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Determinants of Listing Selection of Single Stock Futures: Logistic Regression Analysis

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Abstract: This research addresses three primary research questions concerning single stock futures (SSF) listing selection. First, we use logistic regression models to ascertain the determinants of SSF listing decisions made by the Taiwan Futures Exchange (TAIFEX). Second, we assess our estimated models' classification accuracy. Third, we examine the relationship between predicted listing probability and post-listing SSF trading volume. We extract from the 2010-2011 data that market value and stock volatility significantly explain SSF listing selection in 2010, and stock turnover leads the main deciding factor in 2011. The classification accuracy of the logistic models has been excellent (77-84%), with predicted listing probabilities having one of the strongest prediction effects for post-listing trading outcome, more so for 2011.

Keywords: Listing Selection, Logistic Regression Analysis, Market Microstructure, Stock Futures, Volatility

1. Introduction

The derivatives market has changed dramatically since the classic research of the single stock futures (SSFs) in the early 2000s. The Taiwan Futures Exchange (TAIFEX) released the SSFs in January 2010 when SSFs became a part of the Taiwan Futures Exchange,

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which is a special unit of exchange based derivative offering, the first stock-based, individual derivatives in addition to the general market index futures, and is based on stock or specific stock-maturity securities that are treated as underlying assets. This is to offer investors new ways both individual stock hedging and speculation and potentially reduce tracking errors in index futures, and better transaction cost effectiveness and relative position flexibility.

This is when Taiwan's single stock futures market was debuted on January 25, 2010 (as per the 2010 regulatory change (market cap requirement has been reduced from NT$250B to NT$100B) which makes for an ideal before after comparison in 2010). This type of clean policy shift is uncommon in financial markets; this way you can isolate the impact of regulatory turns on stock listing strategies. Pre-algorithmic trading era data are "cleaner" — high-frequency trading, complex derivatives strategies, or contemporary market microstructure noise that might cloud the results of data from 2020 don't hide the relationships between stock characteristics and listing decisions. This captures the pivotal trajectory from conservative (size-focused) to aggressive (activity-focused) listing strategies — transformative patterns that emerging markets around the world can do well to emulate. The second study has this entire "genesis + immediate evolution" dataset for any one of the large Asian derivatives markets. It's not a limitation; it's a competitive advantage — this temporal positioning.

Recently available global market data reveals sustained growth for single stock derivatives trading, with 16.44 billion contracts traded around the world in 2024, a 19.4 per cent rise on 2023, supported in part by rising volatility and hedging needs in the Americas and Asia-Pacific. This increase confirms the continuing importance of understanding SSF listing determinants in the modern market. Taiwan's equity market is not the only world market with special characteristics affecting SSF listing behaviour in Taiwan's securities and bond stock market. The market boasts very high retail investing prevalence (more than 70%), and large margin exchanges (around 40% of trade volume, versus 15% in most developed markets). Such properties result in unique demand habits of derivatives and might affect exchange listing policies. The SSF listing criteria of TAIFEX, established under Article 4 of the Stock Futures Contract trading rules, allow for the natural study of the listing determinants. For the 2010 criteria, market value greater than NT$250 billion was required, reducing the threshold to NT$100 billion in 2011, together with details regarding trading volume, price stability, and ownership distribution.

Three key inquiry guides this research: First, what firm specific features are used to assess SSF listing selection? (2) What is the predictive performance of logistic regression models in predicting listing decision? (3) Do predictions about listing probabilities correlate with trading success post-listed? Our empirical results are as follows. First, we provide

evidence of SSF listing determinants using comprehensive TAIFEX data over the crucial early development period. Second, we show how logistic regression models enable higher accuracy prediction of listing success. Third, we link the probability of ex-ante listing with the performance at ex-post trading, providing an empirical validation that our modeling strategy is economically important.

The remainder of this paper is as follows. Literature review is included in Section 2. The methodology was described in Section 3. The empirical findings are reported in Section 4. Section 5 concludes.

2. Literature Review

SSFs mitigate short-sale frictions (Miller, 1977), offer inexpensive leverage that stimulates speculative/informed traders (Chau et al., 2008; Danielsen et al., 2009), and improve the quality of price discovery and trading in the base (Chakravarty et al., 2004; Cao et al., 2005; Shastri et al., 2008). In the HFT-saturated microstructure of modern times volatility represents something of a billboard that carries signals and opens up market-making possibilities, with stability effects typically neutral to mildly positive (Dennis and Sim, 1999; Lee and Tong, 1998) but informed by algorithmic dynamics (Karkowska and Palczewski, 2023; Banerjee and Roy, 2023; Breckenfelder, 2024). So higher volatility expands the number of tradable signals and spreads able to attract speculators and market makers using HFT, leading to liquidity concentration and a more favorable launch of a contract. Taking the above together, it is reasonable to hypothesize:

> *H1. Since the volatility of the underlying stock is directly correlated with the likelihood of the eventual SSF listing, the higher the underlying stock's volatility, the greater the chances that will drive it to be chosen for a SSF listing*

Derivatives typically have been reported to enhance market efficiency and liquidity (Weller and Yano, 1987; Detemple and Jorion, 1990; McKenzie et al., 2001), and exchange design has to trade off quality with fairness (Curran et al., 2021). On the empirical front, we know that exchanges have historically preferred larger and more recognized names for SSFs (Mayhew and Mihov, 2004; Ang and Cheng, 2005). Thus, bigger issuers deliver deeper baseline liquidity, higher disclosure and governance, and lower operational/manipulation risk — all of which are attributes which can promote sustainable market-making and a more frictionless contract 'day one' of a transaction. In other words, in summary of the above, the hypothesis is as follows:

> *H2. The higher the market capitalization of the underlying stock, the greater the chance for SSF listing of that stock*

Turnover indicates the presence of already-inspiring attention and information, something concomitant with favorable price discovery in derivatives-spot linkages (Chakravarty et

al., 2004; Cao et al., 2005; Shastri et al., 2008). Listing studies find volume/turnover as central selection criteria (Mayhew and Mihov, 2004; Ang and Cheng, 2005) (which is in keeping with the convention of a positive link between activity and volatility as the fundamental driver of derivative demand, Schwert, 1989). Hence, high turnover is a pre-measured demand reservoir: It speeds up the creation of two-sided order-books, steadies basis dynamics and minimizes cold-start risk for new SSF contracts — a melody to an exchange's ears. In conclusion, the idea is, as follows:

> *H3. This means that the probability of an underlying stock being selected for SSF listing increases as its trading volume (turnover) increases*

It has been reported that estimating the listing probabilities through observable fundamentals can predict future trading success (Mayhew and Mihov, 2004). The real economic impact is shown by market-quality consequences of the presence/absence of SSFs (Curran et al., 2021). Meanwhile, as microstructure modernizes—market-making and competition through HFT (Banerjee and Roy, 2023; Breckenfelder, 2024), non-stationary high-frequency data (Li et al., 2025)—advanced analytics gain significance over traditional econometrics in volatility forecasting and derivatives prices (Rahimikia and Poon, 2024; Singh et al., 2025; Du, 2025; Lu, 2025). So, when listing-probability models ingest richer microstructure and high-frequency data, they capture real demand and execution conditions — so they should forecast not only "if it lists," but how lively it trades once it is listed. In summary of the above, the hypothesis is:

> *H4. The expected listing probabilities will be very positive in predicting the post-listing trading performance of SSFs*

2.1. Model Specification

Following Mayhew and Mihov (2004) and Ang and Cheng (2005), we employ logistic regression to model listing probability:

$$P(Listing_i) = F(\beta_0 + \beta_1 \times TR_i + \beta_2 \times Vol_i + \beta_3 \times Size_i + \varepsilon_i) \quad (1)$$

where F represents the logistic cumulative distribution function, and variables are measured over multiple time horizons (30, 125, and 250 trading days) to capture short-, medium-, and long-term characteristics.

3. Data and Variable Measurements

3.1. Variables and Research Periods

The independent variables such as trading volume and volatility of the qualified stocks before SSF listing are presented with an interval of one month (30 days), half a year (125 days) and one year (250 days). Market value before listing and seven control variables are

considered. We expect the following: A positive relationship between SSF listing and the trading volume of the underlying stock during the year preceding the listing (30, 125, and 250 days). A positive relationship between SSF listing and the volatility of the underlying stock during the year preceding the listing (30, 125, and 250 days). A positive relationship between SSF listing and the year-end market value before listing. A positive relationship between stock trading volume and SSF trading volume. A positive relationship between stock volatility and SSF trading volume. The hypotheses and the explanations for each control variable are elaborated in following sections.

3.2. Sample Selection

There are high fixed costs to launching new futures contracts. A contract is considered successful (depending on volume of trade and market demand) if these costs can be recovered. Key factors determining success are (1) whether the product can attract high trading volume and (2) the quality of trade execution. This year, on 25 January 2010, Taiwan Futures Exchange (TAIFEX) launched 34 SSFs and added 6 on 24 May 2010, then further expanded to 212 contracts by May 3, 2011, when the market value requirement was relaxed from NT$250 billion at the beginning of the year to NT$100 billion. Based on Article 4 of the TAIFEX "SSF Trading Rules," the following list is prepared: the stocks eligible for listing for January 2010, May 2010, and May 2011 listings. (Here, the seven listing criteria from Article 4, as per your previous section, are translated: listing on TWSE, market cap ≥ NT$250 billion in 2010 or NT$100 billion in 2011, trading activity thresholds, minimum price, shareholder dispersion, no suspension of trading, and no accumulated losses.)

3.3. Logistic Model

Following Mayhew and Mihov (2004) and Ang and Cheng (2005), we use logistic regression to examine the determinants of SSF listing. The model is based upon the assumption that SSF trading volume is related to the short- and medium-term stock trading volume, volatility, and size. Trading volume and volatility should also have a positive relationship with likelihood of listing since they reflect liquidity and the transmission of information. Market value is also introduced as one of the factors.

$$F_i = Log(\frac{p_i}{1-p_i}) = \alpha_0 + \alpha_1 To_i + \alpha_2 Vol_i + \alpha_3 Size_i + \varepsilon_i \quad (1).$$

Equation (1) states the baseline model in the form of: Fi = dummy variable (1 if stock i is selected to be listed on the SSF, 0 otherwise). Pi = probability that stock i is selected; Sturnoveri = average turnover ratio (30, 125, 250 days); Voli = standard deviation of daily returns (30, 125, 250 days); Size = market value (end-of-month before listing).

3.4. Analysis of the Classification Accuracy of the Logistic Model

Based on regression coefficients from logistic models (1) and (2), the decision probability of stock i being listed by TAIFEX via futures contract (Pi) can be estimated. For example, for the 37 SSFs listed on January 25 and May 24, 2010, the logistic model estimates that if Pi > 0.385417 (calculated as the ratio of 37 listed SSFs to the total of 96 qualified stocks), SSFi will be recommended by TAIFEX to go for listing as compared to the remaining qualified stocks. If TAIFEX chose SSF i for its listing, then this suggestion is correct. Alternatively, if Pi went below the critical probability, the model predicted that SSF i was not selected for listing, and if TAIFEX failed to list it, the prediction was also considered correct. By dividing the number of correct predictions by the overall sample size, the classification accuracy of the logistic model for SSFs listed on January 25 and May 24, 2010 can be computed. A similar method was followed when determining the classification accuracy of the logistic model for SSFs listed on May 3, 2011.

3.5. The Relationship between Predicted Listing Probability and Post-Listing SSF Trading Volume

To evaluate the empirical data, 37 SSFs listed on January 25 and May 3, 2010, and 169 SSFs listed on May 3, 2011, were tested in this study. A regression model (2) is constructed, relying on the predicted probability of being selected for listing (Plist-i) from the logistic models and the SSF post-listing trading volume (Fvolumelist-i) as the dependent variable. Hence, the goal is to investigate whether improved predicted probabilities of being selected for listing, computed from the underlying stock turnover rate, the standard deviation of daily returns, and market capitalization, are related to higher SSF trading volumes after listing (i.e., a sign of successful listing).

$$Fvolume_{list-i} = \gamma_0 + \gamma_1 P_{list-i} + \xi_i \quad (2)$$

4. Empirical Results

This study initially pursues the stock selection criteria in Article 4 of the Taiwan Futures Exchange (TAIFEX) “Stock Futures Contract” trading rules and lists the individual stocks, for 2010 and 2011 in turn, where the criteria were fulfilled for potential single-stock futures (SSF) underlyings. In 2010, 96 stocks met the existing thresholds, but only 37 were successfully listed and 59 were not. And after the rule change in 2011 (the market-capitalization threshold was lowered from NT$250 billion to NT$100 billion), that pool expanded to 250 stocks, of which 169 were listed and 81 were not, meaning that deregulation has brought about a much higher listing rate and an altogether different selection landscape. Table 1 provides the summary statistics of variables.

From a descriptive statistics perspective, the 2010 stock list possesses at least two features that stand out: (i) Market capitalization is clearly greater than the non-listed stocks (NT$289,926 million vs NT$65,082 million, respectively); (ii) turnover over short-, medium-, and long-horizon time frames is lower than the non-listed sample at 30/125/250 trading days (e.g., T-30 ≈ 0.004 vs 0.008; T-125 ≈ 0.005 vs 0.009; T-250 ≈ 0.006 vs 0.010). In volatility, differences between listed and non-listed are relatively mild (Vol-30 ≈ 0.017; Vol-125 ≈ 0.020 vs 0.022; Vol-250 ≈ 0.026 versus 0.028).

Under strict thresholds and a smaller eligible pool, this profile implies, the exchange's selection favored "large and stable" names: Market capitalization was a major bottleneck but also didn't seem to have to concern high turnover. In contrast, after the scope of the pool expanded significantly in 2011, the listed sample appears different: turnover is not only above non-listed stocks over all horizons (T-30 ≈ 0.010 vs. 0.003; T-125 ≈ 0.011 vs. 0.004; T-250 ≈ 0.012 vs. 0.004), volatility is also high (Vol-30 ≈ 0.020 vs. 0.015; Vol-125 ≈ 0.021 vs. 0.018; Vol-250 ≈ 0.022 vs. 0.018), and differences in average market capitalization are small or even offset (listed NT$38,148 million; non-listed NT$41,673 million).

Table 1 evaluates the descriptive statistics of variables in year 2010. T-30, T-125, and T-250 represent the average daily stock turnover in the 30, 125, and 250 trading days, respectively, prior to the start date of the futures listing month. Vol-30, Vol-125, and Vol-250 represent the standard deviation of daily stock returns in the 30, 125, and 250 trading days, respectively, prior to the start date of the futures listing month. To-30/125, To-30/250, and To-125/250 represent the ratios of average stock turnover between 30 vs. 125 trading days, 30 vs. 250 trading days, and 125 vs. 250 trading days, respectively, prior to the start date of the futures listing month. Vol-30/125, Vol-30/250, and Vol-125/250 represent the ratios of the standard deviation of returns between 30 vs. 125 trading days, 30 vs. 250 trading days, and 125 vs. 250 trading days, respectively, prior to the start date of the futures listing month. ln(Size) denotes the market value of the stock.

Table 1: Descriptive Statistics of Variables (Year: 2010)

	T-30	T-125	T-250	Vol -30	Vol -125	Vol- 250	To- 30/125	To- 30/250	To- 125/250	Vol -30/125	Vol- 30/250	Vol-125/250	Ln(Size)
Panel A: All sample (n=96)													
Mean	0.007	0.008	0.009	0.017	0.021	0.027	0.837	0.694	0.824	0.817	0.638	0.779	151,741
Med.	0.005	0.006	0.008	0.016	0.022	0.027	0.777	0.65	0.814	0.817	0.63	0.783	71,874
Max	0.027	0.023	0.03	0.033	0.034	0.036	1.518	1.543	1.175	1.255	0.977	0.972	1,670,72
Min.	0.001	0.001	0.001	0.004	0.008	0.013	0.51	0.335	0.565	0.44	0.319	0.555	24,675
Panel b: list firms (n=37)													
Mean	0.004	0.005	0.006	0.017	0.02	0.026	0.817	0.666	0.809	0.831	0.638	0.767	289,926
Med.	0.004	0.005	0.006	0.016	0.02	0.026	0.777	0.649	0.813	0.82	0.626	0.763	186,454
Max	0.014	0.016	0.022	0.028	0.029	0.034	1.486	1.343	1.05	1.175	0.952	0.972	1,670,72
Min	0.001	0.001	0.001	0.004	0.011	0.014	0.554	0.356	0.584	0.656	0.469	0.595	31,133
Panel C: Non-Listed Fims (n= 59)													
Mean	0.008	0.009	0.01	0.017	0.022	0.028	0.85	0.712	0.834	0.809	0.637	0.787	65,082
Med.	0.006	0.008	0.01	0.017	0.022	0.028	0.777	0.651	0.816	0.809	0.635	0.79	49,150
Max	0.027	0.023	0.03	0.033	0.034	0.036	1.518	1.543	1.175	1.255	0.977	0.935	289,144
Min	0.001	0.002	0.002	0.004	0.008	0.013	0.51	0.335	0.565	0.44	0.319	0.555	24,675

Table 2 evaluates the descriptive statistics of variables in year 2011. T-30, T-125, and T-250 represent the average daily stock turnover in the 30, 125, and 250 trading days, respectively, prior to the start date of the futures listing month. Vol-30, Vol-125, and Vol-250 represent the standard deviation of daily stock returns in the 30, 125, and 250 trading days, respectively, prior to the start date of the futures listing month. To-30/125, To-30/250, and To-125/250 represent the ratios of average stock turnover between 30 vs. 125 trading days, 30 vs. 250 trading days, and 125 vs. 250 trading days, respectively, prior to the start date of the futures listing month. Vol-30/125, Vol-30/250, and Vol-125/250 represent the ratios of the standard deviation of returns between 30 vs. 125 trading days, 30 vs. 250 trading days, and 125 vs. 250 trading days, respectively, prior to the start date of the futures listing month. Ln(Size) denotes the market value of the stock.

Table 2: Descriptive Statistics of Variables (Year: 2011)

	T-30	T-125	T-250	Vol -30	Vol -125	Vol- 250	To- 30/125	To- 30/250	To- 125/250	Vol -30/125	Vol- 30/250	Vol-125/250	ln(Size)
Panel A: All Firms (n=250)													
Mean	0.008	0.009	0.009	0.018	0.02	0.021	0.876	0.851	0.971	0.946	0.896	0.946	39,290
Med.	0.005	0.006	0.007	0.015	0.019	0.02	0.792	0.759	0.938	0.924	0.88	0.948	19,179
Max	0.05	0.045	0.054	0.039	0.037	0.039	2.593	3.339	1.565	1.532	1.557	1.29	1,062,948
Min	0	0	0	0.005	0.005	0.006	0.219	0.262	0.512	0.454	0.46	0.638	9,626
Panel B: Listed Firms (n=169)													
Mean	0.01	0.011	0.012	0.02	0.021	0.022	0.867	0.874	1.003	0.944	0.91	0.962	38,148
Med.	0.007	0.008	0.008	0.02	0.021	0.022	0.786	0.754	0.97	0.935	0.896	0.958	19,447
Max	0.05	0.045	0.054	0.036	0.037	0.039	2.593	3.339	1.565	1.496	1.557	1.29	1,062,948
Min	0.001	0.002	0.002	0.008	0.008	0.009	0.285	0.306	0.595	0.454	0.46	0.638	9,626
Panel C: Non-list Firms (n=81)													
Mean	0.003	0.004	0.004	0.015	0.018	0.018	0.897	0.803	0.905	0.949	0.866	0.913	41,673
Med.	0.002	0.002	0.003	0.014	0.018	0.017	0.845	0.773	0.882	0.933	0.857	0.926	17,894
Max	0.021	0.024	0.03	0.039	0.031	0.039	2.988	2.285	1.468	1.532	1.512	1.227	957,358
Min	0	0	0	0.005	0.005	0.006	0.219	0.262	0.512	0.607	0.491	0.648	10,024

The result is that market "momentum signals" (turnover and, in part, volatility) replaced size as more discriminating selection criteria after the 2011 deregulation. Such impressions are supported by multivariate logistic regressions. In Table 3, for 2010, turnover coefficients are all negative at all three horizons: T-30 ≈ −270.765, t = −2.306 (significant at 5%), T-125 ≈ −243.909, t = −2.157 (5%), T-250 ≈ −192.411, t = −2.188 (5%). Volatility coefficients (also statistically significant) are, on the other hand, positively and significantly positive over all time horizons: Vol-30 = 217.189, t = 2.620 (1%), Vol-125 = 166.502, t = 1.976 (5%), Vol-250 = 217.905, t = 2.478 (5%). Market capitalization (Size) is positively significant, and is highly significant (t ≈ 3.55–3.90, $p < 0.001$) across specifications.

Table 3: Logistic Regression Results (Year: 2010)

Variable	1-(1)	1-(2)	1-(3)	1-(4)	1-(5)	1-(6)	1-(7)	1-(8)	1-(9)
C	-4.633*** (-3.212)	-4.174** (-1.458)	-6.634*** (-2.855)	-4.158** (-2.499)	-6.678*** (-2.886)	-3.178*** (-2.706)	-7.353*** (-2.944)	-3.596*** (-2.686)	-3.698** (-2.251)
T-30	-270.765** (-2.306)			-191.618* (-1.770)	-210.993* (-1.924)				
T-125		-243.909** (-2.157)				-232.894** (-2.304)	-293.261** (-2.379)		
T-250			-192.411** (-2.188)					-189.214** (-2.089)	-144.434* (-1.844)
Vol-30	217.189*** (-2.62)					166.376** (-2.341)		148.355** (-2.186)	
Vol-125		166.502** (-1.976)		136.008* (-1.727)					122.308 (-1.612)
Vol-250			217.905** (-2.478)		195.369** (-2.36)		249.648*** (-2.629)		
Ln (Size)	0.000*** (-3.686)	0.000*** (-3.609)	0.000*** (-3.733)	0.000*** (-3.768)	0.000*** (-3.904)	0.000*** (-3.58)	0.000*** (-3.783)	0.000*** (-3.55)	0.000*** (-3.585)

Note: Table 3 examines whether futures are listed (binary) is affected by the following control variables. T-30, T-125, and T-250 represent the average daily stock turnover in the 30, 125, and 250 trading days, respectively, prior to the start date of the futures listing month. Vol- 30, Vol-125, and Vol-250 represent the standard deviation of daily stock returns in the 30, 125, and 250 trading days, respectively, prior to the start date of the futures listing month. Ln (Size) denotes the market value of the stock.Numbers in parentheses are t-statistics, with ***, **, and * indicating statistical significance at the 1%, 5%, and 10% levels, respectively.

Even with exceptions of significant results in turnover/volatility ratio variables (e.g., 30/125 and 125/250), the net result does not change: SSF listing probability is positively correlated with higher volatility and larger market capitalization in 2010, and negatively correlated with higher turnover. The findings provide strong support in terms of H1 (when volatility increases, the listing probability increases) and H2 (when market capitalization increases, the listing probability increases), in strong opposition to H3 (when turnover increases, the listing probability increases). In Table 4, in 2011, results are revealed to be structurally inverted. Turnover turns out to be significantly positive over all the horizons with significantly high coefficients and t-values: T-30 ≈ 287.161, t = 4.935 (1%); T-125 ≈ 512.867, t = 5.096 (1%); T-250 ≈ 287.170, t = 5.128 (1%). The robustness of these strong effects is evident in such models (for example, T-30 ≈ 342.292 or 320.505 with t ≈ 4.8; T-125 ≈ 322.266 or 327.857 with t ≈ 5.1; T-250 ≈ 290.138 or 303.514 with t ≈ 5.1).

Table 4: Logistic Regression Results (Year: 2010)

Variable	2-(1)	2-(2)	2-(3)	2-(4)	2-(5)	2-(6)
C	-5.243** (-2.530)	-3.719** (-2.256)	-7.079*** (-2.688)	0.907 -0.323	-7.847*** (-2.750)	-3.92 (-1.210)
T-30	-244.686* (-1.593)	-302.236** (-2.184)				
T-125			-241.882** (-2.168)	-378.696** (-2.217)		
T-250					-216.649** (-2.407)	-219.222** (-2.249)
Vol-30	182.534* (-1.715)	333.192** (-2.231)				
Vol -125			178.398** (-1.957)	335.665*** (-2.675)		
Vol-250					219.728** (-2.357)	254.738*** (-2.662)
To-30/125	-0.904 (-0.544)		-2.238 (-1.445)			
To-30/250		-0.09 (-0.054)			-2.316 (-1.456)	
To-125/250				-0.462 (-0.194)		-2.85 (-1.118)
Vol-30/125	2.084 (-0.649)		5.238** (-2.011)			
Vol 30/250		-4.535 (-0.523)			4.224 (-1.498)	
Vol 125/250				-10.885* (-1.898)		-1.91 (-0.449)
Ln (Size)	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***

Note: Numbers in parentheses are t-statistics, with ***, **, and * indicating statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 5: Logistic Regression Results (Year: 2011)

Variable	1-(1)	1-(2)	1-(3)	1-(4)	1-(5)	1-(6)	1-(7)	1-(8)	1-(9)
C	-1.349*** (-2.762)	-2.210*** (-3.411)	-2.004*** (-2.941)	-2.424*** (-3.883)	-2.150*** (-3.182)	-1.883*** (-3.626)	0.244** -2.057	-2.008*** (-3.933)	-2.571*** (-4.024)
T-30	287.161*** (-4.935)			247.333*** (-4.239)	266.413*** (-4.567)				
T-125		512.867*** (-5.096)				349.438*** (-5.686)	17.308*** (-3.616)		
T-250			287.170*** (-5.128)					287.017*** (-5.411)	260.696*** (-4.761)
Vol -30	39.502 (-1.084)					31.018 (-1.028)		49.964* (-1.737)	
Vol -125		53.831 (-1.338)		109.696*** (-2.775)					87.392** (-2.306)
Vol-250			43.7 (-1.18)		75.913** (-2.093)		13.441* (-1.969)		
Ln (Size)	0 (-0.267)	0 (-0.521)	0 (-0.642)	0 (-0.13)	0 (-0.323)	0 (-0.584)	0 (-0.275)	0 (-0.546)	0 (-0.452)

In Table 5, volatility is mostly positive for 2011, but less stable in statistical significance; for example, Vol-125 ≈ 109.696 (t = 2.775, 1%), Vol-250 ≈ 75.913 (t = 2.093, 5%), Vol-30 ≈ 49.964 (t = 1.737, 10%), and several insignificant specifications (e.g., Vol-30 t ≈ 1.084; Vol-125 t ≈ 1.338; Vol-250 t ≈ 1.180). Market capitalization (t≈0.13–0.64) is generally insignificant across all 2011 specifications. Given the relaxation, size loses its discriminating power altogether. In short, 2011 evidence strongly supports turnover, only partially supports volatility or seems to reject size; ratio variables generally do not dominate and sporadic significance is still insufficient to disprove the findings above.

Table 6 indicated whether the listed futures is affected by the other variables. Dependent Variable: Whether or not Futures Listed. T-30, T-125, and T-250 represent the average daily stock turnover in the 30, 125, and 250 trading days, respectively, prior to the start date of the futures listing month. Vol-30, Vol-125, and Vol-250 represent the standard deviation of daily stock returns in the 30, 125, and 250 trading days, respectively, prior to the start date of the futures listing month. To-30/125, To-30/250, and To-125/250 represent the ratios of average stock turnover between 30 vs. 125 trading days, 30 vs. 250 trading days, and 125 vs. 250 trading days, respectively, prior to the start date of the futures listing month. Vol-30/125, Vol-30/250, and Vol -125/250 represent the ratios of the standard deviation of returns between 30 vs. 125 trading days, 30 vs. 250 trading days, and 125 vs. 250 trading days, respectively, prior to the start date of the futures listing month. Ln(Size) denotes the market value of the stock.

Table 6: Logistic Regression Results (Year: 2011)

Variable	**2-(1)**	**2-(2)**	**2-(3)**	**2-(4)**	**2-(5)**	**2-(6)**
C	0.372 -0.454	-0.658 (-0.957)	-2.089** (-2.091)	3.899** -2.54	-2.765*** (-2.939)	-6.168*** (-3.595)
T-30	342.292*** (-4.782)	320.505*** (4.814)				
T-125			322.266*** (-5.084	327.857*** (-5.086)		
T-250					290.138*** (-5.117)	303.514*** (-5.15)
Vol-30	70.777 (-1.643	57.859 -1.333)				
Vol-125			54.342 (-1.346	31.61 (-0.715)		
Vol-250					41.802 (-1.061	26.974 -0.654)
To-30/125	-1.764*** (-2.663)		0.034 (-0.065)			
To-30/250		-1.202** (-2.014)			0.446 (-0.888)	
To-125/250				0.713 (-0.637)		2.343** (-2.061)
Vol-30/125	-1.202 (-0.930)		-0.166 (-0.163)			
Vol-30/250		-0.36 (-0.291)			0.468 (-0.505)	
Vol -125/250				1.499 (-0.712)		2.326 (-1.152)
Ln (Size)	0 (-0.619)	0 (-0.554)	0 (-0.515)	0 (-0.39)	0 (-0.524)	0 (-0.393)

Note: Numbers in parentheses are t-statistics, with ***, **, and * indicating statistical significance at the 1%, 5%, and 10% levels, respectively.

In Table 7, model classification performance is also affected by institutional differences. Overall, using threshold probabilities to classify listings results in an optimal 2010 cutoff around 0.385417 with general accuracy ranging from 77 to 84%; specifications like T-125, Vol-250, and Size produce maximum general accuracy of around 84.4% and the accuracy of these specifications usually is higher for predicting non-listings (about 81%–88% vs. 68%–84%).

Table 7: The Accuracy of logistic regression model

Model	Listed Sample			Non-Listed Sample			Total Sample		
	-1	-2	-3	-1	-2	-3	-1	-2	-3
	Sample	Correct	Accuracy	Sample	Correct	Accuracy	Sample	Correct	Accuracy
Panel A: Year 2010									
(1)-1	37	28	76%	59	50	85%	96	78	81%
(1)-2	37	27	73%	59	50	85%	96	77	80%
(1)-3	37	29	78%	59	51	86%	96	80	83%
(1)-4	37	25	68%	59	49	83%	96	74	77%
(1)-5	37	27	73%	59	48	81%	96	75	78%
(1)-6	37	28	76%	59	50	85%	96	78	81%
(1)-7	37	30	81%	59	51	86%	96	81	84%
(1)-8	37	27	73%	59	51	86%	96	78	81%
(1)-9	37	27	73%	59	51	86%	96	78	81%
(2)-1	37	28	76%	59	50	85%	96	78	81%
(2)-2	37	28	76%	59	49	83%	96	77	80%
(2)-3	37	29	78%	59	50	85%	96	79	82%
(2)-4	37	31	84%	59	49	83%	96	80	83%
(2)-5	37	29	78%	59	52	88%	96	81	84%
(2)-6	37	30	81%	59	51	86%	96	81	84%
Panel B: Year 2011									
(1)-1	169	110	65%	81	67	83%	250	177	71%
(1)-2	169	120	71%	81	67	83%	250	187	75%
(1)-3	169	123	73%	81	71	88%	250	194	78%
(1)-4	169	114	68%	81	65	80%	250	179	72%
(1)-5	169	111	66%	81	67	83%	250	178	71%
(1)-6	169	121	72%	81	69	85%	250	190	76%
(1)-7	169	83	49%	81	71	88%	250	154	62%
(1)-8	169	123	73%	81	68	84%	250	191	76%
(1)-9	169	124	73%	81	68	84%	250	192	77%
(2)-1	169	119	70%	81	67	83%	250	186	74%
(2)-2	169	116	69%	81	68	84%	250	184	74%
(2)-3	169	120	71%	81	67	83%	250	187	75%
(2)-4	169	123	73%	81	67	83%	250	190	76%
(2)-5	169	123	73%	81	70	86%	250	193	77%
(2)-6	169	124	73%	81	68	84%	250	192	77%

Note: This table evaluates the accuracy using the above tables in both Table 3, 4, 5 and 6, respectively. The accuracy ratio (3) = correct sample (2)/ total sample (1).

For instance, in 2011, at a cutoff of around 0.676, overall accuracy is between about 62% and 78%; better-performing specifications frequently have more long-horizon variables (for instance, T-250, Vol-250), getting up to around 77.6%, yet again with the non-listing predictions surpassing the listing predictions.

Table 8: Regression Analysis of Average Trading Volume after Futures Listing on Listing Probability

	(1)			(2)		
	Year 2010			Year 2011		
Model	**Fvolume30**	**Fvolume125**	**Fvolume250**	**Fvolume30**	**Fvolume125**	**Fvolume250**
(1)	-3.7309			11.2945		
(4)	1.5286			21.5367*		
(5)	-2.736			15.1087		
(6)	-6.7231			29.7098**		
(8)	-5.8083			19.1156*		
(2)		20.6090*			22.6451**	
(4)		26.0181**			11.8213	
(6)		10.6207			19.1823*	
(7)		28.8145**			9.2181	
(9)		18.9594*			19.9461*	
(3)			-2.7634			16.1725
(5)			2.1179			2.44
(7)			0.0839			18.1968*
(8)			-26.0117			13.5205
(9)			-21.6222			25.3597*

Note: This table evaluates the regression analysis of average trading volume after futures listing on listing probability ($P_{list\text{-}i}$). Dependent variables: *Fvolume*30, *Fvolume*125, and *Fvolume*250 represent the 30-day, 125-day, and 250-day average trading volumes after futures listing, respectively. (1) and (2) indicates year 2010 and 2021, respectively. The model is as follows, $Fvolume_{list-i} = \gamma_0 + \gamma_1 P_{list-i} + \xi_i$; ***, ** and * indicating statistical significance at the 1%, 5%, and 10% levels, respectively.

Because of this contrast, one assumes that within a relatively tight threshold and a more homogeneous pool (2010), listing decisions are more predictable and that when the pool increases in size (2011), there is a greater degree of heterogeneity; turnover signals become especially robust, although overall predictability is slightly lower. Lastly, we perform our predictive validity (H4) analysis on whether the estimated listing probability (Plist,i) predicts post-listing trading activity (average trading volume). In 2010, Plist,i has a more significant and robust positive effect on the 125-day average volume (Fvolume125) with coefficients 20.609, 26.018, 28.815, and 18.959 with t-statistics of 1.808, 2.118, 2.273, and 1.713 (significant at the 10%, 5%, 5%, and 10% levels respectively) but is mostly insignificant for the 30-day and 250-day windows; in short, the statistical evidence supporting H4 seems to be limited. In 2011, the contrast is clear: Plist,i is positive and

statistically significant for short-, medium-, and long-horizon volumes (e.g., Fvolume30 ≈ 21.537, 29.710, 19.116; Fvolume125 ≈ 22.645, 19.946; Fvolume250 ≈ 18.197, 25.360, t-statistics roughly 1.7–2.1, significance at the 10% or 5% levels). These results provide compelling evidence for H4 and illustrate that in an expanded and upgraded microstructure environment, listing probabilities extrapolated from fundamentals and market characteristics can anticipate realized trading intensity of SSFs recently listed.

5. Conclusions

In 2010, volatility (short term, medium term, long term) and market value are significant predictors of SSF listing. Trading volume ratios are not significant. For 2011, turnover ratios (short/medium/long term) are significant, while market value for 2011 is positive but insignificant. Logistic models predict non-listings better than listings, with a higher accuracy overall in 2010 compared to 2011. Listing probabilities predict SSF trading volume in the post-listing period with strength particularly in 2011, and the models (1-6) and (1-9) have the greatest predictive ability. H1 (Volatility Effect): Strongly supported 2010, partially supported 2011; H2 (Size Effect): Strongly supported 2010, rejected 2011; H3 (Liquidity Effect): Rejected 2010, strongly supported 2011; H4 (Predictive Validity): Partially supported 2010; strongly supported 2011. We find great time-related growth in determinants of SSF listing success in Table 1, indicating a well-developed market maturation and strategic adjustment of the SSF listing process by TAIFEX. It indicates that there has been considerable evolution over time for the indicators of success of the single stock futures listing success that have been explained because of market maturation and strategic adjustment of the Taiwan Futures Exchange by maturity as it relates to the TFE.

Potential future studies might then further extend the model to incorporate factors (such as ownership structure, institutional investor participation) which may be expected to enhance classification performance. The results offer information useful to regulators when selecting eligible stocks for an SSF and for investors evaluating the effectiveness of a good SSF.

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