $t-1$ and t, the less the firm has shifted its position. As such, this measure is a good proxy of how firms change their positions in the product space.[2] Finally, to both account for the potential enduring effects of historical repositioning and smooth out irregular deviation, we calculate a firm's *repositioning* as the 3-year moving average of its repositioning scores.[3]

To check the validity of this measure, we collect data on firms' actual activities from the Capital IQ Key Development database (Shi et al., 2018). Specifically, we gather information on firms' new product introduction (NPI) and restructuring, as they are often coupled with repositioning. If our measure of repositioning is valid, we should expect to see a significant association between it and NPI/restructuring. Indeed, as reported in Appendix I, we see that firms with greater repositioning engage in more NPI and restructuring activities. We also report in Figure 1 the mean repositioning of three selective industries that are known for being more dynamic: semiconductor, pharmaceutical, and software industries.[4] While semiconductor firms show a similar level of repositioning to other firms, firms in the pharmaceutical and software industries appear to reposition in a wider margin.

3.1.2 | Analyst churn

Analyst churn measures the turnover of a firm's coverage analysts. Prior research has long suggested that analysts tend to adjust their coverage according to investors' demand (Brown et al., 2015), firms' size, performance (McNichols & O'Brien, 1997), innovation (Theeke et al., 2018), positioning (Litov et al., 2012), and corporate structure (Feldman, 2016). This aligns with the idea that analysts primarily strive to adopt their coverage to enhance the accuracy of their forecasts and increase trading commissions (Brown et al., 2015; Groysberg et al., 2011).

[2]While this measure is not typically "category-based," it can capture firms' subtle product repositioning, which might be unobservable at the level of broader categories (e.g., SIC industries). And if we conceptualize each of the W_t words as one distinct product category, this measure could be considered category-based, too (Pontikes, 2012).

[3]In analysis not tabulated here, we simply use 1-year repositioning score as the measure and find similar results.

[4]Specifically, we identify software firms with SIC codes between 7371 and 7374 (Lavie, 2007), pharmaceutical firms with SIC code 2834, and semiconductor firms with SIC code 3674 (Wang et al., 2017).

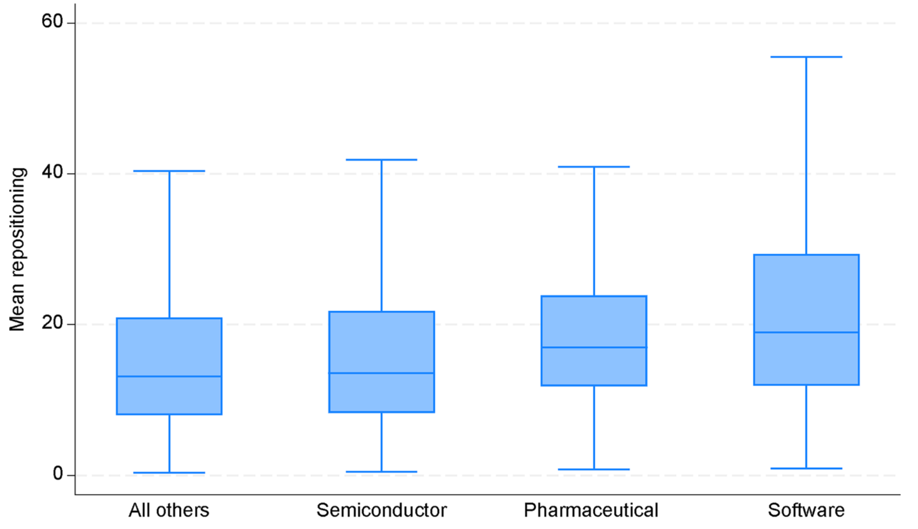

FIGURE 1 Mean repositioning (scaled by 100) in selective industries. The figure shows the mean repositioning in the whole sample from 2001 to 2019. We also conduct *t* test to compare repositioning among these industries. *t* test between semiconductor and others: 0.503 ($p = .615$); *t* test between pharmaceutical and others: 8.553 ($p < .001$); *t* test between software and others: 30.25 ($p < .001$); *t* test between pharmaceutical and semiconductor: 6.727 ($p < .001$); *t* test between software and semiconductor: 17.77 ($p < .001$); *t* test between software and pharmaceutical: 12.13 ($p < .001$).

Based on IBES, we first identify all coverage analysts for each firm each year. An analyst is defined as a firm's coverage analyst if he/she makes any earnings estimates of the firm in a given year. We then identify newly initiated coverage analysts of a firm as those who do not cover the firm at year t but initiate their coverage at year $t + 1$; abandoned coverage analysts as those who cover the firm at year t but stop the coverage from year $t + 1$ (Feldman, 2016). Based on this, we calculate *analyst initiation* of a firm as the logged number of analysts initiating coverage of the firm in year $t + 1$ (Rao et al., 2001); *analyst termination* as the logged number of analysts stopping coverage of the firm in year $t + 1$; and *analyst churn* as the logged number of analysts who either initiate or stop covering the firm in year $t + 1$.

Because these numbers can be related to the total number of coverage analysts at year t, we also use their proportions as alternative measures.[5] Figure 2 depicts the mean proportions of analyst termination and initiation in the three selective industries. It appears that analyst churn is greater in pharmaceutical and software industries, as compared to the semiconductor and other industries, which is in line with what is shown in Figure 1. In other words, from the two simple industry-level illustrations, there seems a correlation between repositioning and analyst churn.

3.1.3 | Forecast accuracy

We use two approaches to measure analysts' forecast accuracy. First, we calculate *relative accuracy* as the absolute differences between forecasting and actual earnings per share divided by

[5]Churn and initiation proportions are winsorized by 1% and 99% to rule out the impact of outliers. For the same reason, relative accuracy, analyst's firm scope, and forecast horizon are also winsorized.

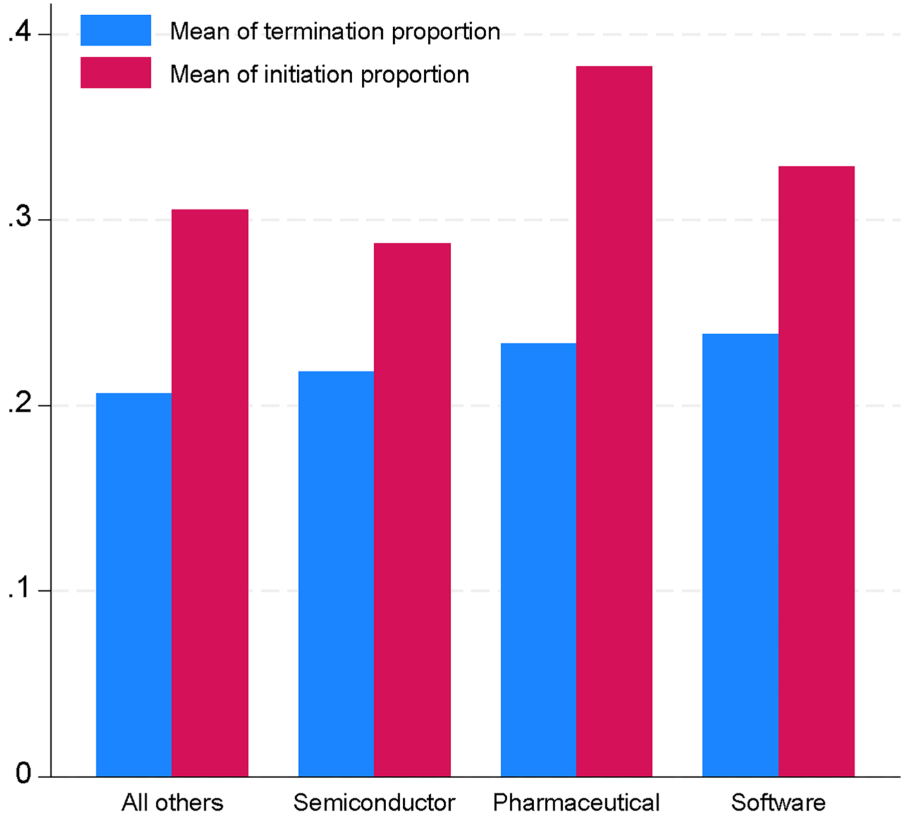

FIGURE 2 Analyst churn in selective industries. The figure shows the mean proportions in the whole sample from 2002 to 2020. We also conduct t test to compare the proportion of analyst churn among these industries. t test between semiconductor and others: −0.453 ($p = .650$); t test between pharmaceutical and others: 7.675 ($p < .001$); t test between software and others: 5.156 ($p < .001$); t test between pharmaceutical and semiconductor: 6.028 ($p < .001$); t test between software and semiconductor: 3.737 ($p < .001$); t test between software and pharmaceutical: −2.761 ($p = .006$).

the absolute value of actual earnings, multiplied by −1 (Loh & Mian, 2006). A forecast is then more accurate if it is closer toward the firm's actual earnings.

$$Relative\ accuracy_{j,i,t} = -1 \times \frac{|\,Forecasted\ earnings_{j,i,t} - Actual\ earnings_{i,t}\,|}{|\,Acutal\ earnings_{i,t}\,|}$$

Second, to better enhance the comparability of accuracy, we also create an alternative measure of *accuracy ranking* (Hong & Kubik, 2003). Specially, we first rank all forecasts for the same firm and time period, based on their absolute forecast errors. The least accurate forecast receives a rank of 1. Then, accuracy rankings are calculated as follows:

$$Accuracy\ ranking_{j,i,t} = \frac{Rank_{j,i,t} - 1}{Number\ of\ Forecasts_{j,t} - 1}$$

where $Rank_{j,i,t}$ is the rank of analyst j's relative forecast errors for firm i at time period t, and *Number of Forecasts*$_{j,t}$ is the number of forecasts provided for firm i and at t. The most accurate forecast gains a score of 1, while the least receives 0.

3.1.4 | Control variables

While we focus on dynamic repositioning of firms, it is necessary to control for how distinctive a firm's initial positioning vis-à-vis its peers. Specifically, we measure firms' positioning in two ways. First, we follow prior studies to calculate whether firms occupy a *unique positioning* in the market space (Litov et al., 2012). For each firm f at year t, we define a sector of its sales percentage across all of N four-digit SIC business segments, as $S_{f,t} = [S_{1,f,t} \cdots S_{N,f,t}]$. We identify a firm's primary segment as the one in which it has the largest proportion of sales. For each primary segment j^* each year t, we then define its centroid as the vector of $Sj*,t = \left[\frac{\sum_{m=1}^{M_{j*}} S_{1,m,t}}{M_{j*}} \cdots \frac{\sum_{m=1}^{M_{j*}} S_{N,m,t}}{M_{j*}}\right]$, where M_{j*} denotes the total number of firms with their primary segment in j^*. Simply speaking, the centroid in each primary segment indicates a hypothetical prototype firm whose sales distribution is averaged cross all of the segments. We then calculate a firm's unique positioning as $(S_{f,t} - S_{j^*,t})' \ (S_{f,t} - S_{j^*,t})$, reflecting how its sales distribution deviates from the centroid (Litov et al., 2012). Second, we also calculate a firm's *competitive similarity* in the product space as the mean of its product similarity with its top 10 competitors (i.e., cosine similarity of firms' product descriptions in 10K filings) (Hoberg & Phillips, 2010). The greater the similarity between a firm and its top competitors, the large the degree of competition. Conversely, a lower similarity indicates a greater level of distinctiveness of a firm in the product space.

We control for a set of other firm-level factors that may otherwise influence the results (Fitzgerald et al., 2021). First, we include *market valuation change* and *MTB ratio change*, to rule out the potential impact of changes in firms' size and performance. Market valuation is measured as the natural log of price per share times the number of shares outstanding, and MTB ratio is measured as the ratio of market equity to book equity (Litov et al., 2012). Their changes are calculated as the difference between year t and $t-1$. *R&D expense* is measured as R&D expenditure in year t divided by lagged total assets[6]; *capital expense* is calculated as capital expenditure in year t divided by lagged total assets. We capture *business diversification* by one minus the Herfindal index of a firm's revenues in SIC-3 segments, based on information from the Compustat Historical Segments dataset. Similarly, we calculate the proportion of foreign revenues as a proxy for firms' *internationalization*. From WRDS's Subsidiary database, we calculate the logged number of *subsidiaries* that a firm has established. *Leverage* is measured as total debt divided by total assets. *Firm age* is calculated as the number of years that a firm has been listed in Compustat (Fitzgerald et al., 2021).[7] We also create a variable of *repositioning variance*, defined as the standard deviation of a firm's repositioning scores in the past 3 years, which

[6]We assign a value of 0 to observations with missing information on R&D expenditure, which allows us to keep a large number of observations. Nonetheless, omitting such observations leads to similar findings.

[7]However, firm age is automatically omitted in some of our estimates as it is fully absorbed by certain fixed-effects. It is the same for some other variables, such as analyst's generic experience. In an unreported analysis, we also measure firm age based on firms' founding years from Jay Ritter's IPO database. The results stay similar.

accounts for temporal deviance of repositioning (Duysters et al., 2020). While some firms keep a more constant level of repositioning, others may make periodic changes.

In estimating forecast accuracy, we also include a set of additional controls. *Forecast horizon* is measured the number of days between the announcement dates of earning forecasts and actual earnings (Liang & Riedl, 2014). *Analyst's firm scope* is defined as the number of firms that an analyze covers at a given year (Merkley et al., 2017). *Analyst's firm-specific experience* is calculated as the number of years that an analyst has been covering the focal firm; *analyst's generic experience* is defined as the number of years that an analyst has been covering any firms (Clement, 1999). *Analyst's prior accuracy* (or prior performance) is calculated as the mean of an analyst's accuracy ranking scores across all of his/her reports in the past 3 years, which reflects general forecast skills (Hong & Kubik, 2003).[8]

4 | ESTIMATION AND RESULTS

To estimate how repositioning affects analyst churn, we employ a set of fixed-effects models, in line with prior studies on analyst coverage (Litov et al., 2012; Zhang et al., 2020). Firm fixed-effects models help account for baseline (i.e., time-invariant) heterogeneity among firms (Thatchenkery & Katila, 2021). Year fixed-effects are also included to control for temporal variance (Boudreau & Jeppesen, 2015; Taeuscher & Rothe, 2023). As the dependent variables are all continuous measures (i.e., logged number or proportion), we use *reghdfe* in Stata that works well with multiple fixed-effects for linear models (Correia, 2016). Robust standard errors are clustered by firms to account for serial correlation (Li & Wibbens, 2023).

Regression results are reported in Table 1. Model 1 shows that the effect of repositioning on total analyst churn is positive ($\beta = .304$; s.e. = 0.062). It suggests that one standard deviation increase of a firm's repositioning will drive the number of churned analysts to increase by about 3.1% ($=e^{0.304\times0.10}$). From Model 2, we see a positive effect of repositioning on analyst termination ($\beta = .168$; s.e. = 0.062). One standard deviation increase of a firm's repositioning will drive the number of terminated analysts to increase by about 1.7% ($=e^{0.168\times0.10}$). In Model 3, we find a positive effect of repositioning on analyst initiation ($\beta = .253$; s.e. = 0.060). One standard deviation increase of a firm's repositioning will drive the number of new analysts to increase by about 2.6% ($=e^{0.253\times0.10}$). In Models 4–6 that estimate the proportion of analyst changes, we receive quite consistent results supporting our Hypothesis 1 regarding firm repositioning and analyst churn.[9]

Next, we turn to examine Hypothesis 2 regarding firm repositioning and analysts' forecast accuracy. Following prior studies (Cao et al., 2020; Clement, 1999), we only estimate the last earnings forecast made by each analyst before a firm's release of its financials for a given period (quarters or years). As our goal here is to estimate the relationship between firm repositioning and forecast accuracy, we employ analyst fixed-effects (Bradley et al., 2020). This helps remove analyst-level heterogeneity (e.g., expertise and status) that affects all of the firms that an analyst

[8]Descriptive statistics are reported in Appendix II. Some control variables have moderately high correlations. To address the potential concerns about multicollinearity, we present estimation excluding all controls in Appendix IV.

[9]In addition to formal regressions, we also present in Appendix III binned scatterplots between repositioning and analyst churn using binsreg in Stata. This allows us to detect the shape of their relationship, examine outliers, and understand which part of the data mainly drives the relationship (Starr & Goldfarb, 2020). In Figure A2, we see a generally positive association between firms' repositioning and the proportion of analyst churn they experience. The pattern appears quite consistent across the distribution, rather than be dominated by outliers.

TABLE 1 Firm-level estimates of analyst churn.

	Logged number			Proportion		
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Variables	Churn	Termination	Initiation	Churn	Termination	Initiation
Repositioning	0.304	0.168	0.253	0.173	0.044	0.132
	(0.062)	(0.062)	(0.060)	(0.046)	(0.020)	(0.041)
	[.000]	[.006]	[.000]	[.000]	[.025]	[.001]
Unique positioning	−0.021	−0.022	−0.003	−0.020	−0.014	−0.006
	(0.022)	(0.020)	(0.023)	(0.016)	(0.007)	(0.015)
	[.342]	[.277]	[.884]	[.209]	[.060]	[.679]
Repositioning variance	−0.192	−0.142	−0.151	−0.074	−0.032	−0.040
	(0.065)	(0.062)	(0.064)	(0.049)	(0.021)	(0.045)
	[.003]	[.022]	[.018]	[.135]	[.126]	[.372]
Competitive similarity	0.467	0.476	0.257	−0.210	0.037	−0.233
	(0.128)	(0.119)	(0.123)	(0.097)	(0.040)	(0.086)
	[.000]	[.000]	[.036]	[.031]	[.363]	[.007]
Internationalization	−0.054	−0.050	−0.038	−0.011	−0.016	0.005
	(0.048)	(0.042)	(0.044)	(0.030)	(0.012)	(0.027)
	[.257]	[.236]	[.396]	[.717]	[.190]	[.863]
Business diversification	−0.028	−0.021	−0.023	0.012	0.004	0.005
	(0.031)	(0.028)	(0.029)	(0.022)	(0.009)	(0.020)
	[.359]	[.443]	[.432]	[.586]	[.665]	[.810]
No. subsidiaries	0.009	0.010	0.006	−0.009	−0.001	−0.008
	(0.004)	(0.004)	(0.004)	(0.003)	(0.001)	(0.003)
	[.022]	[.014]	[.148]	[.002]	[.570]	[.001]
Leverage	−0.079	−0.034	−0.125	0.090	0.037	0.058
	(0.023)	(0.022)	(0.021)	(0.019)	(0.009)	(0.017)
	[.001]	[.132]	[.000]	[.000]	[.000]	[.001]
Capital expenses	0.398	−0.003	0.688	0.010	−0.104	0.117
	(0.065)	(0.058)	(0.078)	(0.067)	(0.023)	(0.066)
	[.000]	[.957]	[.000]	[.880]	[.000]	[.076]
R&D expenses	0.014	−0.059	0.057	0.073	−0.013	0.085
	(0.017)	(0.027)	(0.013)	(0.016)	(0.008)	(0.017)
	[.406]	[.028]	[.000]	[.000]	[.083]	[.000]
Market valuation change	−0.001	−0.148	0.148	0.097	−0.039	0.137
	(0.006)	(0.006)	(0.006)	(0.006)	(0.003)	(0.006)
	[.847]	[.000]	[.000]	[.000]	[.000]	[.000]
MTB ratio change	−0.000	−0.000	−0.001	0.001	0.000	0.000
	(0.000)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)
	[.333]	[.830]	[.061]	[.106]	[.109]	[.310]

TABLE 1 (Continued)

	Logged number			Proportion		
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Variables	Churn	Termination	Initiation	Churn	Termination	Initiation
Constant	1.247	0.781	0.819	0.470	0.189	0.277
	(0.033)	(0.031)	(0.031)	(0.025)	(0.011)	(0.022)
	[.000]	[.000]	[.000]	[.000]	[.000]	[.000]
δ	1.75	1.29	1.90	2.18	1.65	2.49
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	42,431	42,431	42,431	42,431	42,431	42,431
R-squared	.582	.454	.473	.269	.217	0.225

Note: Robust standard errors in parentheses clustered by firms, and p-value in brackets.

covers (Bowers, 2015; Cohen et al., 2010). This approach addresses the potential concern about the "matching" between analysts and firms (e.g., certain types of analysts tend to choose certain types of firms), because it estimates how the same analyst may perform differently in forecasting firms with different degrees of repositioning. Year fixed-effects are also included to account for temporal variance (Taeuscher & Rothe, 2023). We cluster standard errors by analysts to account for heteroscedasticity (Bradley et al., 2017).

The regression results are reported in Table 2. Model 1 includes analyst and year fixed-effects separately to estimate *relative accuracy*. We see a significant negative effect of repositioning on relative forecast accuracy ($\beta = -0.177$, s.e. $= 0.017$). In Model 2, we incorporate analyst × year fixed-effects that may better rule out analyst heterogeneity (Bowers, 2015), and find similar results ($\beta = -0.161$, s.e. $= 0.018$). In Models 3 and 4, we test the effect of firm repositioning on *accuracy rankings* with different fixed-effects specifications. The results stay stable. The effect size is non-trivial. Based on results in Model 1 (or 4), for instance, one standard deviation increase of repositioning will lead the relative accuracy (or accuracy rankings) to decrease by about 3% (2%) of its standard deviation.[10] Our Hypothesis 2 is hence supported that firm repositioning reduces analysts' forecast accuracy.

5 | ROBUSTNESS CHECKS AND EXTENSIONS

In addition to primary estimation, we conduct a set of extensional analyses to examine the robustness of the findings and deepen our understandings of the pattern.

[10]Figure A3 in Appendix III presents the scatterplots between firm repositioning and accuracy with 20 bins, after absorbing analyst × year fixed-effects. We see a negative association between them, which seems consistent throughout the data range, without being dominated by potential outliers.

TABLE 2 Forecast-level estimates of accuracy.

Variables	Relative accuracy		Accuracy ranking	
	Model 1	Model 2	Model 3	Model 4
Repositioning	−0.177	−0.161	−0.013	−0.009
	(0.017)	(0.018)	(0.004)	(0.004)
	[.000]	[.000]	[.001]	[.024]
Unique positioning	−0.016	−0.005	−0.007	−0.007
	(0.006)	(0.007)	(0.002)	(0.002)
	[.013]	[.471]	[.000]	[.000]
Forecast horizon	−0.001	−0.001	−0.001	−0.001
	(0.000)	(0.000)	(0.000)	(0.000)
	[.000]	[.000]	[.000]	[.000]
Analyst's firm-specific experience	0.006	0.006	0.001	0.001
	(0.000)	(0.000)	(0.000)	(0.000)
	[.000]	[.000]	[.000]	[.000]
Analyst's firm scope	0.001		−0.000	
	(0.000)		(0.000)	
	[.007]		[.965]	
Analyst's prior accuracy	0.080		0.051	
	(0.030)		(0.009)	
	[.007]		[.000]	
Repositioning variance	−0.048	−0.049	0.004	0.002
	(0.019)	(0.020)	(0.005)	(0.005)
	[.013]	[.013]	[.466]	[.704]
Competitive similarity	−0.052	−0.020	0.030	0.034
	(0.032)	(0.031)	(0.007)	(0.007)
	[.105]	[.513]	[.000]	[.000]
Internationalization	0.036	0.028	0.002	0.002
	(0.007)	(0.007)	(0.002)	(0.002)
	[.000]	[.000]	[.173]	[.348]
Business diversification	−0.027	−0.026	0.003	0.003
	(0.007)	(0.007)	(0.002)	(0.002)
	[.000]	[.000]	[.090]	[.066]
No. subsidiaries	0.010	0.010	−0.001	−0.001
	(0.001)	(0.001)	(0.000)	(0.000)
	[.000]	[.000]	[.001]	[.002]
Leverage	−0.138	−0.138	−0.016	−0.016
	(0.007)	(0.007)	(0.001)	(0.002)
	[.000]	[.000]	[.000]	[.000]
Capital expenses	−0.022	−0.081	0.028	0.036
	(0.020)	(0.024)	(0.005)	(0.005)
	[.274]	[.001]	[.000]	[.000]

TABLE 2 (Continued)

Variables	Relative accuracy Model 1	Model 2	Accuracy ranking Model 3	Model 4
R&D expenses	−0.071	−0.077	0.003	0.003
	(0.020)	(0.022)	(0.003)	(0.002)
	[.000]	[.001]	[.249]	[.181]
Firm age	0.003	0.003	−0.000	−0.000
	(0.000)	(0.000)	(0.000)	(0.000)
	[.000]	[.000]	[.000]	[.006]
Market valuation change	0.123	0.117	−0.018	−0.020
	(0.004)	(0.004)	(0.001)	(0.001)
	[.000]	[.000]	[.000]	[.000]
MTB ratio change	−0.002	−0.002	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
	[.000]	[.000]	[.225]	[.603]
Constant	−0.273	−0.233	0.679	0.693
	(0.021)	(0.011)	(0.006)	(0.003)
	[.000]	[.000]	[.000]	[.000]
Analyst FE and Year FE	Yes	No	Yes	No
Analyst × Year FE	No	Yes	No	Yes
Observations	1,672,126	1,669,645	1,679,763	1,677,278
R-squared	.075	.128	.102	.143

Note: Robust standard errors in parentheses clustered by analysts, and *p*-value in brackets.

5.1 | Reverse causality

There may be a potential concern about reverse causality that analyst churn might also affect firm repositioning (He & Tian, 2013). In our empirical design, we try to address it by inserting 1-year lag between dependent and independent variables (Gouvard et al., 2023) and developing measures of repositioning over 3-year rolling windows. To more directly tease out reverse causality, we run a falsification test (Taeuscher & Rothe, 2023). Specifically, we use analyst churn to estimate repositioning in the following year, with the same set of controls and model specifications. We see no meaningful effects of analyst churn ($\beta = .003$; s.e. = 0.135; $p = .981$), initiation ($\beta = .069$; s.e. = 0.118; $p = .557$), and termination ($\beta = .012$; s.e. = 0.122; $p = .920$) on firm repositioning. These results alleviate the potential concerns about reverse causality, which helps enhance our confidence about the hypothesized effect of repositioning on analyst churn.

5.2 | Omitted variables

We are also concerned about omitted variables. Some unobserved firm or market factors, for instance, may drive both firm repositioning and analyst churn. While we have included a long list of controls (e.g., performance change) and various fixed-effects, the list is not exhausted. To better assess the potential impact of omitted variables, we employ a diagnosis test developed by Oster (2019), which is widely used in recent studies (Balasubramanian et al., 2024; Shi et al., 2024). It assumes that if R^2 increases dramatically after adding controls but the estimate of firm repositioning stays stable, then our current results should be more robust to the omission of unobserved factors; conversely, if adding controls does not change much of R^2 but reduces the estimate of repositioning dramatically, then our results are more likely to be biased by omitted variables. Essentially, this approach computes a parameter δ, reflecting the amount of variance that should be explained by omitted variables to nullify the effect of repositioning. $\delta = 1$, for instance, suggests that the explanatory power of omitted variables needs to be equally strong as that of our current controls to overrun the results. At the bottom of Table 1, we report the results of these diagnostics tests. δ is larger than one in all models, suggesting that omitted factors would need a stronger power than all of our controls to invalidate our main findings.[11] Because our models include an extensive range of controls and fixed-effects, the diagnosis test results imply that our primary findings are less likely to be overrun by potential omitted variables.

5.3 | Accuracy and prior experience and performance of analysts

Given that firm repositioning undermines forecast accuracy, we find it practically interesting to further explore analyst heterogeneity to see what attributes may help analysts improve their forecasts. Specifically, we focus on two prevalent attributes of analysts: prior experience and performance. Analysts' experience are consistently found to play an important role in determining analysts' forecast accuracy (Clement, 1999; Mikhail et al., 2003), and analysts' prior performance commonly serves as a good proxy of analysts' skills that could shape their future accuracy (Crane & Crotty, 2020). Moreover, following prior work (Clement, 1999), we differentiate analysts' prior experience and performance in two aspects: generic and firm-specific. "Generic" refers to an analyst's overall forecast experience/performance across all firms in the past, "firm-specific" pertains to their specific forecast experience/performance for the focal firm. As such, we consider in total four types of analyst attributes.

To investigate the impact of different experience/performance on analysts' forecasting, we interact each of the four analyst attributes with repositioning to predict accuracy. The results are reported in Table 3 (and selected marginal effects in Appendix V). In Panel a, we do not find a robust moderation effect of analysts' generic experience as it is only significant in one of four specifications (Model 4). As accuracy ranking is our preferred measure of forecast accuracy over relative accuracy, we lean toward the conclusion that generic experience provides limited benefits for analysts to evaluate repositioned firms.

In Panel b, we see quite consistent evidence that firm-specific experience helps improve analysts' forecasts for firms with greater repositioning. This suggests that analysts are more capable of interpreting a firm's repositioning if they have gained more specific experience with it. This seems opposite to what Kovács et al. (2023) find in the book market: Readers who have more specific experience with an author are more likely to misinterpret his/her genre repositioning. We suspect that this may reflect different types of actor-audience relations in the culture and financial markets. Readers and authors mostly make arm-length transactions, whereby readers

[11]Following Balasubramanian et al. (2024), we set $R_{\max}$ to the minimum of 1 or 1.3× R^2 in the full models.

TABLE 3 Analysts' prior experience and performance.

Panel a

	Accuracy ranking		Relative accuracy	
Variables	**Model 1**	**Model 2**	**Model 3**	**Model 4**
Repositioning × Analyst's generic experience	−0.000	−0.000	0.005	0.009
	(0.001)	(0.001)	(0.002)	(0.002)
	[.474]	[.561]	[.054]	[.000]
Other controls	Yes	Yes	Yes	Yes
Analyst FE	No	Yes	No	Yes
Year FE	No	Yes	No	Yes
Analyst × Year FE	Yes	No	Yes	No

Panel b

	Accuracy ranking		Relative accuracy	
Variables	**Model 5**	**Model 6**	**Model 7**	**Model 8**
Repositioning × Analyst's firm-specific experience	0.002	0.002	0.018	0.022
	(0.001)	(0.001)	(0.003)	(0.003)
	[.007]	[.021]	[.000]	[.000]
Other controls	Yes	Yes	Yes	Yes
Analyst FE	No	Yes	No	Yes
Year FE	No	Yes	No	Yes
Analyst × Year FE	Yes	No	Yes	No

Panel c

	Accuracy ranking		Relative accuracy	
Variables	**Model 9**	**Model 10**	**Model 11**	**Model 12**
Repositioning × Analyst's generic performance	0.130	0.121	0.197	−0.068
	(0.061)	(0.054)	(0.236)	(0.211)
	[.033]	[.026]	[.406]	[.749]
Other controls	Yes	Yes	Yes	Yes
Analyst FE	No	Yes	No	Yes
Year FE	No	Yes	No	Yes
Analyst × Year FE	Yes	No	Yes	No

Panel d

	Accuracy ranking		Relative accuracy	
Variables	**Model 13**	**Model 14**	**Model 15**	**Model 16**
Repositioning × Analyst's firm-specific performance	−0.040	−0.011	0.033	−0.002
	(0.024)	(0.023)	(0.097)	(0.093)
	[.091]	[.629]	[.733]	[.982]

TABLE 3 (Continued)

Panel d				
	Accuracy ranking		Relative accuracy	
Variables	Model 13	Model 14	Model 15	Model 16
Other controls	Yes	Yes	Yes	Yes
Analyst FE	No	Yes	No	Yes
Year FE	No	Yes	No	Yes
Analyst × Year FE	Yes	No	Yes	No

Note: Robust standard errors in parentheses clustered by analysts, and *p*-value in brackets.

can be blind to authors' abrupt moves. However, experienced analysts tend to build connections with their portfolio firms (Brochet et al., 2014), such that analysts with more firm-specific experience may be better informed about the firms' repositioning.

In Panel c, we find the moderation effect of analyst's generic performance is positive and significant on accuracy ranking in Models 9 and 10, but nonsignificant on relative accuracy in Models 11 and 12. Considering again our preferred measure of forecast accuracy, we incline to conclude that analyst's generic performance might help analysts better interpret repositioned firms. This is not surprising, as generic performance of analysts reflects their inherent analytical skills and abilities (Crane & Crotty, 2020). Such generic skills might enable analysts to more effectively evaluate firms, even when there are shifts in their positions.

In Panel d, we find no significant impact of analysts' firm-specific performance. We conjecture that because such type of skills are specific to a firm's current business, analyst may find it difficult to maintain their accuracy when it undergoes substantial changes (Feldman, 2016; Theeke et al., 2018). It may imply that the historical firm-specific performance of analysts has a lesser impact on their ability to accurately interpret firms' repositioning, in contrast to their prior firm-specific experience.

5.4 | Prior experience and performance of different analysts

Given these findings above, we continue to compare the prior experience/performance of churned analysts. Specifically, in the presence of firm repositioning, will incoming analysts (who initiate their coverage) have greater or lesser experience/performance, as compared to outgoing ones (who terminate their coverage) and staying ones (who maintain their coverage)? Comparing them can provide valuable insights into how repositioning has reshaped a firm's analyst group. To examine it, we first calculate the mean experience/performance of analysts who terminate, initiate, and maintain their coverage of a firm, respectively. We then calculate their differences with the following formula (Shipilov et al., 2011): $\Delta = \frac{x_i - x_j}{x_i + x_j}$, where x denotes one of the four types of analyst attributes mentioned above, i and j index the three types of analysts. To illustrate, if x is generic experience, and i and j represent the outgoing and incoming analysts, respectively, then Δ captures the difference between outgoing and incoming analysts in their prior generic experience. Finally, we use repositioning to predict each Δ.

The results are reported in Table 4. In Models 1 and 2, repositioning is not associated with the generic experience difference between outgoing and staying analysts, but relates positively to their firm-specific difference. It indicates that when firms undertake greater repositioning, they are more likely to lose analysts who have more firm-specific experience. This is a bit

TABLE 4 Comparison of outgoing, staying, and incoming analysts.

	Model 1 Δ (Outgoers-stayers) generic experience	Model 2 Δ (Outgoers-stayers) firm-specific experience	Model 3 Δ (Outgoers-incomers) generic experience	Model 4 Δ (Outgoers-incomers) generic performance	Model 5 Δ (Outgoers-stayers) generic performance	Model 6 Δ (Outgoers-stayers) firm-specific performance
Repositioning	−0.024	0.134	−0.126	−0.014	0.000	−0.006
	(0.045)	(0.056)	(0.059)	(0.012)	(0.007)	(0.015)
	[.599]	[.017]	[.033]	[.277]	[.966]	[.696]
Other controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	30,034	29,358	25,248	23,116	30,019	30,019
R-squared	.182	.202	.175	.217	.189	.180

Note: Robust standard errors in parentheses clustered by firms, and *p*-value in brackets. Outgoers: analysts who terminate their coverage. Incomers: analysts who initiate their coverage. Stayers: analysts who continue their coverage. Performance is measured as the average forecast accuracy of analysts in prior 3 years. Experience is measured until 1 year before the focal year.

unfortunate because these analysts are found to deal with firm repositioning better in our estimation earlier. In Models 3 and 4, repositioning relates negatively to the generic experience difference between outgoing and incoming analysts, but not to their generic performance difference. It suggests that repositioning will lead firms to attract new analysts who are generally more experienced that those who depart. This is, however, not necessarily beneficial, as we see earlier that analysts' generic experience does not contribute much to the forecasts of repositioned firms. In Models 5 and 6, we see no significant differences between outgoing and staying analysts regarding their prior generic and firm-specific performance.

Together, these patterns suggest that repositioning-driven analyst churn may be suboptimal as it does not necessarily lead to a new set of analysts who can better evaluate repositioned firms. First, while we see in Table 3 that prior generic performance may help analysts evaluate repositioned firms, the results in Table 4 show that incoming analysts did not perform significantly better than outgoing analysts in the past. Second, the results in Table 3 show that firm-specific experience is important for the forecasts for repositioned firms. However, because incoming analysts, by definition, have the least firm-specific experience, they should be less efficient in interpreting repositioned firms, as compared to outgoing and staying analysts.[12]

5.5 | Repositioning and initial positioning

While the focus of this study is on repositioning, we also explore the possible interaction between firms' initial positioning and repositioning. Initial positioning reflects a firm's static identity vis-à-vis its peers, whereas repositioning denotes how the identity is changed over time. We suspect that initial positioning may exert impacts in two different ways. On the one hand, distinctive initial positioning may weaken the negative effect of repositioning on accuracy. When a firm's position deviates from peers, its identity is already atypical and ambiguous to begin with (Litov et al., 2012). For such type of firms, there might be less room for repositioning to further blur their market identities (Pontikes & Barnett, 2015). On the other hand, however, conventional initial positioning facilitate audience evaluation, which usually hinges on relative comparison (Bowers, 2015). When a firm's initial positioning is conventional and similar to peers, its repositioning may be easier to interpret as audiences can readily compare its changes to the conventional others (Gentner & Markman, 1997). If so, conventional positioning may help weaken the negative impact of repositioning on forecast accuracy.

In our current estimation, we already have two proxies for the distinctiveness or conventionality of firms' initial positioning: *unique positioning* (Litov et al., 2012) and *competitive similarity* (Hoberg & Phillips, 2010). The former is based on the sales differentiation of firms within the same industry (i.e., distance in the market space), whereas the latter focuses on firms' product similarity (i.e., overlap in the product space).[13] To explore the role of initial positioning, we interact repositioning with unique positioning and competitive similarity, respectively, and report the results in Table A7 in Appendix VII. We do not see a very consistent pattern. On the

[12]To test this conjecture, we run an additional analysis by interacting repositioning and analyst type (a dummy variable with a value of 1 for incoming analysts and 0 for staying analysts) to predict accuracy. The results are reported in Table A6 in Appendix VI. Across different specifications, we see consistent evidence that incoming analysts deliver worse performance than staying analysts in forecasting firms with greater repositioning.

[13]In Table 2, they behave mostly in line with prior theory that distinctive positioning breeds identity ambiguity (Cutolo & Ferriani, 2024): unique positioning shows a negative relationship with both accuracy measures, and the effect of competitive similarity is positive on accuracy ranking, but nonsignificant on relative accuracy.

one hand, its interaction with unique positioning is positive and significant in models predicting accuracy ranking, albeit nonsignificant in models predicting relative accuracy. The former results imply that the negative effect of repositioning on forecast accuracy ranking is attenuated when a firm's initial positioning is already unique in the market space. On the other hand, the interaction between repositioning and competitive similarity is significantly positive in three of four specifications. It suggests that firms' repositioning can be more easily interpreted when their initial position is more conventional in the product space.

We suspect that such divergence may be driven by the nature of the two variables. First, while competitive similarity focuses on firms' positioning in the *product* space, unique positioning is based on firms' positioning in the *market* space.[14] Firms with different products, for instance, may still target for the same market; firms with similar products may generate revenues from different markets. Second, while unique positioning is category-bounded (referring to a firm's distinctiveness from peers in the focal industry), competitive similarity reflects a firm's general product positioning vis-à-vis others inside and/or outside its industry. As such, they refer to different dimensions of positional distinctiveness/conventionality. In this regard, the divergent findings may align with recent work that different types positioning (or atypicality) can exert different impacts on audience evaluation (Gouvard et al., 2023).

Despite inconsistent findings here, however, we lean toward the results based on competitive similarity in the product space because (1) our repositioning measure is also constructed from the product space and (2) recent work on positional distinctiveness mostly focus on product similarity (Majzoubi et al., 2024; Taeuscher et al., 2021). We therefore conclude that firms' repositioning can be more easily interpreted when their initial position is more conventional in the product space. Nonetheless, more dedicated work is needed to both theorize about and investigate the divergence observed here.

6 | DISCUSSION

The core premise in this study is that market repositioning endures substantial external costs at the audience side as it associates with identity ambiguity. We highlight two important consequences of it. First, as repositioning usually induces mismatch between audiences and actors (Kovács et al., 2023), we contend that these audiences may actively address the mismatch via adjusting their coverage. Second, while prior studies suggest that audiences are less likely to accept actors with repositioning (Leung, 2014; Zuckerman et al., 2003), we emphasize that they are also less capable of accurately evaluating these actors. Using a comprehensive sample of publicly listed US firms from 2001 to 2020, we find that firms' repositioning leads to a greater level of analyst churn and undermines analysts' forecast accuracy of them.

Our study enriches research on market identities by emphasizing the role of repositioning. While market identities are known to be based on actors' positioning, prior studies mostly focus on their cross-sectional positions or categorical memberships (Cudennec & Durand, 2023; Leung & Sharkey, 2014; Pontikes, 2012; Zuckerman, 1999). We draw particular attention to the implications of dynamic repositioning for market identities. Actors constantly adjust their positions in efforts to address regulatory shocks (Bhaskarabhatla et al., 2021; Hou & Yao, 2022), escape competition (de Figueiredo & Silverman, 2007; Dobrev & Kim, 2006; Wang &

[14]To a certain extent, they reflect the two dimensions that Chen (1996) emphasizes in competitive dynamics, resource similarity and market overlap.

Shaver, 2014), or try out new opportunities (Eggers & Song, 2015; Kovács et al., 2023; Negro et al., 2022). Repositioning is an important complement to research on market identities as it helps unveil what is largely neglected by the static view. For example, when a firm jumps from one crisp market category to another crisp one that is distant away, its cross-sectional categorical membership would be considered coherent and clear at any time point if one adopts the static view. However, the distant jump would also lead to some confusion, ambiguities, and interpretation challenges for its audiences (Benner, 2010; Kovács et al., 2023). As such, we underscore the importance for the market identities research to pay more attention to the pathway through which an actor arrives at its position, beyond the position per se. While this has been theorized in prior literature (Leung, 2014; Tripsas, 2009; Zuckerman et al., 2003), we lack direct evidence on how repositioning relates to identity ambiguity and evaluative inaccuracy. In addressing this, our study presents a consistent pattern that firms' market repositioning is associated not only with a greater churn of coverage analysts but also with a decrease in analysts' forecast accuracy, after controlling for their initial positioning.

These findings are largely in line with Kovács et al.'s (2023) recent work on categorical "stickiness," as we both highlight the ambiguity associated with repositioning, beyond what has been discussed in prior research on typecasting (Zuckerman et al., 2003). Yet, this study may still add to it in several ways. First, Kovács et al. (2023) emphasize that audiences may be blind to actors' repositioning as they tend to form expectations based on actors' historical positions. This will result in a mismatch between audience expectation and actual offerings. Extending this, we conjecture that active market audiences (e.g., financial analysts or professional critics) may be able to recognize the mismatch and make "self-selection" efforts to change their coverage scope according to actors' repositioning. In other words, while their research suggests that audiences are vulnerable to the categorical mismatch, we highlight that audiences may actively address the mismatch with their feet. Second, whereas Kovács et al. (2023) show solid evidence that audiences will downgrade actors with greater repositioning, we shift attention to examining whether audiences are able to accurately evaluate the quality of such actors. Attending to evaluation accuracy is important in at least two aspects. First, whereas repositioning-driven downgrading may result from identity ambiguity, inferior quality, or both, the accuracy of audience evaluation reflects more closely the extent to which the identity is ambiguous. Second, for market audiences who actively strive for accurate evaluation (e.g., financial analysts), the analysis of accuracy helps uncover their (in)efficiency in interpreting market repositioning, such that they may better allocate evaluative attention and efforts among various tasks.

Moreover, we also see an interesting pattern that is contrary to what is found in prior studies. Specifically, prior work contends that audiences' direct experience with an actor will make them less aware of the actor's repositioning in the book industry (Kovács et al., 2023). Our study shows the opposite such that analysts with firm-specific experience are particularly accurate in forecasting the repositioned firms. This may indicate the important distinction between cultural and financial markets. In the cultural market, authors and readers mostly keep an arm-length transactional relationship, such that readers may not expect authors' abrupt genre changes. Experienced readers are slower in updating their identity-based expectations on authors, becoming more vulnerable to categorical stickiness and mismatch. By contrast, in the financial market, analysts are more likely to establish professional connections with firms and their top management teams (Brochet et al., 2014). As these connections can channel important information from firms to analysts (Bradley et al., 2020), analysts with more firm-specific experience will be better informed about their covering firms' repositioning. They will not be more blind to the firms' repositioning, but instead be better prepared and able to make sense of these firms, as compared to those without such experience or connections. We suspect that this pattern is not only specific to the financial markets, but can be found among other types of active market audiences such as expert critics or rating bodies (Sharkey et al., 2022). Nevertheless, it suggests that research on repositioning-led ambiguity may need to be more contextualized.

Furthermore, this work also provides implications to the strategy research on competitive repositioning. While earlier work on competitive repositioning examines when and how firms reposition (Dobrev & Kim, 2006; Hou & Yao, 2022; Wang & Shaver, 2014), recent studies call for attention to the costs associated with repositioning (Argyres et al., 2019; Menon & Yao, 2017). However, most studies consider the *internal* production-related costs. Our study, together with other work on repositioning and identities (Kovács et al., 2023), emphasizes the *external* costs from the audience side. As repositioning leads to greater audience churn and biased assessment, firms will incur substantial external costs when altering their market positions.

6.1 | Limitations and future studies

There are limitations to our study that deserve attention and further work. First, we are cautious in claiming that the relationships we observe are causal inferences, despite our extra efforts to rule out other possibilities. Specifically, firms' repositioning can be endogenous to many internal and external factors (Wang & Shaver, 2014). One ideal solution for future work is to leverage external shocks that will drive some firms to reposition and keep the similar others unchanged.

Second, and relatedly, while we capture the degree of firms' product repositioning, we do not distinguish among different approaches by which firms reposition. Firms may change their positions in the product space in many different ways, such as introducing new products, reshuffling existing products, acquiring other firms, or divesting existing businesses (Feldman, 2016; Pontikes & Barnett, 2015).[15] These different approaches may have divergent implications for firms' market identities that deserve further exploration.

Third, our measure of repositioning hinges on the quality of firms' self-reporting about their product positions. Firms, for instance, may tend to update major product changes rather than minor revisions, such that this measure may underestimate the extent of repositioning that firms have undertaken.[16] Nonetheless, this product words-based measure should be more effective to capture subtle firms' positioning and repositioning (Hoberg & Phillips, 2010), as compared to the other broader measures based on segment entry and exit (Hou & Yao, 2022).

Moreover, we also see possibilities to incorporate other categorical perspectives into repositioning research. Considering the contrast of categories, for instance, firms may reposition from a fuzzy category to a crisp category, or the other way around. While the repositioning distance is the same for both cases, their implications for market identities can be quite different.

[15]Our logic is consistent with Feldman's seminal studies on spin-offs (Feldman, 2016; Feldman et al., 2014). Still, our study differs from Feldman's work in several ways. First, while legacy spin-offs are a very specific type of corporate strategy, our analysis of product market changes aims to provide a more general test of competitive repositioning in a broad sample of firms. Second, we employ a very different theoretical lens. While Feldman's (2016) work emphasizes the specialized skills of analysts, our research develops theory around market identities.

[16]This issue is less concerning if all firms consistently do so. In such scenarios, our measure would underestimate the repositioning of all firms by similar margins. However, our estimation will be biased if only some firms underreport or firms underreport intermittently in some periods. For instance, if firms with greater (lower) actual repositioning are more likely to underreport, then our findings may overestimate (underestimate) its impact.

Our extensional analysis sheds some light on this, by showing that repositioning is less confusing when firms' initial positions are more conventional. Nonetheless, more dedicated effort is needed.

Furthermore, it is also interesting to consider actors' performative positioning highlighted in recent literature (Gouvard et al., 2023). Different from the traditional categorical positioning, performative positioning focuses on how actors interact with audiences to produce identities. Whereas our research on repositing is essentially category-based, future work can explore the implications of performative repositioning, that is, the extent to which firms change how they "do" identities.

Finally, as discussed above, the repositioning-led identity ambiguity can be quite context-dependent. Our theory and findings may not be simply generalizable to other contexts. Despite these, we believe that our study helps further develop understanding of competitive repositioning and market identities, which also sets a broad stage for future work.

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SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

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