Do Analysts Cater to Investor Beliefs?

Evidence from Dual-Listed Chinese Firms*

Dawn Matsumoto
Michael G. Foster School of Business
University of Washington
Paccar Hall, Box 353226
Seattle, WA 98195
damatsu@uw.edu

Jenny Li Zhang
Sauder School of Business
The University of British Columbia
2053 Main Mall
Vancouver BC, Canada V6T 1Z2
jenny.zhang@sauder.ubc.ca

Yuxiang Zheng
Sauder School of Business
The University of British Columbia
2053 Main Mall
Vancouver BC, Canada V6T 1Z2
yuxiang.zheng@sauder.ubc.ca

October 29, 2020

* Matsumoto would like to thank the Gerhard Mueller Professorship at the University of Washington for financial support. Zhang acknowledges the financial support from the Social Sciences and Humanities Research Council of Canada (SSHRC). We thank helpful comments from two anonymous reviewers at HARC Conference, Darren Bernard, Russell Lundholm, Jason Huafeng Chen, and University of Washington brown bag workshop.

Abstract: We take advantage of a unique setting in China to provide novel evidence on a catering theory for analyst optimism. Our study utilizes the Stock Connect programs that allowed foreign investors to invest in Chinese stocks as an exogenous shock to investor beliefs. We further focus our study on a subset of Chinese firms with both "A shares" (listed in mainland China) and "H shares" (listed in Hong Kong) to provide a clean test of our hypotheses. We find that A share analysts become less optimistic in their recommendations following the introduction of less optimistic investors through the Stock Connect programs. In addition, catering theory predicts that when investors hold heterogeneous beliefs, analysts tend to segment the market and slant toward extreme positions in order to attract target investors. Consistent with this prediction, we find that A share analysts with buy or strong buy (sell or underperform) recommendations of a given firm become more optimistic (pessimistic) in their forecasts and research report tone after the Stock Connect programs. Finally, we show that in updating their earnings forecasts, analysts are more (less) responsive to earnings surprises that are consistent (inconsistent) with their stock recommendations. Overall, the results suggest that analysts cater to investors' opinions.

1. Introduction

Do analysts bias their reports to cater to investors' beliefs? Prior literature has extensively studied the question of what causes financial analysts to produce overly optimistic reports. Studies have shown that optimism can arise because of various analyst incentives, such as compensation (Hayes 1998), promotion and turnover (Mikhail, Walther, and Willis 1999, Hong and Kubik 2003), investment banking relationships (Lin and McNichols 1998), and currying favor with management (Chen and Matsumoto 2006; Mayew 2008). Cognitive biases can also influence analysts' outputs, including optimism (Easterwood and Nutt 1999) and overconfidence (Hilary and Menzly 2006). Importantly, these explanations imply that analysts' outputs influence investors' judgments, not vice versa. In contrast, a catering theory of analyst bias suggests that analysts' outputs are influenced by investors' beliefs – that is, analysts issue optimistic (pessimistic) reports to cater to investors' optimistic (pessimistic) beliefs. The purpose of this study is to provide empirical evidence on this catering theory.

We base our predictions on the model of media bias outlined in Mullainathan and Shleifer (2005, hereafter M-S) and adapted to the analyst setting by Lai (2004). The models require two general assumptions: 1) investors hold biased beliefs and prefer to read information that is consistent with their beliefs and 2) analysts can bias or "slant" their outputs to cater to investors' beliefs. Based on these assumptions, the models provide two predictions. First, when investors share homogeneously optimistic (pessimistic) beliefs, analysts will cater to these beliefs and bias their reports optimistically (pessimistically). Second, when investors hold heterogeneous beliefs, analysts will segment the market and slant toward extreme positions – the optimistic analysts will become more optimistic and the pessimistic analysts will become more pessimistic. The prediction is analogous to the idea that newspapers tend to slant more on topics where there is greater reader heterogeneity of beliefs (e.g., on political topics).[1]

We examine these predictions in a unique setting that captures an exogenous shock to investor composition: the capital market liberalization programs in China. These programs – the Shanghai-Hong Kong Stock Connect program adopted in November 2014 and the Shenzhen-Hong Kong Stock Connect adopted in December 2016 (collectively referred to hereafter as the "Stock Connect programs") – allowed relatively free movement of investor funds between mainland China and the rest of the world for the first time. Prior to these programs, shares of Chinese firms traded on the Shanghai and Shenzhen Stock Exchanges (referred to as "A shares") were largely unavailable to foreign investors.[2] Chinese firms who wished to make shares available to foreign investors could list their shares on the Stock Exchange of Hong Kong (referred to as "H shares"). The Stock Connect programs allowed foreign investors to purchase A shares and mainland Chinese investors to purchase H shares. Thus, the Stock Connect programs represent an exogenous shock to the investor bases of certain companies in China (we discuss these programs in more detail in Section 2).

This shock provides a unique opportunity to investigate the catering theory, *assuming foreign investors' beliefs differ from mainland Chinese investors*. We base this assumption on the following arguments. The Chinese economy experienced unprecedented growth and strong returns to A share stocks since the opening of their two stock exchanges. In addition, mainland

---

[1] The intuition behind this prediction is that, in a competitive market, the duopolist trades off market share with higher prices. Slanting reduces market share but allows the newspaper to charge higher prices. The price effect dominates and can lead newspapers to slant toward positions that are even more extreme than their readers' beliefs.
[2] In 2002, the Chinese government introduced the Qualified Foreign Institutional Investor (QFII) program, which allowed specified licensed international investors to participate in mainland China's stock exchanges under a quantitative quota system. However, since QFII applicants must meet many prerequisites, some of which are meant to limit short-term speculation, studies find that QFII failed to make a long-term impact on the stock market and its participants (Tam et al., 2010, Deng et al., 2019).

Chinese investors face strict capital controls that limit their investment opportunities. With limited opportunities to invest elsewhere and a strong domestic economy, local investors likely developed an optimistic sentiment toward domestic firms. In contrast, the Hong Kong investment community is characterized as mostly sophisticated institutional investors from around the world, who tend to trade on fundamentals, and have a multitude of investment opportunities. In fact, the well-known premium of A shares over H shares has been at least partially attributable to differences in investor sentiment (Arquette et al. 2008). Thus, we base our analysis on the assumption that, on average, Chinese investors have more optimistic beliefs than foreign investors and the Stock Connect programs represent a shock to average investor beliefs. In other words, prior to the Stock Connect program, investors of A shares would hold more homogeneous and optimistic beliefs; after the implementation of the programs, investors in A shares (which would now include foreign investors) would hold more heterogeneous and less optimistic beliefs.[3]

Our tests are based on a sample of 107 Chinese companies with both A and H shares traded at some point between 2007 to 2018. Importantly, these shares offer the same voting and cash-flow rights and identical disclosure requirements by the three stock exchanges. In addition, analyst reports are associated with a particular share type; thus, analysts issuing reports on A shares (H shares) are referred to as A share (H share) analysts. We presume the reports are written for the investors of each type of share.[4] Since both A share and H share analysts are

[3] Our study is primarily focused on the effect of the Stock Connect programs on the A share investor base and the resulting impact on A share analyst outputs. It is also true that the influx of optimistic Chinese investors into H shares might also incentivize H share analysts to bias their reports upward. However, our examination of the second prediction from the M-S model is based on changes in investor heterogeneity and the effect of the Stock Connect programs on investor heterogeneity is clearer for A shares than H shares.

[4] We randomly sampled 10 firms and 3 pairs of analyst reports for each firm. These reports are written by A and H share analysts for the same firms. We noted that, prior to the Stock Connect programs, A share reports are almost always written in simplified Chinese while H share reports are almost always written in either English or traditional Chinese (which is commonly used in Hong Kong). More generally, 80.24% of analyst reports for A shares in our sample are written in Chinese while 89.93% of H share reports are in English. Overall, these evidences are consistent with the notion that the reports were geared toward the respective investor bases.

providing recommendations and forecasts for the same underlying firm, differences in their outputs can not be due to differences in underlying firm economics. Thus, we use the H share analysts as a control group in a difference-in-differences design, examining changes in analyst outputs before and after the Stock Connect Programs for A and H share analyst pairs.

Our design is much stronger than any cross-sectional study on the catering hypothesis as concerns over reverse causality would be particularly problematic in such a study – that is, an association between investor beliefs and analyst optimism could be due to analyst optimism *influencing* investor beliefs. The same criticism could be made of our study if we only examined differences in A and H share analyst optimism *prior* to the Stock Connect program (that is, optimism in A share analyst reports might be the *cause* of overall optimistic beliefs by Chinese investors). However, under our assumption that the Stock Connect programs represented an exogenous shock to investor beliefs, our difference-in-differences design identifies the effect of investor beliefs on analyst outputs – a cleaner test of the catering hypothesis.

We begin our analysis by testing whether A share analysts cater to the homogeneously optimistic beliefs of Chinese investors in the pre-Stock Connect period by producing more optimistic outputs (relative to their H-share counterparts) and whether this optimism is reduced in the post-Stock Connect period following the influx of sophisticated foreign investors with presumably less optimistic views. We use monthly consensus recommendations as a summary measure of analysts' research outputs. We find that A share analysts have more optimistic recommendations in the pre-Stock Connect Program relative to H share analysts, and this optimism is significantly reduced in the post period. In contrast, H share analysts' outputs remain relatively unchanged between the two periods. We also find cross-sectional evidence that the differential effect of the Stock Connect program on A-share analyst recommendations is stronger for firms and sectors where we expect foreign investors to have relatively more pessimistic views. Overall, the results are consistent with predictions from the catering hypotheses.

Based on this evidence, we next test the implication of catering theory when investor heterogeneity increases, specifically, that analysts will tend to segment the market and slant toward extreme positions. Consistent with the theory, we find that, A share analysts with "buy" or "strong buy" recommendations become even more optimistic in their earnings and target price forecasts, as well as in their research report tone, following the Stock Connect programs, while H share analysts exhibit no change. Further, A share analysts with "underperform" or "sell" recommendations, become *less* optimistic in their quantitative and qualitative research outputs (while H share analysts do not). Overall, this evidence is consistent with the catering theory: greater investor heterogeneity increases individual analysts' bias or slant. Importantly, it highlights that while investor heterogeneity reduces average bias/slant (and thus, is beneficial if investors consume information from multiple sources), it increases the bias/slant of individual sources and thus, can detrimentally affect the information received by readers who consume only information from one source.

Next, we explore one way in which analysts might introduce bias/slant into their outputs: ignoring or underreacting to firm information that is inconsistent with their positions. Specifically, we investigate whether optimistic analysts respond less to negative earnings surprises relative to positive earnings surprises (and vice versa for pessimistic analysts). We find that an optimistic analyst is less responsive to negative earnings surprises relative to positive earnings surprises when updating their next year's earnings forecasts. More importantly, this asymmetric response is more pronounced after the Stock Connect program and only for A share analysts. However, we do not find similar results for pessimistic analysts. Overall, we provide some evidence of a particular mechanism optimistic analysts use to introduce bias into their outputs: underreacting to negative news.

Our study makes important contributions to the extant literature. We are one of the first papers to provide empirical evidence of analysts' catering to investors' beliefs. While prior research has documented the effect on analyst bias of numerous economic incentives and cognitive biases, the implication of most of these studies is that analysts' bias influences investors' beliefs. In contrast, catering theory introduces the possibility of the reverse – that investor beliefs influence analysts' outputs. Lai (2004), an unpublished working paper, provides some empirical support for his model on analyst catering, but is only able to address the "direction of causality" issue econometrically, through the use of simultaneous equations and other cross-sectional robustness tests. In contrast, we are able to provide stronger evidence by capitalizing on a setting that represents an exogenous shock to investor beliefs – the market liberalization programs in China.

A few recent studies have a similar theme to catering theory, but we believe are distinct in their explanation for analyst bias. First, Zhang (2019) finds that analysts who eventually move to buy-side institutions issue more favorable recommendations on stocks that are important to their future employers, suggesting they bias their outputs to curry favor with their future employer. Second, using a granular database on how mutual funds allocate trading commission to brokerages in China, Gu et al. (2013) and Firth et al. (2013) find that analysts provide optimistic research on stocks held by their mutual fund clients (from which their brokerages receive trading commissions). While both studies suggest that analysts bias their reports in response to their investors' preferences, the catering theory explored in this study is not necessarily driven by economic incentives nor is it specific to a particular investor. Moreover, the policy implications of these prior studies are quite different from ours. For example, the European Union implemented MiFID II in 2018 in an attempt to improve investor protection and increase transparency in capital markets by requiring asset managers to unbundle payments made for analyst research and brokerage trading commissions. This regulatory change addresses the incentive effects investigated in Gu et al. (2013) and Firth et al. (2013). However, our results suggest that if investors' preference to read research that confirms their own beliefs is a factor that is driving analyst bias, then having these investors pay for the research independently (instead of bundled through brokerage commissions) might not eliminate this bias. Our results suggest that reforming the organizational structure and incentives of brokerage houses will not completely eliminate analyst bias.

Finally, we also contribute to the behavioral finance and accounting literature on catering, the underlying theme of which is that corporate decisions can be explained by the preferences of their clients and the market. For example, catering has been used to explain capital structure (Baker and Wurgler 2002), dividend payouts (Baker and Wurgler 2004), and earnings management (Rajgopal et al., 2007). We add to this stream by providing evidence on catering effects on analyst outputs.

The rest of the paper is as follows. Section 2 provides institutional background. Section 3 reviews the related literature and develops our hypotheses. Section 4 discusses our sample and key variables. Section 5 describes our research design and results. Section 6 concludes.

2. Institutional background

2.1 Segmented A and H shares prior to Stock Connect

China has two domestic stock exchanges: the Shanghai Stock Exchange (SSE) established in 1990 and the Shenzhen Stock Exchange (SZSE) established in 1991. Since their establishment, the Chinese economy and security markets have experienced unprecedented growth. As of 2018, the number of listed companies at these two exchanges totaled 3,584, nearly tripled the amount in 2002. These listed firms have a total market capitalization of 6.32 trillion U.S. dollars, representing nearly 50% of China's GDP in 2017.[5] These domestically listed shares are referred to as "A shares" and are traded in RMB. Prior to Nov 17, 2014, China imposed stringent capital controls, which prevented foreign investors from freely moving capital across its borders. As a result, A shares were predominantly traded by local investors.

Many Chinese firms also chose to list their stocks on The Stock Exchange of Hong Kong (SEHK); these shares are referred to as "H shares." By the end of 2018, 243 Chinese firms had H shares trading on the SEHK, with a total market value of 5.94 trillion Hong Kong dollars and accounting for 19.9% of the market capitalization of the SEHK. H share investors come from all over the world: 38% of the SEHK's total trading volume comes from local Hong Kong investors and 46% comes from other parts of the world, including the United States, the United Kingdom, continental Europe (the remaining 16% comes from dealers). In addition, the majority of trading volume stems from institutional investors (61%) versus retail investors (23%).[6]

For our study, we focus on a group of 107 companies with both A and H shares issued that we refer to as A-H dual-listed companies. It is important to note that A and H shares of these firms offer the same voting and cash-flow rights and identical disclosure requirements by the

[5] Source: https://www.theglobaleconomy.com/China/stock_market_capitalization_dollars/
[6] https://www.hkex.com.hk/-/media/HKEX-Market/Market-Data/Statistics/Consolidated-Reports/HKEX-Fact-Book/HKEX-Fact-Book-2018/FB_2018.pdf?la=en

three stock exchanges involved in listing these shares. Among the 107 A-H pairs, 20 listed their A shares on the Shenzhen Stock Exchange and 87 on the Shanghai Stock Exchange.

The law of one price does not apply for these dual-listed shares due to market segmentation. Prior to 2014, A shares were traded primarily by Chinese residents and H shares were almost exclusively traded in Hong Kong by Hong Kong and foreign investors. The capital controls made it impossible for people to arbitrage any price gap between the dually listed A and H shares. Instead, the prices of A and H shares reflected risk preferences and beliefs of local and foreign investors. In general, the popular press and research firms held the view that mainland Chinese investors tended to focus on the stocks of firms that might benefit from government policies, and tended to chase market sentiment and growth potential, while foreign investors put more emphasis on fundamentals (Jia et al. 2017, Burdekin and Siklos 2018). As a result, A shares have generally traded at a premium relative to H shares (Chung et al. 2013).

2.2 Capital Market Liberalization through Stock Connect

The Shanghai-Hong Kong Stock Connect was a pilot program established by the Chinese government to connect the stock markets in Shanghai and Hong Kong. The program marked an important step in China's capital market liberalization, allowing relatively free movement of investment funds between Hong Kong and Mainland China stock markets.

The Shanghai-Hong Kong Stock Connect program was announced on April 10, 2014 and launched on November 17, 2014. Under the program, eligible investors in Mainland China could purchase eligible shares listed on the Hong Kong Stock Exchange through their own local broker, while Hong Kong and international investors could purchase eligible Shanghai-listed shares through Hong Kong brokers.[7] Under the program, there were 569 eligible shares on the Shanghai exchange available to foreign investors and 315 shares on the Hong Kong exchange available to mainland investors, including all A-H dual-listed shares.[8] Further, starting from March 2, 2015, foreign investors were technically allowed to short A-shares through the Stock Connect program.[9]

The Chinese government subsequently followed the successful launch of the Shanghai-Hong Kong Connect program with the Shenzhen-Hong Kong Connect program, which was launched on December 5, 2016. Under this program, 881 A-share companies can be traded by international investors via Hong Kong security companies, roughly 300 more than the Shanghai-Hong Kong program and including hundreds of small-cap stocks traded in Shenzhen, Under the Shenzhen-Hong Kong Connect program, there are no aggregate quotas, which means that investors on both sides can trade shares freely on each other's markets.

3. Hypothesis development

Our hypotheses are based on the idea that analysts cater to the beliefs of their investors and draws on a model of media bias by Mullainathan and Shleifer (2005). There are two main

---

[7] All Hong Kong and overseas investors are considered eligible investors. However, only mainland institutional investors and individual investors who have a minimum balance of 500,000 Yuan in their brokerage account are eligible to trade in Hong Kong.

[8] The group of stocks on SSE that were eligible for trading by foreign investors included constituent stocks of the SSE 180 or SSE 380 as well as A-H dual listed shares. The group of stocks on the SEHK that were eligible for trading by mainland investors included constituent stocks of the Hang Seng Composite LargeCap and MidCap Indices as well as all A-H dual listed shares. In addition, trading was initially subject to daily and aggregate quota restrictions. The daily quota for net buying value of northbound (southbound) trades was 13 billion (10.5 billion) RMB, which represented roughly 20% of the daily turnover in each market. If trading exceeded the quota at any time during regular trading hours, new buy orders are rejected until sell orders freed up the quota. These quotas were subsequently raised. The aggregate quotas limited the cumulative buying and was initially set at 300 billion (250 billion) for northbound (southbound) trading. The aggregate quotas were abolished on August 16, 2016. For more detailed description, please see Yoon (2018).

[9] Although short selling was technically allowed, the scarcity of lendable shares and high borrowing cost (7-8% annually) made short sale activity largely absent in China during our sample period.

assumptions in the model: 1) readers hold beliefs which they like to see confirmed, and 2) newspapers can slant stories toward these beliefs. They show that if readers share homogeneous beliefs, a monopolist newspaper will slant news towards the homogeneous readers' beliefs. Moreover, they show that media slant exists even in a competitive media setting: competition results in lower prices, but common slanting toward reader biases. When readers' beliefs diverge (i.e., when there are heterogeneous readers), newspapers segment the market and slant toward extreme positions: the left moves more to the left, while the right moves more to the right. This strategy is optimal for the newspaper because the readers get more utility out of confirming their prior beliefs, so the newspaper can charge a higher price, which can offset the effect of losing some readers by positioning the newspaper further away from the others.

Lai (2004) adopts the Mullainathan and Shleifer model to the context of financial analysts. In the same way that newspapers slant news to cater to their readers, analysts may slant their reports to cater to the views of investors. Under the MS model, competition does not eliminate the bias when investors have homogeneous views. Thus, despite the fact that the financial analyst market is presumably competitive, we might still expect bias in their reports when investor beliefs are somewhat homogeneous.

A key assumption in these models is that investors hold beliefs that they prefer to have confirmed. This bias is consistent with a long literature in psychology referred to as "confirmation bias," which suggests individuals have a tendency to collect and process information in a way that confirms or strengthens their priors (sometimes referred to as positive hypothesis testing) and that they have an inclination to retain a favored hypothesis (Klayman 1995). Confirmation bias can manifest both through the information that individuals acquire as well as through the way in which they assimilate that information. For example, Lord et al.

(1979) find that undergraduates exposed to two purported studies, one confirming and one disconfirming of their beliefs (regarding the death penalty), rated the results and procedures in the confirming study as more convincing. The likely underlying mechanism behind the confirmation bias is “cognitive dissonance”. Fundamentally, individuals experience psychological discomfort from inconsistent thoughts, beliefs, or attitudes and actively avoid situations and information that are likely to increase them (Festinger 1957). Together these theories suggest that investors with positive opinions on a stock (e.g., if they have already purchased the stock) would prefer to hear opinions confirming this opinion and, as a result, analysts would have an incentive to cater to these beliefs.

Two key institutional features create incentive for analysts to cater to the needs of institutional investors. First, the primary source of revenue and a key performance measure of research departments at brokerage houses are trading commissions from institutional investors. Gu et al. (2013) show that, due to commission fee pressure, Chinese A share analysts cater to their affiliated institutional investors’ needs and provide optimistically biased reports on stocks in which the fund companies have taken large positions. Second, each year, New Fortune magazine organizes the most influential star analyst ranking in China by polling votes from large fund managers. Analysts who rank high in this contest often enjoy an immediate, sizeable increase in compensation and become highly sought-after talents among brokerage firms. Canvassing the fund manager for votes in the contest creates another incentive for analysts to please institutional investors (Lobo et al. 2019).

We test this catering theory using the A-H dual-listed shares around the time of the Stock Connect programs. Our tests are predicated on the argument that the beliefs of the A and H share investors differed; as such, analysts covering the A shares would have different catering incentives than analysts covering the H shares. Moreover, these catering incentives would change following the Stock Connect program because of changes in the investor bases. In particular, our predictions are based on the argument that mainland Chinese (local) investors of A shares tend to have homogeneously *positive* views of the future prospects of Chinese firms. There are several factors that likely contribute to this optimism. First, the Chinese stock market has experienced unprecedented returns since the opening of the two exchanges. These returns are the result of both growth in the overall Chinese economy as well as government restrictions on share buybacks and equity issuances, common tools managers use to reveal their private information and correct perceived overvaluation (Mei et al. 2009). [10] Second, Chinese investors are subject to strict capital controls imposed by Chinese authorities to prevent wealthy Chinese individuals and corporations from moving money out of China, resulting in a necessarily domestic investment focus. The combination of limited alternative investment opportunities and strong returns in A share stocks would likely lead to an optimistic market sentiment.

In contrast, foreign investors who invest in H shares are likely to hold more *heterogeneous* beliefs. These investors are mostly sophisticated institutional investors who put more emphasis on firm fundamentals and have a multitude of investment opportunities. Moreover, the SEHK has a relatively well-developed short-selling market that attracts investors with negative views of a firm and creates demand for negative opinions from analysts. Consistent with these arguments, prior research has documented an A share premium relative to H shares (Chung et al. 2013).

[10] The Shanghai Stock Exchange was re-established in November 1990 and between 1991 and 2014 (when the Stock Connect Scheme was implemented), China's annual GDP growth averaged approximately 10.12%. See: https://data.worldbank.org/indicator/NY.GDP.MKTP.KD.ZG?locations=CN

Given these different beliefs, we expect A share analysts to be more optimistic relative to H share analysts. A key feature of our study is that the main difference between A shares and H shares are their respective investor bases, since the underlying economics of the firms are the same. Thus, we are able to directly test the catering hypothesis – i.e., whether analysts bias their reports toward the beliefs of their investors. Moreover, to address the possibility of reverse causality – that analysts' optimistic views are responsible for the overall optimism of mainland Chinese investors – we use the two stock connect programs as an exogenous shock to the investor base of A shares. Specifically, since foreign investors can directly buy A shares following the Stock Connect Program *and* these investors tend to have less optimistic views of Chinese firms, we expect the gap in A and H share analysts' optimism to be reduced following the regulatory change.

H1: Relative to H shares, analyst optimism in stock recommendations for A shares will be reduced after the 2014 Shanghai-Hong Kong and the 2016 Shenzhen-Hong Kong Stock Connect programs.

Another key proposition from the MS model for media bias is that if readers have heterogeneous beliefs, media slant by individual newspapers increases – newspapers segment the market and choose extreme position. While the biases of individual media sources tend to offset, leading to greater accuracy across the media sources, any particular news source becomes more biased. Similarly, we anticipate that in the analyst setting, when investor heterogeneity increases, analysts will segment the market and tend to *slant toward extreme positions*. One way in which this segmentation and increased slant might manifest in the analyst context is that analysts will take favorable or unfavorable positions on a stock by issuing optimistic or pessimistic recommendations (segment the market) and then increase the slant in their reports by biasing upward or downward the underlying quantitative and qualitative information that support these positions. Thus, A share analysts with optimistic (pessimistic) recommendations will have relatively more optimistic (pessimistic) EPS and target price forecasts to support their recommendations, as well as more positive (negative) tone in the language in their research reports. To control for changes in other market-wide or firm-specific factors that might have changed the underlying characteristics of the dual-listed firm, we use H share analysts as a benchmark.

H2: Relative to analysts following H shares, A share analysts with optimistic (pessimistic) recommendations will issue relatively more optimistic (pessimistic) EPS forecasts, target price forecasts, and research report tone after the Stock Connect program.

Finally, we consider the channel through which analysts slant their reports to cater to their investors' view. Throughout the year, analysts receive a sequence of positive and negative "pieces" or news about a firm (e.g., earnings announcements, product launches, store openings, capital investments, etc.). An analyst who does not slant would issue their report incorporating all the news without bias. In contrast, an analyst who wishes to slant upward (downward) might ignore or underreact to negative (positive) information.

Given firms regularly announce earnings, we examine analysts' incorporation of earnings surprises as a channel to slant their reports. We assume an unbiased analyst (who does not slant) will immediately revise their forecasts downward (upward) following a negative (positive) earnings surprise. If, however, analysts have incentives to slant their reports toward investors' optimistic (pessimistic) views, they might underreact to negative (positive) earnings surprises. To the extent this is a mechanism used to slant their reports, we expect A share analysts will become even less responsive to the news that does not support their recommendation after the Stock Connect Programs.

H3: After the implementation of the Stock Connect Programs, A share analysts with optimistic (pessimistic) recommendations will slant more by omitting negative earnings news (positive earnings news).

4. Sample and Key Variables

4.1 Sample

There are 107 dual-listed Chinese firms from 2007 to 2018. We choose to start the sample in 2007 because China implemented a key structural reform in 2006, which allowed previously non-tradable State-Owned Enterprises (SOEs) to become tradable. These A-H dual-listers are typically large firms from key industries of China, such as banking, energy, and insurance.

Our tests of H1 and H2 utilize self-constructed consensus on recommendations, EPS and target price forecasts, as well as analyst report tone, at the share-month level.[11] Panel A of **Table 2** describes the sample selection/construction procedure for this sample. For our recommendation sample, we start with IBES detailed recommendation data (84,372 detailed recommendations) and then impose ***four*** sample restrictions. First, we require that the same analyst/broker is in both the pre- and post- sample periods. By doing this, we hold the analyst/broker constant, and ensure that changes in analyst opinion are not driven by shifts in the composition of analysts/brokers in the A share market.[12] Second, we keep only share-month observations that have at least three recommendations to form the consensus. Third, we require that, for a given firm-year, both A and H shares are in our sample. This is to ensure we strictly follow a paired sample design. Finally, we exclude stocks that do not appear in both the pre- and post-Stock Connect Periods. These steps yield 63 unique firms, and 37,054 individual recommendations. We then aggregate

[11] We do not use IBES consensus data because our first sample restriction requires analysts/broker identification, which is not available in the summary file.
[12] In order to identify analyst and broker, we use the IBES recommendation detail data. We then self-constructed a monthly summary file after requiring constant analysts/brokers.

these individual recommendations into 6,266 share-month consensus observations. Of these firms, 53 (10) have their A shares listed on the Shanghai (Shenzhen) Stock Exchange.

We form our sample for EPS and target price forecasts following a similar process.[13] This process results in a final sample of 59,417 and 9,267 individual EPS and target price forecasts, respectively, for 63 and 37 unique firms. These individual forecasts then form 6,266 (1,648) EPS (target price) consensus at the share-month level.

Panel B of **Table 2** describes the sample construction for analyst report tone using a similar filtering process. The only exception is that we do not require the same analysts/broker before and after the A-H Connect because the two databases from which we obtain analysts' reports do not have a common identifier for analyst/broker. In addition, analysts' names are typically displayed as an analyst team with several team members. Our final sample for tone covers 45,783 analysts' reports for 63 dual-listers, which is then converted into 6,136 share-month observations.

In order to perform the difference-in-differences tests, we need to identify the pre- and post-periods. Consensus and detailed analysts' recommendations and forecasts span from January 2007 through March 2019, which cover fiscal years 2007 to 2018. We use the months prior to November 2014 (December 2016) as the Pre-Connect periods for A shares listed on SSE (SZSE). The month of the scheme start date and those thereafter are classified as the Post-Connect periods. **Figure 1** depicts the timeline.

We obtain detailed analyst recommendations, analyst forecasts for EPS and target price, and monthly closing prices from IBES International files. We obtain financial analyst reports from Thomson Financial's Investext database. Investext's coverage of A share is scarce; thus, we

[13] We use annual EPS forecasts because A and H share analysts do not regularly make quarterly EPS forecasts.

supplement it with A share analyst reports from the Choice database compiled by a local Chinese vender: East Money Information Co., Ltd.

4.2 Variable Definitions

To test H1, we measure optimism in analysts' overall opinion based on the consensus recommendation outstanding at the end of each month. Specifically, $REC_{a,i,s,m}$ is the latest recommendation issued by analyst a, for firm i, share class s, as of month m. $MeanRec_{i,s,m}$ ($MedRec_{i,s,m}$) is the mean (median) $REC_{a,i,s,m}$ for firm i, share class s, as of month m. In IBES, analyst recommendations range from 1 to 5, representing strong buy, buy, hold, underperform, and sell. We multiply the number value of the stock recommendation by -1 so that a higher value indicates more optimistic recommendations.

H2 predicts that optimistic (pessimistic) analysts slant toward more extreme positions after the stock connect. Thus, we first classify each analyst into optimistic and pessimistic groups based on their most recent stock recommendations: those with recent "buy" and "strong buy" recommendations are in the optimistic group and those with "underperform" and "sell" recommendations are in the pessimistic subsample. For each subgroup, we then consider the relative optimism of the following three analyst output variables: 1) annual EPS forecasts;[14] 2) target price forecasts; and 3) analyst report tone. We average the output variables for each subgroup and then subtract the consensus value for that output measure in that month (defined as the mean value of all analysts as of that month). Thus, our measures capture the *relative* optimism of a given analyst subgroup benchmarked against the consensus of the month. Specific

[14] One potential concern with using EPS forecasts are differences in financial reporting standards between A- and H-shares. Dual-listed firms can either report the same set of financial reports to their respective securities regulators (using either Chinese Accounting Standards (CAS) or International Financial Reporting Standards (IFRS)) or they file separate reports to the two regulators. The differences in accountings standards should not affect our results because 1) CAS was largely converged with IFRS during our sample period and 2) our measures using EPS forecasts are benchmarked against the consensus for the same share-class (see variable definition description below).

definitions and data sources are detailed in **Table 1** but we briefly describe and justify our measurement choices below:

1) *Opt_EPS_MeanAdj*$_{i,s,m}$: mean of the latest EPS forecasts issued for firm i, share class s, as of month m, for all analysts with a buy or strong buy recommendation, less the mean consensus forecast, deflated by the weighted average lagged price. Because A shares generally trade at a premium relative to H shares, we use a common deflator for both A and H share forecast. Specifically, we scale by the weighted average of the A-H share price at the beginning of the fiscal year. If we were to instead scale the forecast optimism by each share's respective lagged price, the forecast optimism for A shares will be biased downward due to the larger scaler.[15] *Pess_EPS_MeanAdj*$_{i,s,m}$ is defined similarly except for analysts with a sell or underperform recommendation.

2) *Opt_PTG_MeanAdj*$_{i,s,m}$: mean of the latest target price forecast issued for firm i, share class s, as of month m for all analysts with a buy or strong buy recommendation, less the mean consensus forecast, deflated by the lagged closing price for each respective share type. Because the numerator represents differences in expected target prices by subgroups of analysts for each share and we presume analysts' target prices incorporate the A-share premium, we do not use a common deflator and instead deflate by the lagged closing price for each respective share type. *Pess_PTG_MeanAdj*$_{i,s,m}$ is defined similarly except for analysts with a sell or underperform recommendation.

3) *Opt_Tone_MeanAdj*$_{i,s,m}$: mean tone in analyst reports for firm i, share class s, in month m for all analysts with a buy or strong buy recommendations, less the mean "consensus" tone (i.e., the mean tone of *all* analyst reports issued for firm i, share class s, in month m). We

[15] A shares are traded in RMB, while H shares are traded in HK dollars. We convert HK dollars to RMB using daily exchange rate.

measure analyst report tone using frequency counts of positive and negative words. *Pess_Tone_MeanAdj*$_{i,s,m}$ is defined similarly except for analysts with a sell or underperform recommendation.

The bulk of A share analyst reports (80.24%) are in Chinese while a large portion of H share analyst reports (89.93%) are in English. We measure textual tone in English reports based on the dictionary of Loughran and McDonald (2011), which is specifically designed for financial disclosures (Davis et al. 2015). Unfortunately, a similar word list specifically designed for business contexts is not yet available in Chinese. There are three commonly used word lists used for textual tone in Chinese: (1) Tsinghua Natural Language Processing and Computational Social Science Lab Chinese Tone Dictionary (THU); (2) Dalian University of Technology Information Research Lab Chinese Tone Dictionary (DUT); (3) HowNet Knowledge Database Chinese Tone Dictionary (HowNet). Currently, there is no consensus in the Chinese literature regarding which one is the most appropriate for tone analysis in financial disclosure context (Yao et al. 2020); as a result, we use all three wordlists (DUT, THU, and HowNet) to ensure that our results are not driven by one particular list.[16]

We use the above four wordlists to count both positive and negative words used in each analyst report. Our language measure, TONE, is the difference between the positive words and the negative words in a given analyst report, scaled by the sum of positive and negative words. For each Chinese report, we have three tone measures: TONE_D, TONE_T, TONE_H, corresponding to the three Chinese word lists: DUT, THU, and HOWNet.[17]

---

[16] Since the majority of H share analyst reports are in English while most A share reports are in Chinese, one concern is that any difference in tone between A and H share reports could be driven by the word lists we use. However, this concern is largely mitigated by our design where we examine *relative* optimism (i.e., by subtracting the mean tone of all analyst reports for each share class before comparing A and H analyst groups).

[17] Since each English report uses the Loughran and McDonald (2011) wordlist we do not index the variable name to indicate the use of the L&M wordlist.

4.3 Descriptive Statistics

Table 3 provides descriptive statistics for the aforementioned list of variables, partitioned by A (**Panel A**) and H shares (**Panel B**) and by pre- and post-sample periods. We note that H share analysts' recommendations remain relatively stable across the two sample periods (mean = –2.38 and –2.43 for pre- and post- periods, respectively). In contrast, A share analysts have noticeably lower stock recommendations in the post-periods (mean= –1.93 and –2.62 in the pre- and post- periods, respectively). The patterns of these differential changes between A and H analysts are consistent with the predictions outlined in Hypothesis 1.

Table 3 also provides summary statistics on EPS, target price forecast, and analyst report tone, for the sub-samples of analysts with optimistic/pessimistic opinions on a given stock. Generally, these analyst outputs remain relatively stable across the two sample periods for H shares, while optimistic (pessimistic) analysts following A shares appear to issue more optimistic (pessimistic) outputs across the two periods. **Panel A** shows that, for A share analysts, the mean of each relative optimism measure increases for the optimistic group and decreases for the pessimistic group. T-tests suggest that most of these changes in mean are statistically significant, with the exception of $Pess\_PTG\_MeanAdj_{i,s,m}$. Although we have not controlled for time trend or firm level characteristics by benchmarking these changes against H shares, our observation is nevertheless consistent with Hypothesis 2.

We also present a graph of the monthly consensus stock recommendations over time. **Figure 2** plots the percentage of optimistic ("Strong Buy" and "Buy") and pessimistic ("Underperform" and "Sell") recommendations for paired A-H shares by month, where month 0 is the month the two Stock Connect programs were introduced. Prior to the Stock Connect programs, A shares (represented by the solid lines) almost always had more (less) optimistic (pessimistic) recommendations than H shares (represented by the dashed lines). However, that relation reverses soon after the Stock Connect. We notice a large decrease (increase) in optimistic (pessimistic) recommendations in A shares relative to H shares.

Additionally, we plot differences in the A-share recommendation relative to the H-share recommendation around the adoption of Stock Connect programs. For each Stock Connect Program, we set zero to be the quarter that marks the start of the Stock Connect, such that one quarter before A-H Connect is −1 and one quarter after A-H Connect is +1. We then estimate the following regression:

$$MeanREC_A - MeanREC_H = \beta_1 C^{-12} + \beta_2 C^{-11} + \cdots + \beta_{25} C^{12} + \varepsilon_{it} \qquad (1)$$

where the dummy variable C^n equals one for observations in the nth quarter after the Stock Connect, while the dummy variable C^{-n} equals one for firms in the nth quarter before the Stock Connect, respectively. We consider a twenty-four-quarter window, spanning from twelve quarters before A-H Connect until twelve quarters after. We then plot the estimated coefficients on the Stock Connect dummy variables (which captures differences in consensus recommendations between A and H shares) and provide 95% confidence intervals.

Figure 3, Panel A shows how the difference in mean recommendation between A- and H-shares evolves over time for our full sample. The graph shows that: (1) prior to the Stock Connect Programs, A-share recommendations are generally higher than H-share recommendations (consistent with our assumption), and 2) there is a distinct drop in the difference between A- and H-share analyst consensus recommendations following the adoption of the Stock Connect programs. However, we also note a slight downward trend in the difference in the quarters leading up to the Stock Connect programs. One possible explanation for this downward trend is analysts' and investors' anticipation of the programs. This anticipation effect was likely to be particularly acute for the Shenzhen-Hong Kong Connect program, which followed the Shanghai-Hong Kong Connect program. In Panel B, we plot a similar graph excluding the dual-listed firms from the Shenzhen exchange and find the downward trend largely missing from this graph.[18,19] The overall theme of the graphs and the summary statistics is consistent with our first hypothesis: A share analysts have more optimistic outputs than H share analysts prior to the Stock Connect Program, but this difference is reduced in the post period.

5. Empirical Analysis

5.1 Regression analysis for H1

To formally compare how analysts change their recommendations in response to the Stock Connect programs, we estimate the following difference-in-differences OLS model, at the firm-share-month level (subscripts suppressed for brevity):

$$MeanREC\ (MedREC) = \beta_0 + \beta_1 AShare + \beta_2 POST + \beta_3 AShare \times \mathrm{POST} + \varepsilon_{it} \qquad (2)$$

The dependent variable is the monthly consensus recommendations (*MeanREC* or *MedREC*). *AShare* is an indicator for A shares. *POST* is an indicator variable for periods after the Shanghai-Hong Kong Stock Connect (2014) and the Shenzhen-Hong Kong Stock Connect (2016) regulation change, respectively. Based on H1, we expect $\boldsymbol{\beta_3 < 0}$, suggesting that A share analysts respond to the influx of foreign investors (who tend to have less optimistic views on Chinese firms) by reducing optimism in their outputs after the Stock Connect programs.

[18] The overall trend resembles Figure 3 when we use median instead of mean recommendations.

[19] In untabulated tests, we formally test the parallel trends assumption underlying the DiD design. Specifically, we follow Roberts and Whited (2013) and create a pseudo-adoption date by altering the implementation year of A-H Connect to prior years. Using 2010, 2011, or 2012 as the pseudo-adoption date, we do not find a significant change in the consensus recommendations for the A-share sample, relative to the H-share sample, in the pseudo post-implementation period. Overall, these tests suggest that our sample of A-H dual-listed firms are suitable for our DiD estimation and that the parallel trends assumption is satisfied.

Table 4 reports the results of estimating equation (2), clustering standard errors by firm-year. The coefficient on the *AShare* indicator variable is positive and significant, indicating that prior to the Stock Connect programs, A share analysts tend to have more favorable recommendations than H share analysts. The coefficient on *Post* is insignificant, indicating no change in the level of recommendation for H share analysts in the post period. In contrast, the coefficient on the interaction term: *AShare×Post* is significantly negative, indicating that, relative to H share analysts, A share analysts' recommendations become less optimistic after the Stock Connect program. The average A share analyst's consensus recommendation changed from "buy" to somewhere between "buy" and "hold". Overall, the results provide support for H1: A share analysts appear to cater to the less optimistic views of incoming international investors. Given our paired A-H design and the exogenous change in investor bases following the Stock Connect programs, these results provide strong evidence that analysts cater to investors' beliefs.

5.2. Empirical Analysis for H2

We next investigate whether the introduction of investor heterogeneity leads A share analysts to segment the market and slant toward extreme positions. Specifically, H2 predicts that A-share analysts with "buy" or "strong buy" ("underperform" or "Sell") recommendations will become even more optimistic (pessimistic) in their earnings and target price forecasts, as well as in their report tone, after the Stock Connect programs.

Similar to our prior analysis, we estimate the following difference-in-differences OLS regression for our measures of EPS, price target, and tone calculated for each sub-group of optimistic and pessimistic analysts:

$$\textit{Analyst\_Output} = \beta_0 + \beta_1 \times \text{AShare} + \beta_2 \times \text{POST} + \beta_3 \times \text{AShare} \times \text{POST} \qquad (3)$$

Analyst_Output is one of the ten measures described in section 4: 2 analyst groupings (*Opt_* and *Pess_*) and 5 outputs (*_EPS, _PTG, _Tone_D, _Tone_T, _Tone_H)*. These mean adjusted analyst research outputs capture *relative* optimism of each subgroup of analysts, as compared with the monthly consensus.

H2 predicts a positive coefficient on β_3 for the *Opt_* variables, indicating higher relative EPS forecasts, target price forecasts, and report tone for optimistic A share analysts following the Stock Connect programs, relative to optimistic H share analysts. In contrast, we expect a negative coefficient on β_3 for the *Pess_* variables, indicating *lower* relative EPS forecasts, target price forecasts, and report tone for pessimistic A share analysts following the Stock Connect, relative to pessimistic H share analysts. When estimating our model with the EPS forecast variables, we include horizon fixed effects (i.e., the month relative to the earnings announcement date) to control for potential changes in biases as the year-end approaches (i.e., potential "walk-down effects"). We cluster standard errors at the firm-year level.

Table 5 reports the regression results. Panel A, B and C show the results for EPS forecasts, target price forecasts, and analyst report tone, respectively. The first (second) columns of each table use the research output produced by analysts with an optimistic (pessimistic) view of the firm. Across all ten specifications, the coefficient estimates of the key interaction term – *AShare×Post* – is positive for analysts with optimistic views of the firm and negative for those with pessimistic views of the firm. All of these coefficients except the one of *Pess_PTG* are statistically significant at the 10% level.[20] Overall, these results are consistent with A share analysts responding to the increased investor heterogeneity by issuing more extreme outputs to

[20] In untabulated additional tests, we use ten measures of corresponding median-adjusted analyst research outputs for the same set of analysis. Our results are inferentially similar. In all ten cases, the coefficients on the interaction term are consistent with expectation, except that the coefficient on the interaction term for *Pess_PTG_MedAdj* is insignificant.

support their positions, presumably to cater to the views of their "readers." Thus, analysts with optimistic views of a given stock support their positions by increasing their EPS forecasts, target price forecasts and the tone of their reports after the Stock Connect programs, whereas pessimistic analysts decrease these outputs. This pattern is consistent with H2 and supports the catering hypothesis as outlined in the M-S model.

This evidence provides a nuanced picture of the effect of heterogeneous investor beliefs on analyst bias under a catering theory. On the one hand, the introduction of investors with diverse beliefs, allows some analysts to cater to less optimistically biased investors, thereby reducing the average (consensus) optimism across analysts (as our results for H1 support). However, any *individual* analyst introduces greater bias into his/her outputs in order to cater to the subset of the market that he/she is attracting. Thus, a conscientious investor who consumes information from multiple sources will receive less biased information. However, investors who only consume information from one source will receive *more* biased information.

5.3 Empirical Analysis for H3

Our final analysis investigates one way in which analysts might slant or bias their reports – namely, by ignoring or underreacting to news that does not support their recommendations (H3).

To investigate this possibility, we examine how analysts revise their EPS forecasts after earnings announcements. The difference between the earnings outcome and an analyst's last forecast (the earnings surprise) conveys new information that should result in a revision of the analyst's belief about the firm's future performance. We assume that an unbiased analyst will revise his/her forecast of next year's earnings in the same direction as the earnings surprise: a positive (negative) earnings surprise will lead the analyst to adjust his/her forecast of next year's earnings upward (downward). To the extent that an analyst with catering incentives are more likely to ignore or underreact to news that does not support his/her recommendation, an analyst's forecast revision will be less sensitive to earnings surprises that are inconsistent with his/her recommendation (relative to an earnings surprise that supports their recommendation). In other words, analysts with optimistic (pessimistic) recommendations will be more responsive to a positive (negative) earnings surprise relative to a negative (positive) earnings surprise.

Panel C of **Table 2** describes how we form an individual analyst forecast sample to test H3. Note that this test is conducted at the analyst-firm-share-year level (versus our prior tests which were conducted at the firm-share-month level). The first three steps ensure a paired A-H constant sample design. We then keep only analyst-firm-year observations where the analyst's last forecast of next year's earnings is within 6 months of the earnings announcement and his/her first post-earnings announcement forecast is within one month of the earnings announcement, to ensure that the EPS forecast revision is driven by the earnings surprise. As shown in Panel C, these steps yield 71 unique firms and 4,815 individual analyst EPS updates. Since our focus is on the most optimistic group of analysts, we only keep observations where the analyst's pre-earnings announcement recommendation and post-earnings announcement recommendation are both above "Hold" (i.e. "Strong Buy" or "Buy"). Consistent with our prior analysis, we require the same firms to be in both the Pre- and Post-Stock Connect sample periods and have both A and H share data for a given year. After these requirements, our sample size is rather small: 409 and 306 analyst-share-year observations for A shares (818 and 430 for H shares), in the pre and post periods, respectively.

We estimate the following regression for a group of A share analysts with **optimistic** views of a firm (with "buy" or "strong buy" recommendations) around a given earnings announcement:

$$\Delta FORECAST = \alpha_1 + \alpha_2 SURP + \alpha_3 SURP \times MISS \quad (4)$$

ΔFORECAST is the change in an analyst's EPS forecast for year t+1 in response to the earnings announcement for year t. It is calculated as the difference between one year ahead EPS forecasts (made within one month after the earnings announcement) minus the most recent two-year ahead EPS forecast made by the same analyst before the earnings announcement, deflated by the lagged weighted average A and H price. *SURP* is the analyst-specific earnings surprise, calculated as actual EPS minus the last EPS forecast made by a given analyst prior to the earnings announcement, deflated by the lagged weighted average A and H price. $MISS$ is a dummy variable equal to one when the actual EPS is lower than the specific analyst's most recent EPS forecast before the earnings announcement.

Equation (4) examines the asymmetric EPS forecast revision after negative news for A share analysts with optimistic views of a firm. For ease of interpretation, we estimate this equation for the A share sample in the Pre- and Post- periods separately. H3 predicts α_3 to be more negative in the post-Stock Connect period: the analysts with a positive stance become even less responsive to negative earnings surprise in updating next year's EPS forecast after the A-H Stock Connect. We perform an F-test for the difference in α_3 between the pre- and post-samples

To control for possible time-period specific effects, we also run a specification including H share analysts as a control group:

$$\Delta FORECAST = \alpha_1 + \alpha_2 SURP + \alpha_3 SURP \times MISS + \alpha_4 SURP \times AShare + \alpha_5 SURP \times MISS \times AShare \quad (5)$$

We again estimate Equation (5) separately for the pre- and post-Stock Connect samples and expect α_5 to be more negative in the post-Stock Connect period than in the pre-period. We perform an F-test for the difference in α_5 between the pre- and post-samples.

We run an analogous specification for A share analysts with *pessimistic* opinions of a given stock (with “underperform” or “sell” recommendations):

$$\Delta FORECAST = \alpha_1 + \alpha_2 SURP + \alpha_3 SURP \times BEAT \quad (4)'$$

$$\Delta FORECAST = \alpha_1 + \alpha_2 SURP + \alpha_3 SURP \times BEAT + \alpha_4 SURP \times AShare + \alpha_5 SURP \times BEAT \times AShare \quad (5)'$$

Equation (4)’ examines the asymmetric forecast revision after positive news for A share analysts. H3 predicts α_3 to decrease in the post-liberalization period: we expect pessimistic A share analysts to become less responsive to good news. When compared with their H-share counterparts, we expect the decline in responsiveness to be greater for A share analysts: we expect α_5 to be lower in the post-Stock Connect period.

Table 6 reports the regression results of testing H3 for a sample of optimistic analysts. Panel A presents results for estimating equation (4) for A share optimistic analysts in the pre- and post-periods separately. Panel B shows the results for estimating equation (5), which includes H shares analyst as a control group (with pre- and post-periods shown separately).

Turning to Panel A, we find large, positive coefficients on *SURP* for both sample periods, indicating that analysts generally respond to positive earnings surprises by revising their next year’s earnings forecast upward. The coefficients on the interaction term *SURP*×*MISS* are significantly negative in both columns (–0.458 in the pre-period and –0.992 in the post-period, respectively). The difference is –0.534 and statistically significant at the 5% level, consistent with H3. Taken together, these results indicate that the group of A share analysts with optimistic recommendations are less responsive to earnings news that is inconsistent with their recommendations. More importantly, this asymmetric response becomes more pronounced in the post-Stock Connect period.

The results in Panel B largely echo those reported in Panel A. In the first column, we find a significantly positive coefficient on *SURP* (0.798) and a significantly negative coefficient on *SURP×MISS* (-0.385). Together, these results indicate that H share analysts who have optimistic recommendations exhibit a similar pattern of underreacting to news that is inconsistent with their recommendations. The coefficients on *SURP×AShare*, *SURP×MISS×AShare* are insignificant, suggesting no systematic difference in A share analysts' tendency to omit negative earnings news relative to H share analysts in the pre-period. However, in the post-period, the coefficient on *SURP×AShare* is significantly positive and the coefficient on *SURP×MISS×AShare* is significantly negative. An F-test of the difference in coefficients on *SURP×MISS×AShare* between the pre- and post-periods is significant at the 10% level. These results largely support H3 and suggest that, relative to H share analysts, optimistic A share analysts become *more* sensitive (*less* sensitive) to good (bad) earnings news in the post-Stock Connect period, as they try to slant their outputs to cater to their optimistic investors.

Table 7 reports the results for the sample of pessimistic analysts. We note that our sample is even smaller, with 176 and 261 forecast revisions (363 and 247) in the pre- and post-periods for A shares (H shares), respectively. Panel A presents the results for the A-share sample, while Panel B reports results for the paired A-H sample. Turning to column (1) of Panel A, we find that the coefficients on *SURP* and *SURP×Beat* are both positive (0.169 and 0.451, respectively), suggesting that pessimistic A share analysts are actually *more responsive* to good news in the pre-period. The next column shows that the interaction term becomes insignificant, indicating a weakened response to positive news. However, the difference is not statistically different (p-value=0.534). Overall, the results in this panel fail to support H3.

Panel B reports the results for the paired A and H sample. In the first column, the coefficients on both *SURP* and *SURP*×*Beat* are significantly positive, while the coefficients on *SURP*×*AShare* and *SURP*×*Beat*×*AShare* are insignificant. Overall, these results mirror those from Panel A, indicating that the group of pessimistic analysts are generally more willing to incorporate good news in the pre-period and this tendency does not differ between A and H shares. Looking across the two columns, we notice an increase in the coefficient on *SURP* while the coefficient on *SURP*×*Beat* loses significance. These changes together suggest that H share analysts become more (less) responsive to news that supports (does not support) their recommendation. However, a comparison of the coefficients on *SURP*×*Beat*×*AShare* across the two periods is insignificant(p-value=0.665), failing to support H3.

Table 6 and Table 7 provide some evidence exploring the channel through which analysts slant their EPS forecasts to support their recommendation. We show that, in providing EPS forecasts, optimistic analysts become less responsive to earnings news that undermine their recommendations, although we fail to document the same pattern in pessimistic analysts.

5.4 Additional analysis

In this section, we explore conditions under which the catering effect is expected to be more pronounced. Specifically, we attempt to identify the firms for which foreign investors held relatively more pessimistic opinions. For these firms, the introduction of foreign investors through the Stock Connect programs would presumably have a greater impact on analysts' catering incentives. We identify two alternative measures to capture foreign investors' negative opinions on A shares.[21]

[21] As discussed previously, we are unable to directly capture foreign investors' negative opinion by tracking northbound short sale activity because short sale activity was largely absent in China during our sample period.

First, in a recent research report, UBS China's equity team identified the four hottest sectors by northbound investors through the Stock Connect (UBS 2019): consumer, financials, tech, and healthcare.[22] Our first cross-sectional variable is an indicator variable for firms **not** in these sectors (*Other_Ind*). Second, each day HKSE discloses a list of the top ten most popular SH/SZ stocks in terms of trading volume from HK investors. We calculate the monthly average number of times a stock is included in the list, then multiply it by -1 so that greater value indicates lower popularity among HK investors (*Unpopularity*). Overall, *Other_Ind* and *Unpopularity* capture the lack of positive sentiment from foreign investors. Therefore, we expect the catering effect to be stronger among these firms.[23]

Table 8 presents the results of adding each of our two cross-sectional variables (Cvar), and its interaction with all other terms – Ashare×Cvar, POST×Cvar, and Ashare×POST×Cvar – to equation (2).[24] We expect the coefficient on the three-way interaction term to be negative for both variables, i.e., the reduction in analysts' optimism is stronger among the stocks that experience greater negative opinions by foreign investors through the Stock Connect programs. We have two observations: 1) as in Table 4, the coefficients on Ashare×POST are always negative and statistically significant, indicating a reduction in analyst optimism even for those A-share firms for which foreign investors are relatively more optimistic; and 2) across both cross-sectional variables and two alternative dependent variables (mean consensus and median

[22] These are the fastest-growing sectors in the Chinese economy. In addition, these sectors are driven by fundamental trends, such as urbanization and innovation, which remain relatively shielded from the impact of US-China trade tensions.
[23] For example, Mainland Chinese investors are known to be short-term focused and tend to chase stocks they believe will benefit from government policies. In contrast, foreign investors put more emphasis on fundamentals. One can infer that those sectors **not** preferred by foreign investors represent those they believe are potentially over-valued by local investors and thus, represent the stocks for which foreign investors hold a relatively more pessimistic opinion.
[24] Note that the results are identical if we estimate the regressions for sub-samples split by *Other_Ind*. However, our pooled sample regression generates more power to detect cross-sectional variation when the variable of interest is a continuous variable.

consensus recommendations), we find significantly negative coefficients on Ashare×POST×Cvar. The results indicate that the reduction in A share analysts' optimism is even more pronounced among firms facing relatively more negative opinions from incoming foreign investors, consistent with the catering theory.

6. Conclusion

We test a catering theory of analyst optimism using a unique setting in China – the Stock Connect programs that exogenously changed the investor bases of Chinese firms. Our results support the theory that analysts tailor their stock recommendations in order to cater to the belief of their investors, similar to theories of media bias (Mullainathan and Shleifer 2005). In addition to capitalizing on the exogenous regulatory change that allowed foreign investors to trade shares on Chinese markets, we also narrow the focus of our analysis to dual-listed firms who also had shares trading on the SEHK (A-H firms) to more cleanly benchmark changes in analyst research outputs. We find that A share analysts' summary outputs (i.e., recommendations) were more optimistic prior to the Stock Connect programs but are significantly reduced in the post-Stock Connect period. In contrast, H share analysts exhibit no change in their recommendations.

We also find that A share analysts with optimistic views of the firm express even greater optimism in their quantitative and qualitative research outputs after the introduction of more foreign investors with more heterogeneous beliefs. This result is consistent with the M-S model which suggests that in competitive markets with heterogeneous investors, analysts will segment the market and take extreme positions. This evidence provides a nuanced picture of how catering theory manifests in analyst bias. At a simple level, introducing more heterogeneous beliefs will reduce the overall average bias across analysts; however, individual analysts take more extreme positions to cater to the segment of the market that they attract.

In addition, we find some evidence that the mechanism through which analysts bias their reports is by underreacting to earnings news that is inconsistent with their positions. Optimistic analysts underreact to negative news relative to positive news and more so in the post-Stock Connect period. Finally, we show cross-sectional evidence that A shares, faced with negative/divergent opinions by foreign investors, experience greater reduction in analyst optimism in recommendation.

Overall, our evidence supports a catering theory for analyst bias and adds to our understanding of the determinants of these biases. In contrast to prior studies that focus on explicit economic incentives that influence analyst bias (e.g., trading commissions), catering theory suggests a more implicit economic incentive stemming from investors' preference to consume information that is consistent with their beliefs. Thus, rather than analyst bias influencing investors' beliefs, catering theory suggests investors' beliefs influence analyst bias. Distinguishing between these two explanations for forecast bias is important because the policy implications for each differ.

While our research design has many features that strengthen our inferences, they are based on a few key assumptions. First, we assume that Chinese investors' beliefs were relatively homogeneous and optimistically biased in the pre-Stock Connect period. This assumption is consistent with anecdotal reports and the generally positive A-H stock price premium. Second, we assume that foreign investors' beliefs were more heterogeneous and less optimistically biased and, thus, their introduction changed analysts' catering incentives. Third, we assume that A share (H share) analysts cater primarily to A share (H share) investors. To the extent any of these assumptions are false, our inferences would be suspect.

References:

Arquette, G.C., Brown Jr., W.O., and Burdekin, R.C. (2008). US ADR and Hong Kong H-share discounts of Shanghai-listed firms. *Journal of Banking & Finance*, 32 (9), pp. 1916-1927.

Baker, M., and J. Wurgler. (2002). Market timing and capital structure. *Journal of Finance* 57, 1–32.

Baker, M. and J. Wurgler. (2004). A catering theory of dividends. *Journal of Finance* 59(3), 1125-1165.

Burdekin, R.C.K. & Siklos., P.L. (2018). Quantifying the impact of the November 2014 Shanghai-Hong Kong stock connect. *International Review of Economics & Finance*, 57 pp. 156-163.

Chen, S., & Matsumoto, D. A. (2006). Favorable versus unfavorable recommendations: The impact on analyst access to management-provided information. *Journal of Accounting Research*, 44(4), 657-689.

China Securities Regulatory Commission (CSRC). (2008). *China Capital Markets Development Report*. Beijing, PRC: CSRC.

Chung, T.K. Hui, C.H., Li., K.F. (2013). Explaining share price disparity with parameter uncertainty: evidence from Chinese A- and H-shares. *Journal of Banking & Finance*, 37 (3) (2013), pp. 1073-1083.

Davis, A. K., W. Ge, D. Matsumoto, and J. L. Zhang. (2015) "The Effect of Manager-Specific Optimism on the Tone of Earnings Conference Calls." *Review of Accounting Studies* 20: 639–73.

Deng, Y., Hope, O.K., Wang, C.& Zhang, M. (2018). Market Liberalization and Asymmetric Audit or Behavior Evidence from a Quasi Experiment. Working paper. University of Toronto.

Easterwood, J. C., & Nutt, S. R. (1999). Inefficiency in analysts' earnings forecasts: Systematic misreaction or systematic optimism? *Journal of Finance*, 54(5), 1777–1797.

Festinger, L. (1957). A Theory of Cognitive Dissonance. *Stanford University Press*

Firth, M., Lin, C., Liu, P., and Xuan, Y. (2013). The client is king: Do mutual fund relationships bias analyst recommendations? *Journal of Accounting Research*, 51(1):165–200.

Gu, Z., Li, Z., and Yang, Y. G. (2013). Monitors or predators: The influence of institutional investors on sell-side analysts. *The Accounting Review*, 88(1):137–169.

Hayes, R. M. (1998). The impact of trading commission incentives on analysts' stock coverage decisions and earnings forecasts. *Journal of Accounting Research*, 299-320.

Hilary, G., & Menzly, L. (2006). Does past success lead analysts to become overconfident? *Management Science*, 52(4), 489-500.

Hong, H., & Kubik, J. D. (2003). Analyzing the analysts: Career concerns and biased earnings forecasts. *Journal of Finance*, 58(1), 313-351.

Jia, C., Wang, Y., and Xiong., W. (2017): "Market Segmentation and Differential Reactions of Local and Foreign Investors to Analyst Recommendations", *Review of Financial Studies*, Vol 30, (9): Pages 2972–3008.

Klayman. J., (1995). Varieties of confirmation bias. *Psychology of Learning and Motivation.* Vol 32, pp. 385-418.

Lai, R. 2004. A catering theory of analyst bias. Working paper. Harvard Business School.

Lin, H. W., & McNichols, M. F. (1998). Underwriting relationships, analysts' earnings forecasts and investment recommendations. Journal of Accounting and Economics, 25(1), 101-127.

Lobo, G., Tan, Y., Wen, Y., and Zhao, H. 2019. How do star analyst rankings affect analysts' performance? University of Houston working paper.

Loughran, T., & McDonald, B. (2011). When is a liability not a liability? Textual analysis, Dictionaries, and 10-Ks. *Journal of Finance*, LXVI (1), 35–65.

Lord, C. G., Ross, L., & Lepper, M. R. (1979). Biased assimilation and attitude polarization: The effects of prior theories on subsequently considered evidence. *Journal of Personality and Social Psychology, 37*(11), 2098–2109.

Mayew, W. J. (2008). Evidence of management discrimination among analysts during earnings conference calls. Journal of Accounting Research, 46(3), 627-659.

Mei, J., J. Scheinkman, W. Xiong. (2009). Speculative trading and stock prices: Evidence from Chinese A-B Share Premia, Annals of Economics and Finance (10-2): 225-255.

Mikhail, M. B., Walther, B. R., & Willis, R. H. (1999). Does forecast accuracy matter to security analysts? *The Accounting Review*, 74(2), 185-200.

Mullainathan, S., and Shleifer, A. (2005). The Market for News. American Economic Review, 95 (4): 1031-1053.

Rajgopal, S., and Shivakumar, L., and Simpson, A. (2007) A Catering Theory of Earnings Management. Available at SSRN: https://ssrn.com/abstract=991138.

Roberts, M., and Whited, T. (2013). Endogeneity in corporate finance. In *Handbook of the Economics of Finance*, Volume 2, Part A, Chapter 7, edited by G. M. Constantinides, M. Harris, and R. M. Stulz, 493–572. Philadelphia, PA: Elsevier B.V.

Shanghai Stock Exchange (SSE). (2017). *Shanghai Stock Exchange Markets & Infrastructure 2017.* Shanghai, PRC: SSE.

Shanghai Stock Exchange (SSE). (2019). *Shanghai Stock Exchange Markets & Infrastructure 2019.* Shanghai, PRC: SSE.

Tam, O.K., Li, S. G., Zhang, Z., and Yu, C.P. (2010). Foreign Investment in China and Qualified Foreign Institutional Investor (QFII). *Asian Business and Management* 9(3): 425-448.

Yao, J, F. Xu, Z. Wang, R. Ji, W. Zhang. 2020. Tone, Sentiment and Textual Analysis: the Construction of Chinese Sentiment Dictionary in Finance. Tianjing University Working Paper.

Yoon, A. (2018). Shaping of Private Disclosure in Weak Institutions: Evidence from a Market Liberalization in China. Working Paper.

Zhang, B. (2019). Analyst Optimism and Buy-Side Institutions: Evidence from Analyst Transition from Sell-Side to Buy-Side. University of Rochester working paper.

Figure 1 – Timeline of Shanghai-Hongkong Connect and Shenzhen-Hongkong Connect

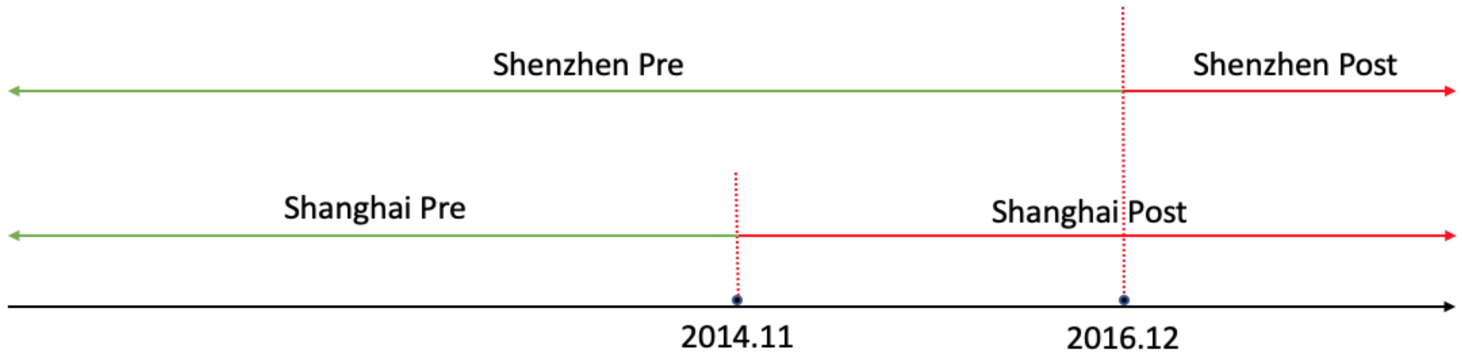
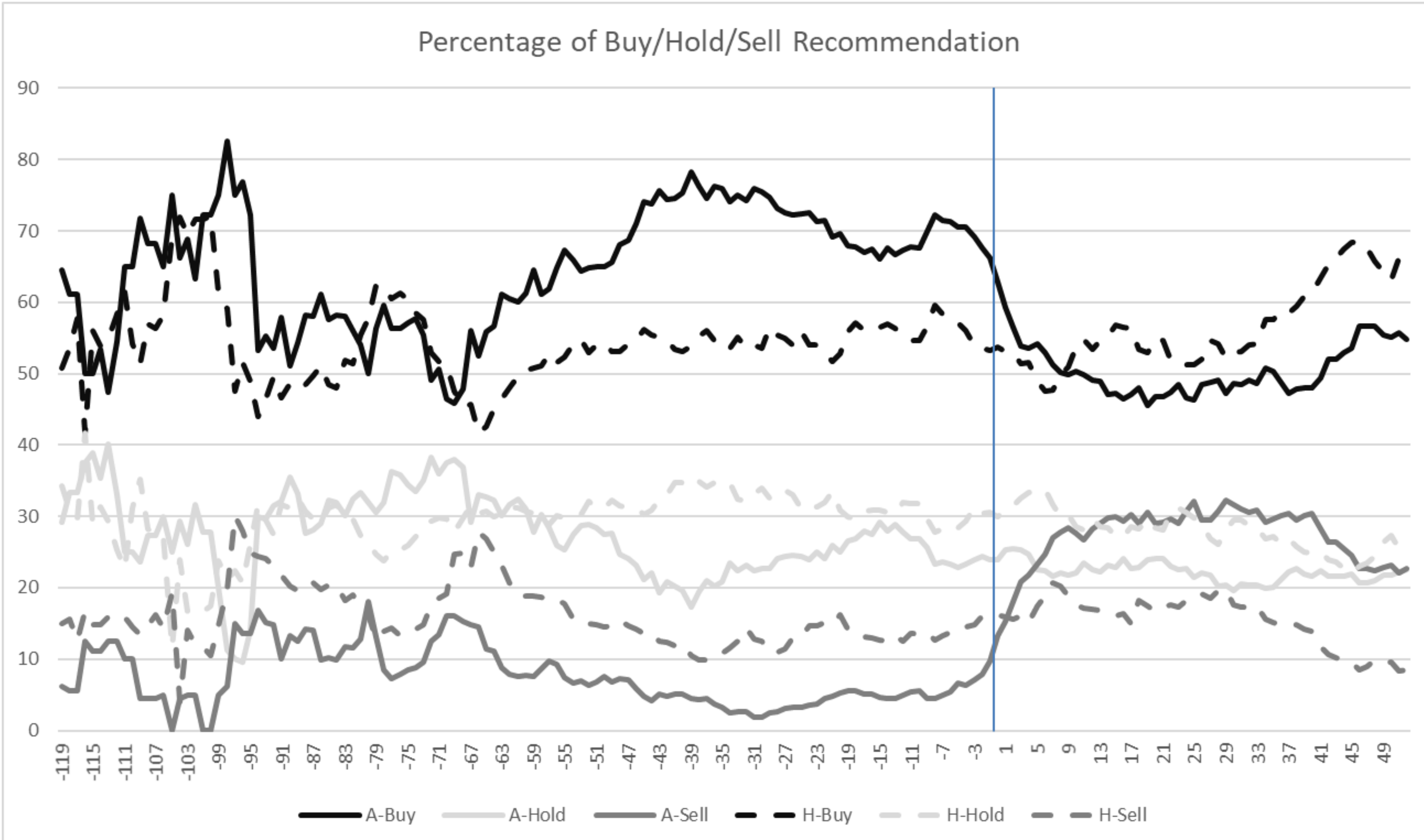


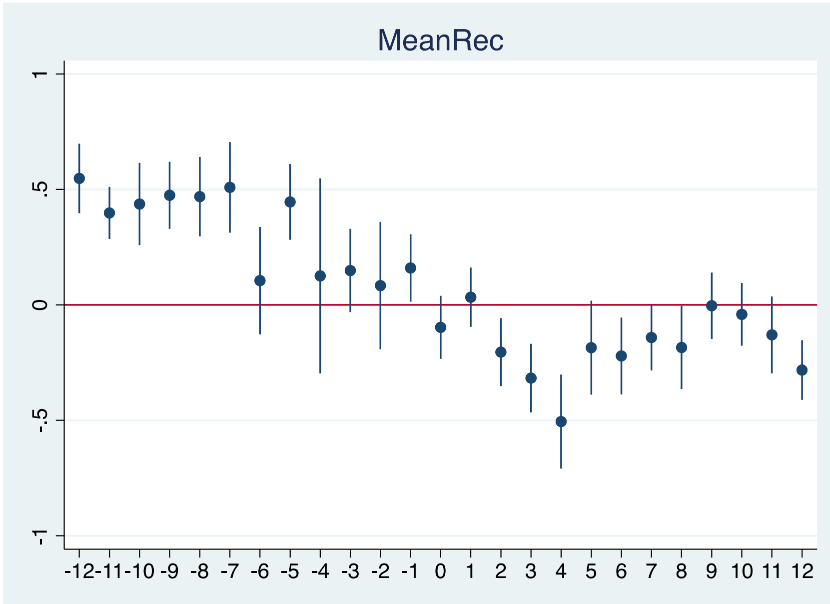
Figure 2 – Percentage of Analyst Buy and Sell Recommendation Over Time



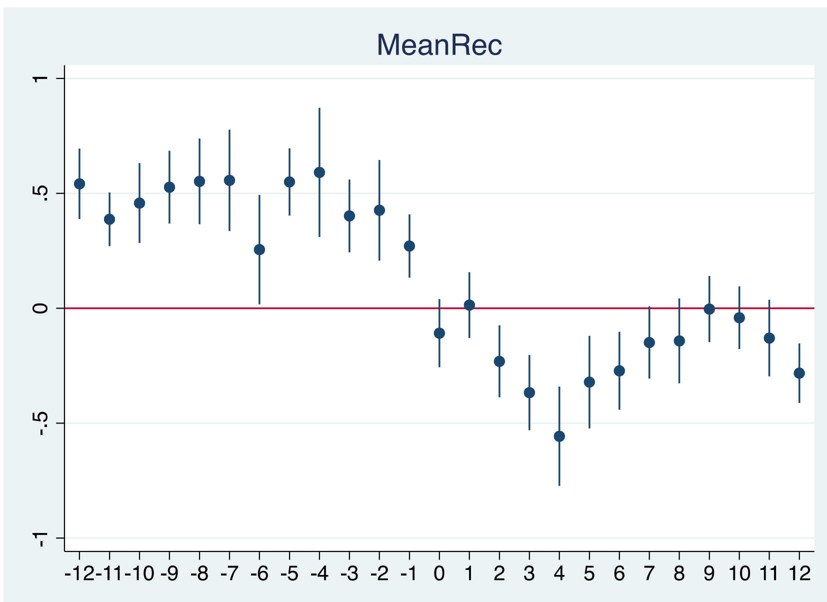
This figure plots the time series of percentage of optimistic ("Strong Buy" and "Buy") and pessimistic ("Underperform" and "Sell") recommendations by month to the Stock Connect.

Figure 3: Change in A-share Analyst Consensus Recommendation relative to H-share Analyst Consensus Recommendation around Stock Connect Program Adoption

Panel A: 2014 Shanghai-Hong Kong and 2016 Shenzhen-Hong Kong Stock Connect



Panel B: 2014 Shanghai-Hong Kong Stock Connect Only



This figure plots the impact of A-H Connect on A share analysts' consensus recommendations (relative to H). Panel A uses the sample from both SH-HK and SZ-HK Stock Connect programs. Panel B uses the sample from SH-HK Stock Connect only to remove the anticipation effect for SZ-HK Connect. The Y-axis represents the difference in analysts' quarterly mean recommendations between A and H shares. The X-axis represents quarter to A-H Connect, where zero is the quarter of the start of the Stock Connect. The dot denotes the estimated coefficients ($\beta 1$, $\beta 2 \ldots \beta 25$) for equation (1), while the solid lines represent 95% confidence intervals.

Table 1. Variable Definition

Variable	Definition
$REC_{a,i.s,m}$	Latest recommendation issued by analyst a, for firm i, share class s, as of month m obtained from IBES detailed database. Recommendations are multiplied by -1: -5=Sell; -4=Underperform; -3=Hold; -2=Buy; -1=Strong Buy
$EPS_{a,i,s,m}$	Latest current year annual EPS forecast issued by analyst a, for firm i, share class s, as of month m, obtained from IBES detailed database.
$PTG_{a,i,s,m}$	Latest price target issued by analyst a, for firm i, share class s, as of month m, obtained from IBES detailed database.
$Tone_{a,i,s,m}$	Tone measured as (number of positive words – number of negative words)/(number of positive words+number of negative words) of the report issued by analyst a, for firm i, share class s, in month m, obtained from Investext and Choice database.
$MeanREC_{i,s,m}$	Mean of $REC_{a,i.s,m}$ for firm i, share class s, as of month m.
$Mean\_EPS_{i,s,m}$	Mean of $EPS_{a,i.s,m}$ for firm i, share class s, as of month m.
$Mean\_PTG_{i,s,m}$	Mean of $PTG_{a,i,s,,m}$ for firm i, share class s, as of month m.
$Mean\_Tone_{i,s,m}$	Mean of $Tone_{a,i,s,m}$ for firm i, share class s, in month m.

Table 1. Variable Definition Continued

Variable	Definition
$Opt\_EPS\_MeanAdj_{i,s,m}$	Mean of $EPS_{a,i,s,m}$ for analysts with $REC_{a,i.s,m}$ of Buy or Strong Buy for firm i, share class s, as of month m less $Mean\_EPS_{i,s,m}$, divided by the weighted average of lagged year A and H share price. Weighting based on number of shares outstanding.
$Pess\_EPS\_MeanAdj_{i,s,m}$	Mean of $EPS_{a,i,s,m}$ for analysts with $REC_{a,i.s,m}$ of Sell or Underperform for firm i, share class s, as of month m less $Mean\_EPS_{i,s,m}$, divided by the weighted average of lagged year A and H share price. Weighting based on number of shares outstanding.
$Opt\_PTG\_MeanAdj_{i,s,m}$	Mean of $PTG_{a,i,s,m}$ for analysts with $REC_{a,i.s,m}$ of Buy or Strong Buy for firm i, share class s, as of month m less $Mean\_PTG_{i,s,m}$, divided by the lagged year price for each respective share type.
$Pess\_PTG\_MeanAdj_{i,s,m}$	Mean of $PTG_{a,i,s,m}$ for analysts with $REC_{a,i.s,m}$ of Sell or Underperform for firm i, share class s, as of month m less $Mean\_PTG_{i,s,m}$, divided by the lagged year price for each respective share type.
$Opt\_Tone\_MeanAdj_{i,s,m}$	Mean of $Tone_{a,i,s,m}$ for analysts with $REC_{a,i.s,m}$ of Buy or Strong Buy for firm i, share class s, in month m less $Mean\_Tone_{i,s,m}$.
$Pess\_Tone\_MeanAdj_{i,s,m}$	Mean of $Tone_{a,i,s,m}$ for analysts with $REC_{a,i.s,m}$ of Underperform or Sell for firm i, share class s, in month m less $Mean\_Tone_{i,s,m}$.
$\Delta FORECAST_{a,i,s,t}$	Analyst forecast revision measured as EPS forecast for year t+1 issued by analyst a, for firm i, share class s, following year t earnings announcement less the EPS forecast by the same analyst made prior to the year t earnings announcement, scaled by the weighted average of lagged year A and H price.
$SURP_{a,i,s,t}$	Analyst specific earnings surprise, measured as the difference between annual EPS for firm i, share class s, year t and the most recent pre-earnings announcement EPS forecast made by analyst a, for firm i, share class s, year t, scaled by weighted average of lagged year A and H price.

Table 2. Sample Construction

Panel A. Self-constructed Share-month Consensus on Recommendations and Forecasts

	Recommendation (H1)		**EPS (H2)**		**Price Target (H2)**	
	N Firms	N Recommendations	N Firms	N Forecasts	N Firms	N Forecasts
A-H Dual-Listed firms	107		107		107	
with valid IBES Detail Data	94	84,372	105	109,017	91	35,497
require same analyst/broker before and after A-H Connect	94	79,281	104	102,438	91	30,833
require at least 3 forecasts each share month	91	64,462	84	78,529	81	22,685
drop if not covered both before and after A-H Connect	79	63,265	70	76,875	65	22,092
drop if not covered on both A and H market	**63**	**37,054**	**63**	**59,417**	**37**	**9,267**
Aggregate to share-month consensus	**63**	**6,266**	**63**	**8,604**	**37**	**1,648**

Panel B. Self-constructed Share-month Tone Consensus (H2)

	N Firms	N Analyst Reports
Unique Firms in Recommendation Sample	63	
with analyst report data	63	76,486
require at least 3 forecasts each month	63	68,682
recommendation identifiable in the report	63	61,082
drop if not covered both before and after A-H Connect	63	61,082
drop if not covered on both A and H market	**63**	**45,783**
Aggregate to share-month consensus	**63**	**6,136**

Table 2. Sample Construction Continued

Panel C. Sample for Detailed Analyst Forecast Revision around Earnings Announcement (H3)

	N Firms	N Forecasts Revisions
Dual-Listed firm:	107	
with valid* IBES Detail Data:	105	109,017
require same analyst/broker before and after the Connect	104	102,438
drop if not covered both before and after A-H Connect	84	93,516
drop if not covered on both A and H market	71	80,440
keep analysts' last forecast (within 6 month) before earnings announcement	71	14,490
require analysts to update EPS forecast within 1 month	**71**	**4,815**

Table 3. Summary Statistics

Panel A. A share Sample

	A Pre			**A Post**		
VARIABLES	N	mean	median	N	mean	median
$MeanREC_{i,s,m}$	1,609	-1.934	-1.833	1,524	-2.620***	-2.600***
$MedREC_{i,s,m}$	1,609	-1.874	-2.000	1,524	-2.624***	-2.500***
$Opt\_EPS\_MeanAdj_{i,s,m}$	2,114	0.001	0.000	1,688	0.002***	0.001***
$Pess\_EPS\_MeanAdj_{i,s,m}$	1,886	0.000	-0.000	1,852	-0.001***	-0.001***
$Opt\_PTG\_MeanAdj_{i,s,m}$	194	0.111	0.071	415	0.198***	0.160***
$Pess\_PTG\_MeanAdj_{i,s,m}$	102	-0.138	-0.108	499	-0.150	-0.126
$Horizon_{i,s,m}$	2,318	5.700	6.000	1,984	5.379***	5.000***
$Opt\_Tone\_D\_MeanAdj_{i,s,m}$	1,549	0.024	0.000	1,483	0.053***	0.000***
$Pess\_Tone\_D\_MeanAdj_{i,s,m}$	117	-0.221	-0.214	325	-0.477***	-0.478***
$Opt\_Tone\_T\_MeanAdj_{i,s,m}$	1,549	0.024	0.000	1,483	0.043***	0.000***
$Pess\_Tone\_T\_MeanAdj_{i,s,m}$	112	-0.218	-0.189	318	-0.402***	-0.426***
$Opt\_Tone\_H\_MeanAdj_{i,s,m}$	1,549	0.033	0.000	1,483	0.051***	0.000***
$Pess\_Tone\_H\_MeanAdj_{i,s,m}$	117	-0.241	-0.118	325	-0.494***	-0.588***

Panel B. H share Sample

	H Pre			**H Post**		
VARIABLES	N	mean	median	N	mean	median
$MeanREC_{i,s,m}$	1,609	-2.379	-2.333	1,524	-2.430***	-2.333
$MedREC_{i,s,m}$	1,609	-2.393	-2.000	1,524	-2.398	-2.000***
$Opt\_EPS\_MeanAdj_{i,s,m}$	2,230	0.002	0.001	1,782	0.002*	0.001
$Pess\_EPS\_MeanAdj_{i,s,m}$	2,008	-0.002	-0.001	1,776	-0.001***	-0.001*
$Opt\_PTG\_MeanAdj_{i,s,m}$	203	0.120	0.092	561	0.115	0.092
$Pess\_PTG\_MeanAdj_{i,s,m}$	152	-0.149	-0.137	471	-0.135	-0.107
$Horizon_{i,s,m}$	2,318	5.700	6.000	1,984	5.379***	5.000***
$Opt\_Tone\_D\_MeanAdj_{i,s,m}$	1,535	0.030	0.015	1,478	0.035	0.000***
$Pess\_Tone\_D\_MeanAdj_{i,s,m}$	463	-0.060	-0.062	518	-0.104***	-0.108**
$Opt\_Tone\_T\_MeanAdj_{i,s,m}$	1,530	0.032	0.017	1,477	0.032	0.000***
$Pess\_Tone\_T\_MeanAdj_{i,s,m}$	449	-0.071	-0.078	516	-0.092	-0.103
$Opt\_Tone\_H\_MeanAdj_{i,s,m}$	1,535	0.049	0.025	1,478	0.041	0.000***
$Pess\_Tone\_H\_MeanAdj_{i,s,m}$	463	-0.086	-0.095	518	-0.097	-0.116*

Table 3 reports summary statistics for all the regression variables. Panel A (B) reports mean for A (H) share sample, partitioned by pre- and post periods, respectively. *, **, *** indicate that the difference in mean or median in pre- and post- periods are statistically significant at 10 percent, 5 percent, and 1 percent levels, respectively. All continuous variables are winsorized at 1 percent and 99 percent level.

Table 4. Consensus Recommendation before and after A-H Connect (H1)

VARIABLES	MeanRec	MedRec
A_Share	0.445***	0.518***
	(0.031)	(0.039)
Post	-0.051	-0.005
	(0.044)	(0.048)
A_Share*Post	**-0.635*** **	**-0.745*** **
	(0.044)	**(0.052)**
Constant	-2.379***	-2.393***
	(0.028)	(0.033)
Observations	6,266	6,266
R-squared	0.157	0.132
Horizon FE	No	No
Cluster by Firm-Year	Yes	Yes

This table reports the mean and median recommendation change after the A-H Connect using the self-constructed consensus recommendation data. *, **, *** indicate significance at 10 percent, 5 percent, and 1 percent levels, respectively. Standard errors are reported in the brackets below the coefficient estimates. The standard errors are clustered at firm-year level. All continuous variables are winsorized at 1 percent and 99 percent level.

Table 5 - Optimistic and Pessimistic Analysts' Forecast and Tone before and after A-H Connect (H2)

Panel A. EPS Forecast

	Buy&StrongBuy	**Underperform&Sell**
VARIABLES	*Opt_EPS_MeanAdj*	*Pess_EPS_MeanAdj*
A_Share	-0.001***	0.002***
	(0.000)	(0.000)
Post	-0.000	0.001*
	(0.000)	(0.000)
A_Share*Post	**0.001*** **	**-0.002*** **
	(0.000)	**(0.001)**
Constant	0.002***	-0.002***
	(0.000)	(0.000)
Observations	7,814	7,522
R-squared	0.017	0.013
Horizon FE	Yes	Yes
Cluster by Firm-Year	Yes	Yes

Table 5 - Optimistic and Pessimistic Analysts' Forecast and Tone before and after A-H Connect (H2)

Panel B. Target Price Forecast

	Buy&StrongBuy	**Underperform&Sell**
VARIABLES	*Opt_PTG_MeanAdj*	*Pess_PTG_MeanAdj*
A_Share	-0.009	0.010
	(0.013)	(0.020)
Post	-0.005	0.014
	(0.012)	(0.020)
A_Share*Post	**0.092*** **	**-0.025**
	(0.017)	**(0.023)**
Constant	0.120***	-0.149***
	(0.010)	(0.016)
Observations	1,373	1,224
R-squared	0.070	0.069
Horizon FE	No	No

Panel A of Table 5 reports how optimistic and pessimistic analysts' EPS forecasts change after the A-H Connect; Panel B of Table 5 reports how optimistic and pessimistic analysts' price targets forecasts change after the A-H Connect. These tests use the A-H paired self-constructed monthly consensus data. Optimistic (pessimistic) analysts are defined as analysts who issue "StrongBuy" and "Buy" ("Underperform" and "Sell") recommendations. *, **, *** indicate significance at 10 percent, 5 percent, and 1 percent levels, respectively. Standard errors are reported in the brackets below the coefficient estimates. All continuous variables are winsorized at 1 percent and 99 percent.

Table 5 - Optimistic and Pessimistic Analyst Forecast and Tone before and after A-H Connect (H2)

Panel C: Tone in Analyst Reports

	Buy&StrongBuy			Underperform&Sell		
VARIABLES	*Opt_Tone_D_ MeanAdj*	*Opt_Tone_T_ MeanAdj*	*Opt_Tone_H_ MeanAdj*	*Pess_Tone_D_ MeanAdj*	*Pess_Tone_T_ MeanAdj*	*Pess_Tone_H_ MeanAdj*
A_Share	-0.006	-0.008*	-0.016***	-0.161***	-0.147***	-0.156**
	(0.006)	(0.005)	(0.006)	(0.051)	(0.043)	(0.061)
Post	0.005	0.000	-0.008	-0.044**	-0.020	-0.011
	(0.005)	(0.005)	(0.006)	(0.017)	(0.016)	(0.020)
A_Share*Post	**0.024*** **	**0.018*** **	**0.026*** **	**-0.211*** **	**-0.164*** **	**-0.241*** **
	(0.008)	**(0.007)**	**(0.008)**	**(0.060)**	**(0.051)**	**(0.071)**
Constant	0.030***	0.032***	0.049***	-0.060***	-0.071***	-0.086***
	(0.004)	(0.003)	(0.004)	(0.010)	(0.010)	(0.011)
Observations	6,045	6,039	6,045	1,423	1,395	1,423
R-squared	0.006	0.003	0.002	0.197	0.175	0.171
Horizon FE	No	No	No	No	No	No

Panel C of Table 5 reports how optimistic and pessimistic analysts' use of tone in their reports change after the A-H Connect, using the self-constructed, A-H paired monthly consensus data. We provide three sets of results based on three widely used Chinese wordlists to determine tone: DUT(TONE_D), THU(TONE_T), and HOWNET(TONE_H), while we use Tone_LM for all English reports. We obtain analyst reports from Investext (mostly for H share) and Choice (for A share). Optimistic(pessimistic) analysts are defined as analysts who issue "StrongBuy" and "Buy" ("Underperform" and "Sell") recommendations. *, **, *** indicate significance at 10 percent, 5 percent, and 1 percent levels, respectively. Standard errors are reported in the brackets below the coefficient estimates. All continuous variables are winsorized at 1 and 99 percent.

Table 6. Optimistic Analyst EPS Forecast Revision after Earnings Announcement (H3)

Panel A. A share Sample

	Pre	Post
VARIABLES	*ΔFORECAST*	*ΔFORECAST*
SURP	0.992***	1.556***
	(0.117)	(0.129)
SURP*Miss	***-0.458****	***-0.992****
	(0.157)	***(0.167)***
Constant	-0.002**	-0.002*
	(0.001)	(0.001)
Post-Pre	**-0.534****	
P-value	**0.023**	
Observations	409	306
R-squared	0.272	0.455

Panel B. A and H share Sample

	Pre	Post
VARIABLES	*ΔFORECAST*	*ΔFORECAST*
A_Share	-0.001	-0.002*
	(0.001)	(0.001)
SURP	0.798***	0.981***
	(0.100)	(0.105)
*SURP*Miss*	-0.385***	-0.368**
	(0.126)	(0.152)
*SURP*A_Share*	0.193	0.575***
	(0.149)	(0.174)
SURP*Miss*A_Share	**-0.072**	**-0.624*****
	(0.195)	**(0.235)**
Constant	-0.001*	0.001
	(0.001)	(0.001)
Post-Pre	**-0.661***	
P-value	**0.071**	
Observations	1,227	736
R-squared	0.212	0.357

Table 6 reports how optimistic analysts update their two-year ahead EPS forecast after the one-year ahead EPS forecast is realized at earnings announcement (EA) in the pre- and post- A-H Connect periods. Panel A includes only A-share analyst forecasts; panel B pools A-share and H-share sample together. The tests use the IBES detail data. Optimistic analysts are defined as analysts who issue "StrongBuy" and "Buy" recommendations both before and after the EA. *, **, *** indicate significance at 10 percent, 5 percent, and 1 percent levels, respectively. Standard errors are reported in the brackets below the coefficient estimates. All continuous variables are winsorized at 1 and 99 percent.

Table 7. Pessimistic Analyst EPS Forecast Revision after Earnings Announcement (H3)

Panel A. A share Sample

	Pre		**Post**
VARIABLES	*ΔFORECAST*		*ΔFORECAST*
SURP	0.169		0.352***
	(0.116)		(0.108)
SURP*Beat	**0.451***		**0.230**
	(0.271)		**(0.220)**
Constant	-0.003		0.002
	(0.002)		(0.002)
Post-Pre		**-0.221**	
P-value		**0.534**	
Observations	176		261
R-squared	0.070		0.107

Panel B - A and H Share Sample

	Pre		**Post**
VARIABLES	*ΔFORECAST*		*ΔFORECAST*
A_Share	-0.001		-0.001
	(0.002)		(0.002)
SURP	0.205***		0.423***
	(0.057)		(0.096)
*SURP*Beat*	0.522***		0.112
	(0.153)		(0.218)
*SURP*A_Share*	-0.036		-0.071
	(0.124)		(0.148)
SURP*Beat*A_Share	**-0.071**		**0.119**
	(0.299)		**(0.317)**
Constant	-0.001		0.002
	(0.001)		(0.002)
Post-Pre		**0.190**	
P-value		**0.665**	
Observations	539		508
R-squared	0.117		0.118

Table 7 reports how pessimistic analysts update their two-year ahead EPS forecast after the one-year ahead EPS forecast is realized at earnings announcement (EA) in the pre- and post- A-H Connect periods. Panel A includes only A-share analyst forecasts; panel B pools A-share and H-share sample together. The tests use the IBES detail data. Pessimistic analysts are defined as analysts who issue "Underperform" and "Sell" recommendations both before and after the EA. *, **, *** indicate significance at 10 percent, 5 percent, and 1 percent levels, respectively. Standard errors are reported in the brackets below the coefficient estimates. All continuous variables are winsorized at 1 and 99 percent.

Table 8. Cross-sectional Test

		Dep Var = MeanRec		Dep Var = MedRec	
VARIABLES	Predicted sign	***Cvar = Other_Ind***	***Cvar = Unpopularity***	***Cvar = Other_Ind***	***Cvar = Unpopularity***
A_Share		0.405***	0.465***	0.509***	0.535***
		(0.05)	(0.05)	(0.06)	(0.06)
Post		-0.132*	-0.149**	-0.045	-0.111
		(0.07)	(0.07)	(0.08)	(0.08)
A_Share*Post		-0.470***	-0.800***	-0.634***	-0.918***
		(0.07)	(0.07)	(0.08)	(0.08)
CVar		-0.180***	-0.117***	-0.143**	-0.124***
		(0.06)	(0.03)	(0.07)	(0.04)
A_Share*Cvar		0.075	0.018	0.017	0.015
		(0.06)	(0.04)	(0.08)	(0.05)
Post*Cvar		0.155*	-0.097*	0.079	-0.104*
		(0.09)	(0.05)	(0.10)	(0.06)
A_Share*Post*Cvar	**–**	**-0.300*** **	**-0.152*** **	**-0.199***	**-0.160*** **
		(0.09)	**(0.05)**	**(0.10)**	**(0.06)**
Constant		-2.284***	-2.510***	-2.317***	-2.532***
		(0.04)	(0.04)	(0.05)	(0.05)
Observations		6,266	6,266	6,266	6,266
R-squared		0.174	0.223	0.143	0.186
Horizon FE		No	No	No	No
Cluster by Firm-Year		Yes	Yes	Yes	Yes

Table 8 reports cross-sectional tests of H1 (the mean and median recommendation change after the A-H Connect), based on two proxies for the impact of A-H Connect: 1) *Other_Ind*: an indicator variable for a firm **not** in the four hot sectors among northbound investments; 2) *Unpopularity*: the average number of times an A share is on the top 10 list by Hong Kong investors in a month, we then multiply this number with -1, so that higher value suggests unpopularity among HK investors. *, **, *** indicate significance at 10 percent, 5 percent, and 1 percent levels, respectively. Standard errors are reported in the brackets below the coefficient estimates. All continuous variables are winsorized at 1 and 99 percent.