Government Equity Market Intervention and the Cross-Section of Stock Returns

Nick DeRobertis*, Andy Naranjo†, and M. Nimalendran‡

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*University of Florida, PhD Candidate, Tel: (352)392-4669, Email: Nicholas.DeRobertis@Warrington.ufl.edu

†University of Florida, John B. Hall Professor of Finance and Chairman of the Finance, Insurance, and Real Estate Department, Tel: (352)392-3781, Email: Andy.Naranjo@Warrington.ufl.edu

‡University of Florida, John H. and Mary Lou Dasburg Professor of Finance, Tel: (352)392-9526, Email: Mahen.Nimalendran@Warrington.ufl.edu

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Abstract

As part of their QQE (Quantitative and Qualitative Easing) strategy to encourage investments in risky assets and spur economic growth, the Bank of Japan (BOJ) has been aggressively purchasing shares of ETFs tracking Japan's major stock indices, reaching as much as ¥23.5 trillion in holdings by December of 2018, amounting to 72% of the outstanding ETF shares. This unprecedented intervention in the stock market has resulted in a significant impact and distortions in stock prices. We show that the BOJ purchases ETFs on days when the underlying firms have negative returns. Futher, we find that a 1% increase in BOJ ownership leads to 1.78% higher returns per day and 0.29% higher alphas per day in the window of (-1, 1) around BOJ purchase days, and the outperformance persists for at least 20 trading days. We further show that there is a significant price-based distortion in stock returns as the BOJ purchases assets proportionally to their index weighting and not their market value. We analyze the Nikkei 225 as a price-weighted target index, providing evidence that firms with high price-weightings but low market capitalization out-perform by 9.12% annually compared firms with low price-weightings but high market capitalization, and further show that this out-performance is due to higher BOJ ownership.[1]

JEL Classification: E31, E42, E44, E52, E58, E61, G12, G14, G15

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[1] We thank ... for their helpful comments and suggestions.

I Introduction

Central banks have employed numerous strategies to increase growth in their respective economies. The most common strategy is to purchase government debt, thus increasing the money supply and lowering interest rates. Japan had a large asset bubble peaking in 1989, followed by more than two decades of deflation and a stagnant economy. During these two decades, the BOJ purchased government debt, keeping interest rates near zero, even negative in real terms, but this was not enough to encourage growth, so deflation continued.

After decades of failed policy, Japan's policymakers decided that more action was needed, with the goal of ending deflation and increasing inflation to 2% (BOJ, 2013b). By June of 2013, in addition to fiscal measures, the BOJ increased its buying of government bonds to ¥60-70 trillion annually (BOJ, 2013a). Starting in 2009, the BOJ also began purchasing corporate debt in the form of both bonds and commercial paper (BOJ, 2009). These purchases accelerated during 2011 and 2012, but since 2013 the BOJ has held a roughly constant amount of corporate debt. The BOJ also began purchasing exchange-traded funds (ETFs) tracking Japan's largest indices: the Nikkei 225, TOPIX, and Nikkei 400, proportionally to their market capitalizations at a pace of ¥450 billion annually (BOJ (2010b) and BOJ (2014)). By 2016, this pace increased to ¥5.7 trillion annually. An overview of the bank's asset purchases is given in Figure 1. A central bank purchasing equities at a broad scale with the intention of increasing growth in the economy is an unprecedented strategy. While there is a case of Hong Kong directly purchasing equities in the 1998 Asian Financial Crisis, this was at a much smaller scale and only for a short duration during a market crash (Su, Yip, and Wong (2002) and Cheng, Fung, and Chan (2000)).

While the BOJ plans aggregate annual ETF purchase amounts in advance, the Bank does not reveal the timing of its purchases until afterwards. Instead, the BOJ purchases on days which the market is dropping. By plotting the returns relative to BOJ purchase-days, we provide empirical evidence of this strategy in Figure 3, showing negative returns on BOJ purchase days for all firms, but even more negative for BOJ-held firms. We provide a formal analysis of this in section IV.E.

[Figure 1 about here.]

[Figure 2 about here.]

[Figure 3 about here.]

Both the contemporaneous purchases and the overall level of BOJ ownership may influence the stock performance of Japanese firms. We base our analysis on the theoretical framework proposed by Miller (1977). Miller argues that rational investors have differing opinions about the value of a share due to uncertainty in forecasting, and given a fixed supply of shares, the market price will be set by a subset of investors who have an opinion of a price higher than the average price under homogeneous expectations. As the number of investors whose forecasted price is greater than the market price increases, the price of that share in the market also increases, as the number of shares available has not changed. When each BOJ purchase is viewed as an additional investor whose valuation is higher than the market price, then prices should increase with each purchase, leading to short-term returns. The fundamentals of the firms have not changed, however, so their fundamental future price should be unchanged. As time passes and more information is revealed, the future market price should approach the fundamental future price, and so long-term returns will be reduced. We also theorize that the BOJ's level of ownership will have effects similar to other large passive ownership stakes, such as index ownership. If this is the case, then the BOJ's purchases should cause a lasting increase in price in the targeted firms ((Beneish and Whaley, 1996) and (Chang, Hong, and Liskovich, 2015)).

Overall, we find that both returns and alphas from Fama and French (2015) regressions are higher around BOJ purchase dates. The outperformance persists for up to a month beyond the BOJ purchase date. Further, we find that firms with high BOJ ownership earn consistently higher returns and alphas. While it seems that overall, stock prices have increased due to the BOJ's purchases, it is important to consider cross-sectional variation in firms' response to the policy. An important driver of this variation is the amount of purchases allocated to each firm.

If the BOJ wanted to provide equal support to each firm, then it should purchase shares according to the market capitalization weights of the firms. By this process, the BOJ would own an appoximately equal percentage in each firm. The BOJ purchases from 2010 to 2016, however, targeted the Nikkei 225, TOPIX, and Nikkei 400 indices by the market capitalization weight of each index, resulting in over 50% of the value purchased being directed towards ETFs tracking the Nikkei 225. The Nikkei 225 is a price-weighted index, so the BOJ has purchased shares in these firms according to their price weights[2]. This is how the BOJ has ended up with a large variance in their percentage stakes across firms. We construct the Nikkei Float Price Weight Distortion (PVD) measure (details given in III.D) as the price weighting minus the float-adjusted market capitalization weighting, and examine its effect on stock returns as a measure of the BOJ's differential effects on firms in the economy. Overall, we find that firms with high PVD have greater returns and alphas than firms with low PVD. A long-short trading strategy based on PVD also generates positive alphas. We set PVD to zero for TOPIX firms, as the TOPIX is a float-adjusted market capitalization-weighted index[3].

[2]As the number of shares for a firm can vary substantially and is not directly related to firm value, firms with the same valuation can have very different prices. To adjust for this, the Nikkei 225 has the concept of a par value with this issue. Each stock has a par value, and the share price is adjusted using the par value before calculating the index value and weightings. The par value is adjusted for corporate actions including share splits. For any new firm, the par value is one of ¥50, 500, 5,000, or 50,0000, so there is not enough flexibility to have firms enter the index with a weighting equal to the value weighting. Further, the share split adjustments can move the price weight even further from the value weight. The rebalancing for corporate actions depends on whether that action was of large scale. It is unclear what this scale means, and is likely subjective. The Nikkei 225 does give examples of a 1:1.2 split being small and a 1:2 split being large. If it is a large action, the par value is adjusted, which will appropriately update the weight and index value. With small actions, only the divisor of the index is changed, but the firm's weight is not adjusted in any way. Therefore a firm completing a small reverse share split will increase its weight in the index.

[3]The TOPIX uses free-float adjusted market capitalization weighting, where only the shares available for trading in the market are used to calculate the market capitalization of each firm for weighting purposes (Japan Exchange Group (2018b) and Japan Exchange Group (2018a)). Theoretically, as we are comparing the actual weight to the free-float adjusted market capitalization weight, the PVD measure should be zero for all TOPIX firms. As we use Capital IQ for our source of free float, and the TOPIX has a different source, empirically if we calculate a similar measure to PVD for the TOPIX it has small, non-zero values. In

[Table 1 about here.]

As shown in Table 1, through these purchases, the BOJ has accumulated a substantial stake in many firms. For example, the BOJ owns 25.08% of the firm Fast Retailing Co., Ltd., which also has a very high PVD.

In section II, we provide additional background on BOJ purchasing activity and review the relevant literature. Section III explains the data sources for our empirical analysis. In section IV, we present and discuss results showing the outperformance of portfolios formed on PVD and regressions showing a positive effect of both BOJ ETF purchases and PVD on returns and alphas. Section V concludes.

II Background & Literature Review

Section II.A gives background on Japan's economy and monetary policy steps the BOJ has taken in response to low growth and deflation. Section II.B explains our theory for how the BOJ ETF purchases will affect stock prices. Section II.C reviews the literature on governments intervening in stock markets. Section II.D explores the effects which may come from the BOJ being a passive owner in the purchased firms. Finally, section II.E examines any differences in the effects that may arise from the BOJ being part of the Japanese government.

II.A BOJ Quantitative Easing

Japan had a large asset bubble peaking in 1989, followed by a stock market and property crash in 1990. Over the period of 1992-2012, Japan experienced deflation at a rate of 0.3% per year, while their policy goal is targeting 2% inflation per year. In 1998, the BOJ began their zero-interest rate policy. This policy was only targeting short maturity government

unreported results, we combined this measure with PVD rather than setting PVD to zero for TOPIX firms. Results are qualitatively similar.

bonds to adjust rates. While they paused the strategy for the second half of 2000, they otherwise continued the strategy until an economic recovery over 2005-2007. During the recovery, the BOJ tightened monetary policy.

Over 2008-2009, the economy was in a deep recession, with -1% GDP growth in 2008 and -5.5% GDP growth in 2009. In response to the worsening of the economy, the BOJ began loosening monetary policy again in October of 2008, still by purchasing short maturity government bonds, lowering short-term rates. After hitting virually zero short-term rates, in 2010 the BOJ began targeting longer-term assets, including Japanese Government Bonds (JGBs) with maturities of 1-3 years, as well as corporate debt and stock ETFs. In 2013, the program was expanded again to purchase ¥60-70 trillion of JGBs with maturities up to 40 years, and the ETF purchase amount increased. Finally throughout 2016, the BOJ began pursuing negative short-term interest rates, then increased the ETF purchase amount again, and then re-targeted the purchase policy to target a zero 10-year JGB rate as well (Shirai, 2018).

II.A.1 ETF Purchases

In October of 2010, the BOJ began purchasing exchange-traded funds (ETFs) tracking Japan's largest indices: the Nikkei 225 and TOPIX, proportionally to their market capitalizations at a pace of ¥450 billion annually. It also began purchasing ETFs of Real Estate Investment Trusts (REITs) at this time (BOJ (2010b) and BOJ (2010a)). Since its initiation, the ETF purchasing behavior was modified six times by mid-2017. It was expanded to ¥1 trillion in May of 2013, to ¥3 trillion in October of 2014, and to ¥5.7 trillion in August of 2016. The composition of the purchases also changed over time. In November of 2014, ETFs which track the Nikkei 400 index were added to the purchases (BOJ, 2014). In April of 2016, the program was expanded to include ETFs which support "Human and Physical Capital."[4]

[4] The BOJ specified that ETFs which support human and physical capital are those for which each firm tracked by the ETF has increasing investment in either physical capital (capital expenditures, R&D) or human capital (number of employees, employee wages, work environment, employee training, etc.). The tracked firms must also be growing in response to these investments. The ETF as a whole has to have

Finally in October of 2016, the BOJ increased the weighting of the TOPIX in the purchases. Under that change, ¥2.7T out of ¥5.7T will go directly to the TOPIX, while the remaining ¥3T will be split as before between the Nikkei 225, Nikkei 400, and TOPIX based on the market value of each index (BOJ, 2016a).

II.A.2 Corporate Debt Purchases

The BOJ began buying both corporate bonds and commercial paper in February of 2009. The disclosure placed limits on the amount of bonds or commercial paper purchased for a particular issuer: 100 billion yen of a particular instrument and 25% of the total value of bonds and commercial paper for that issuer. Securities are selected by an auction where banks and securities dealers offer blocks of securities at different yields (BOJ, 2009). In the beginning, only about ¥2 trilion of corporate debt was purchased. Then the holdings decreased throughout the remainder of 2009 and 2010. From 2011 to 2013, the BOJ's corporate debt holdings increased to ¥4.5 trillion. Since then, the holdings have remained at this level.

II.B Mechanism of Action

We base our theory that an increase in purchases will increase the price of an asset in the work of Miller (1977). This study shows that because rational investors have differing opinions about the value of a share due to uncertainty in forecasting, and because only a fixed number of shares are available, the market price of the share will be set by a subset of investors who have an opinion of a higher price. As the number of investors whose forecasted price is greater than the market price increases, the price of that share in the market also increases, as the number of shares available has not changed. When each BOJ purchase is viewed as an excess investor whose valuation is higher than the market price, then prices

firms which invest in physical capital as well as those investing in human capital. The fund must also be creditworthy, have enough constituents, be liquid enough, be from an experienced provider, and shall avoid industry concentration (BOJ, 2016b).

should increase with each purchase, leading to short-term returns.

We theorize that the BOJ ETF purchases will have a positive overall impact on stock returns of the firms tracked by the purchased ETFs, by the following mechanism. The BOJ purchases ETF shares in the secondary market. Following the preceeding analysis, these additional purchases drive up the price of the ETF in the short run. This creates an arbitrage opportunity as the value of the ETF is now greater than the value of the sum of the shares held in the ETF. Authorized participants will then seek to take advantage of the abritrage opportunity by buying the underlying assets, creating and selling ETF shares. As more ETF shares are sold, this will cause the ETF price to decrease, but at the same time, as more underlying shares are purchased, the underlying firms' prices will increase.

II.C Government Stock Market Intervention

Most developed countries use only indirect interventions to support the stock market, in the form of bank bailouts, negotiated mergers, acquisitions, and takeovers. Direct interventions can avoid sharp price declines, but reduce price efficiency of the market. Governments frequently directly intervene in foreign exchange markets, but most avoid doing so in stock markets as to avoid sending a negative signal to market participants (Khan and Batteau, 2011). The exceptions are often during a financial crisis. During a crisis, the incremental impact of the negative signal may be lower, and the benefits to market intervention may be higher.

A common strategy when the market is falling is to temporarily suspend trading, often called a circuit breaker. Circuit breakers can help overcome informational problems and improve a market's ability to absorb volume shocks during a market crash (Greenwald and Stein, 1991). Empirical evidence shows that they can be helpful to reduce order imbalance and initial price loss but have no effect on long-run price response (Lauterbach and BenZion, 1993).

Khan and Batteau (2011) discusses Russia's use of a circuit breaker during the 2008 financial crisis. Overall, they found the intervention to be ineffective at reducing price drops. As Su, Yip, and Wong (2002) and Cheng, Fung, and Chan (2000) document, Hong Kong took a more direct approach during the 1998 Asian economic crisis, by directly purchasing $15 billion of shares of the 33 stocks comprising the Hang Seng Index. These direct purchases were shown to have a lasting positive price effect for those stocks, while other stocks had short-term price increases. Permanent direct ownership and control through state-owned enterprises (SOEs) is another method of stock market intervention used by China. This strategy may not be desirable as SOEs have been shown to have lower investment efficiency (Chen, Sun, Tang, and Wu, 2011).

While intervening in the markets is not new, Japan's approach is unique both because of its direct nature and because of the scale of the program in terms of both purchase volume and time span. With the BOJ taking as large as a 25.08% stake in Fast Retailing Co., Ltd., ownership levels for some firms have reached levels which give the BOJ a lot of potential control over the firm. While the BOJ currently does not vote with its shares, if it chose to start then some firms would effectively become SOEs.

II.D Passive Ownership Effects

Passive ownership, in and of itself, has not been shown to be related to returns (Bauguess, Moeller, Schlingemann, and Zutter, 2009), but sudden increases in passive ownership have been shown to positively impact price in the index addition and deletion literature for the S&P 500 (Beneish and Whaley, 1996) and Russell 2000 (Chang, Hong, and Liskovich, 2015), among other indices. These studies show a positive price impact upon index addition which remains while the stock is in the index. If additional demand from the BOJ impacts stocks similarly to additional demand from being added to an index, we may expect a positive price impact from the BOJ purchasing shares, which will only be reversed once the BOJ sells its shares.

There may be other effects from the concentration of passive ownership in BOJ-owned firms. Schmidt and Fahlenbrach (2017) find that an increase in passive ownership can lead to an increase in managerial power through decreased monitoring, leading to value-destroying mergers and acquistions. While some studies show positive governance effects from an increase in passive ownership, this is due to those passive owners exerting influence through large voting blocks (Appel, Gormley, and Keim, 2016). In the case of the BOJ, it does not vote with its shares, so no benefits will come through voting channels. The BOJ does also not monitor the firms and cannot sell its shares in response to corporate actions it disagrees with. The lack of monitoring and voting from a large blockholder could negatively impact governance at the targeted firms.

II.E Government Ownership Effects

A series of papers by William Megginson and coauthors explores the impact of government ownership on firms' market valuation and cost of debt. Boubakri, Ghoul, Guedhami, and Megginson (2018) shows that firms which are owned by governments tend to have higher market valuations. The authors also document important cross-sectional differences in the value response to government ownership, highlighting that firms with the government as a second blockholder recieve the value premium. If the government owns over 50%, the premium disappears, and so too if the government ownership is very small. The authors identify that the channel for the premium is improved access to financing, a reduced discount rate, and monitoring from the government. Firms in developed countries see less of a premium, while those with better legal systems see a greater premium.

The BOJ has a large range of percentage ownerships in various firms, as high as the 25.08% stake seen in the firm Fast Retailing Co., Ltd., and as low as zero. For some firms, the BOJ is the largest or second-largest blockholder, and for some it has an insignificant share. We should observe cross-sectional variation in the value response to government ownership depending on the level of ownership. The entire effect may be mediated, however, due to the lack of monitoring from the BOJ, which was one of the channels for the value premium, as well as due to Japan being a developed country. On the other side, we may observe more of a premium as Japan has a strong legal system (Shleifer and Vishny, 1997).

Consistent with government ownership reducing the cost of financing, similar studies show that the cost of debt decreases for government-held firms during recessions. The opposite occurs outside of recessions, consistent with government ownership distorting investment (Borisova, Fotak, Holland, and Megginson (2015) and Borisova and Megginson (2011)). We hypothesize that the cost of debt will decrease for BOJ-targeted firms as the BOJ is a passive owner, so it should not be distorting investment beyond the investment distortion effects of misvaluation of shares (Warusawitharana and Whited, 2015).

III Data

III.A Main Sample

The main sample is constructed by merging financials and BOJ purchases to stock returns. Financials are from Capital IQ, stock returns are from Datastream, and BOJ purchases are described in section III.C. The sample period is from October 2011 to December of 2017, as data on monthly index weightings are available only from October 2011. Portfolios are formed on PVD_{t-1} for a portion of the analysis, and this is described in detail in Section III.E. Sample summary statistics by PVD_{t-1} portfolio are given in Table 2. The YEN-USD exchange rate was obtained from the St. Louis Federal Reserve's Federal Reserve Economic Data (FRED).

[Table 2 about here.]

III.A.1 Stock Returns

Returns are calculated from Datastream by using Datastream's total return index, which includes the effect of share splits, repurchases, and dividends. Datastream contains information on each security of each issuer, but does not identify the primary security for a given issuer. To determine the primary security, we selected the Japan-listed ticker if one was available. If there were no Japan-based tickers, we selected the one which reported most frequently, but this was only a few cases.

In calculating weekly and monthly returns, if stock information was missing on the date which should be used for the calculation, we forward-fill the total return index by up to 1 and 2 days, respectively. Weekly returns are Wednesday to Wednesday and monthly returns are end of month to end of month.

III.A.2 Stock Return Factors

The Five-Factor model of Fama and French (2015) is used to evaluate the performance of portfolios formed on PVD_{t-1}. In calculating factors for Japan, Ken French used data from Bloomberg. As we have used Datastream, the factors from Ken French's website do not match up well to the sample.[5] Therefore we have calculated factors from the sample following Fama and French (2015). Correlations of portfolio returns and calculated factors are presented in Table 3. An overview of the cumulative performance of the factors throughout the sample period is given in Figure 4.

[Table 3 about here.]

[Figure 4 about here.]

III.A.3 Financials

Capital IQ quarterly financials were used with minor modifications. If Capital IQ is missing data, it is often filled with a zero, so we replaced zeroes in most financials columns with missing. In the case of corporate restructures, where a new company is created which acquires the old company, Capital IQ has often moved the historical financials to the new

[5] For an analysis of how our calculated factors match up to those from Ken French's website, see Appendix B

company identifier. We have manually determined these cases and replaced the historical identifiers with the original identifiers.

III.A.4 Industry

Industry classifications were obtained from Datastream. We manually identified industries containing financial firms by reviewing the classifications. We have identified Banks, Real Estate Hold, Dev, Investment Services, Specialty Finance, Real Estate Services, Consumer Finance, Financial Admin., Ind. & Office REITs, Asset Managers, Life Insurance, Prop. & Casualty Ins., Residential REITs, Diversified REITs, Retail REITs, Mortgage Finance, Hotel & Lodging REITs, Specialty REITs, and Insurance Brokers as the financial industries.

III.A.5 Free Float

Data on free float shares were collected from Capital IQ for all the firms in the sample. While most of the observations had valid data, outliers were removed from the float data before merging it into the sample. Any firm which experienced a 300% or greater absolute value change in float in a single period was removed from the sample. Further, any observations where float percentage was outside (5%, 99%) were removed.

III.A.6 Sample Selection

Financial industries were excluded from the main sample, then it was restricted to October of 2011 - December of 2017. Firms that were missing stock information in more than 10% of periods were then removed from the sample, as well as any observations missing information for total assets or total equity. Extreme outliers were then removed, which upon manual examination were due to data errors. Firms for which total equity changes by more than 50% in absolute value in at least 10% of periods were then dropped. Then the smallest 5% of firms by average market capitalization were dropped, as they had frequent data errors. Finally, the sample was trimmed at the 0.05 and 99.95 percentiles of the following variables: Institutional

Ownership, Book Debt to Assets, Market to Book Equity, CAPEX/Total Assets, Profit Margin, Operating Margin, and Return.

III.B Issuer ISIN

The International Securities Identification Number (ISIN) is an identifier commonly used in international research. This is a security-level identifier, so each issuer may have multiple ISINs. The format of the ISIN is: first two digits are country code, the following nine digits are a country-specific identifier, and the last digit is a check digit. As each country implements its own identifier for the nine digit portion, there is no general way to extract the issuer from the ISIN.

In the U.S. and Japan, however, the nine digit country code has a specific format. The first six digits identify the issuer, the following two digits identify the security of that issuer, and the ninth digit is a check digit. Therefore for the U.S. and Japan, digits three through eight of the ISIN signify the issuer of the security. We extract these digits and call them the Issuer ISIN. The Issuer ISIN is the main identifier for firms in the study.

III.C BOJ Float Ownership (%)

The BOJ Float Ownership (%) variable is constructed by comparing the cumulative Yen value purchased for an individual issuer to the float-adjusted market capitalization of that issuer. To determine the Yen value purchased for an individual issuer, first we determine the Yen value purchased of each index, then attribute a proportion of those purchases to the issuer depending on its weighting in the index. The float-adjusted market capitalization is the percentage of shares that are available for investors to trade multiplied by the market capitalization.

III.C.1 Purchases By Index

The BOJ purchases ETFs of the Nikkei 225, Nikkei 400, and TOPIX indices. Prior to October of 2016, the purchases for each index were proportional to the market capitalization of the index relative to the total market capitalization of the three indices. From October 2016, 2.7 trillion of the 5.7 trillion Yen marked for purchases is directly used to purchase TOPIX ETFs, and the remaining 3 trillion Yen is split as before. The BOJ reports daily purchases on its website. We obtain the end of month values of the Nikkei 225 and Nikkei 400 from the Nikkei Inc. website, and the end of month values for the TOPIX from the Japan Exchange Group website. In each month, we total the daily BOJ purchases to get a monthly amount. Then we find the total of the market capitalizations of the three indices, and calculate the weight of each index as its market capitalization divided by the total. The purchases for each index in each month are simply the monthly BOJ purchases multiplied by the index weight. From October 2016 and beyond, we follow the proceeding process for 52.63% (3/5.7) of the purchases, and attribute the remaining 47.37% (2.7/5.7) of the purchases directly to the TOPIX.

III.C.2 Purchases By Issuer

We obtain ETF holdings from Morningstar to determine the weight of each issuer within each index. For each index, we select the top three ETFs by market value for examination. Then we examine the data on each ETF to see which has the best coverage of identifiers and weightings for the index. For the Nikkei 225, we selected Nomura Asset Management's Nikkei 225 ETF, which is the largest Nikkei 225 ETF. For the TOPIX, we selected Daiwa's TOPIX ETF, which is the second largest TOPIX ETF. For both selected ETFs, observations were still missing identifiers. To get full coverage, we completed a name-matching process for each ETF's holdings. More details of the name-matching process are described in appendix A.

Then the purchases for each issuer are just the weight of the issuer multiplied by the appropriate BOJ index purchase value calculated in section III.C.1. For each issuer, the cumulative purchases up until a time period are divided by the float-adjusted market capitalization at that time period to yield BOJ Float Ownership (%). If the issuer is listed in multiple indices, which is the case for the Nikkei 225 firms as they are also listed in the TOPIX, the cumulative purchases across the indices are combined before dividing by the float-adjusted market capitalization to yield BOJ Float Ownership (%).

III.C.3 Acquisitions and Restructures

In the case of acquisitions and restructures, the BOJ ownership in the company must be transferred. For each transaction, we determined the share exchange ratio as the number of buyer shares transacted divided by the number of seller shares transacted, provided that it was a share-only deal. If there was cash in the deal, the cash was converted into a number of shares for the purpose of the share exhange ratio calculation by dividing the cash transferred by the contemporaneous market price of the firm. In a transaction, the number of BOJ-held shares for the buyer increase by the seller's BOJ-held shares multiplied by the share exchange ratio.

III.D PVD

Information on the actual weightings in the Nikkei 225 were obtained from Morningstar ETF data. Float-adjusted market capitalization is calculated by multiplying the market capitalization of the firm by the percentage of float shares for the firm. Then the float-adjusted market capitalization weighting of each firm in the Nikkei 225 at each time period was calculated as the float-adjusted market capitalization of the firm at that time divided by the total float-adjusted market capitalization of the Nikkei 225 at that time. The PVD measure is simply the price weighting of the firm minus the value weighting. For any firm outside of the Nikkei 225, PVD will be zero as the firm is not being purchased according to a price weight. An example of PVD construction is shown in Appendix C.B.

III.E Portfolio Formation

Each year, observations are sorted into three portfolios based on PVD_{t-1}. PVD is lagged by one period before forming portfolios, as we seek to evaluate returns, and PVD itself is affected by returns.[6] Within each existing portfolio, portfolios are formed on Market Value, Institutional Ownership, Price, and Market to Book Equity, so that the number of observations in each resulting portfolio are approximately equal, though the cutoffs will differ.

At the end of every quarter, breakpoints are formed for portfolios by sorting observations in that quarter by PVD_{t-1}. Breakpoints are selected at every 1/3 of firms in that quarter, then firms are sorted into portfolios, where below the first breakpoint is considered the Low portfolio and above the highest breakpoint is considered the High portfolio. The Mid portfolio represents firms which are between the two breakpoints. The Zero portfolio represents only firms which have zero PVD_{t-1}. Equally and market-capitalization-weighted portfolio returns are then calculated by portfolio-month. Long-short portfolios are then formed by subtracting the short-side portfolio return from the long-side portfolio return in each month. Market returns, factors (SMB, HML, RMW, and CMA), and alphas are calculated following Fama and French (1992) and Fama and French (2015), using Datastream returns for the entire sample. Returns are calculated from Datastream by using Datastream's total return index, which includes the effect of share splits, repurchases, and dividends. Then Fama and French (2015) regressions are run by portfolio over time. Then within each portfolio formed on PVD_{t-1}, a second set of breakpoints is calculated, for every 1/3 of Market Value within the original portfolio. Observations are sorted into Market Value portfolios by these breakpoints.

[6] We evaluate the effect of return on PVD with a simple model in Appendix C.A.

IV Results

Overall, we find evidence that both PVD_{t-1} and BOJ Ownership (%) are positively associated with returns and five-factor alphas. We conducted a variety of analyses to confirm this.

IV.A Portfolios formed on PVD_{t-1}

[Table 4 about here.]

Table 4 shows the performance of portfolios formed on PVD_{t-1}, including two long-short trading strategies.

We find that a portfolio which is long firms with high PVD_{t-1} and short firms with low PVD_{t-1}, rebalanced quarterly, has an annual outperformance of 10.20% on an equally weighted basis and 9.12% on a value-weighted basis, after adjusting for risk exposure. For the equally weighted results, the performance of the long-short portfolio is driven by the short side, while for the value-weighted results, the long side also has outperformance. A second long-short portfolio is formed by replacing the short side with the firms that have zero PVD_{t-1}. While this portfolio shows equally weighted outperformance of 7.20%, it does not have a significant alpha on a value-weighted basis.

The average market value in each portfolio varies significantly. Zero firms are the smallest as these are firms which are too small to be in the Nikkei 225 index. As for non-zero PVD_{t-1}, there is a U-shaped pattern in size due to two competing effects. Larger market value, holding price constant, will lower the value of PVD_{t-1}, and so the Low PVD_{t-1} portfolio has the largest average market value. Conversely, higher price, holding market value constant, will increase the value of PVD_{t-1}. Considering that log price and log market value have a correlation of 0.38, those high priced firms in the High PVD_{t-1} portfolio also tend to have high market values. This leads to the Mid portfolio having the lowest average market value among the non-zero portfolios.

The long-short portfolios have few significant loadings on the five factors, so they seem to be low-risk strategies. The High-Low portfolios have a beta of -0.10, and the High-Zero equally-weighted portfolio has a beta of 0.10, which are significant but should have a small effect compared to the alphas. The High-Zero has large negative loadings on SMB, which is logical as the Zero portfolios have a large positive loading on SMB.

[Figure 5 about here.]

Figure 5 shows the performance of the long-short PVD_{t-1} portfolios over time.[7] Both of the variations on the strategy, using either Low or Zero as the short portfolio, show positive outperformance in every year except 2017, reaching as high as 21.2% annually for the High - Low long-short portfolio and 14.3% annually for the High - Zero long-short portfolio. Further, the alphas are greatest in 2015 and 2016, which is the approximate time span that the BOJ is accelerating their purchases.

IV.B Portfolios formed on PVD_{t-1} Port and Market Value Port

[Table 5 about here.]

As shown previously in Table 4, market value varies considerably across portfolios, as do SMB loadings. To assuage concerns that results are being driven by firm size, we have taken the portfolios formed on PVD_{t-1} and further split them into sub-portfolios by market value in Table 5.

We show that across returns and alphas, high PVD_{t-1} portfolios significantly outperform low PVD_{t-1} portfolios, even within the same size category. The performance of the long-short portfolio formed with low PVD_{t-1} firms as the short side is positive and statistically significant for both small and large firms, whether looking at returns or alphas on an equally- or value-weighted basis. Long-short portfolios formed with small firms tend to see more out-performance, especially after adjusting for risk factors, with an annualized alpha of 10.92%

[7] The figure shows equally-weighted averages of returns. In unreported results, we also complete this analysis with value-weighted averages. Results are qualitatively similar.

on an equally-weighted basis and 9.87% on a value-weighted basis. Long-short portfolios formed with large firms firms still see a positive effect of 8.85% on an equally-weighted basis and 8.53% on a value-weighted basis. Therefore we can conclude that our main result is not being driven by firm size.

That is not to say that firm size has no effect on returns. Long-short portfolios formed by taking the large firm PVD_{t-1} portfolio minus the short firm PVD_{t-1} portfolio tend to outperform as well, reaching as much as a 16.58% equally-weighed annualized alpha for the long-short portfolio formed with Mid PVD_{t-1} portfolios.

IV.C Return and Alpha Regressions

[Table 6 about here.]

In Table 6, we regress monthly returns and five-factor alphas of individual stocks on PVD_{t-1}, for firms in the Nikkei 225. The Low dummy represents the bottom 1/3 of PVD_{t-1} firms. We find evidence across both OLS and Fama-Macbeth regressions of both returns and alphas that firms with low PVD_{t-1} are associated with lower returns. Compared to the other firms in the Nikkei 225, the low PVD_{t-1} firms had up to 13.80% lower returns and 13.68% lower alphas on an annualized basis during the sample period. As the alpha coefficient for PVD_{t-1} is lower than the return coefficient, this suggests that lower PVD_{t-1} firms have more factor exposure than other firms, which is confirmed in Table 4.

[Table 7 about here.]

In Table 7, we regress monthly returns and five-factor alphas of individual stocks on PVD_{t-1} and BOJ Float Ownership $(\%)_{t-1}$ for all firms. While we do not find results for simple linear regression on returns, once controls are added, we see a significantly positive effect of PVD_{t-1} and BOJ Float Ownership $(\%)_{t-1}$ on both returns and alphas. A 1% increase in PVD_{t-1} is associated with an annualized increase of 2.04% for returns and 3.96% for alphas, while a 1% increase in BOJ Float Ownership $(\%)_{t-1}$ is associated with an annualized increase of 9.12% for returns and 4.92% for alphas. As the alpha coefficient for PVD_{t-1} is higher than the return coefficient, this suggests that high PVD_{t-1} firms have less factor exposure than other firms, which is confirmed in Table 4. Similarly, one could infer that high BOJ Float Ownership $(\%)_{t-1}$ firms have higher factor exposure than other firms due to the effect on alphas being smaller than the effect on returns.[8]

IV.D Event Study

[Table 8 about here.]

As there may be a differential reaction over time to BOJ purchases, we also examine short- and long-run returns relative to BOJ purchase dates in Table 8 using an event-study methodology (Dodd and Warner, 1983). The index addition and deletion literature would suggest that there should be a positive price impact on the event date but thereafter abnormal returns should be zero, which would be inline with the efficient-market hypothesis (Fama, 1970). Other studies suggest other patterns for the post-event price drift. De Bondt and Thaler (1985) and Sentana and Wadhwani (1992) provide evidence for the overreaction hypothesis, which would suggest that there would be negative price drift, reversing part of the initial return.

First, BOJ purchase dates are selected as days in which the BOJ reported purchases for the "Main ETF" series. Then a data set of returns and alphas in windows around the purchase dates is constructed. From this data set, returns and alphas are cumulated across the windows, yielding a single observation per event day per firm with window returns and alphas. Then financial and stock information is merged to the event-day-firm observations.

Overall, it seems that firms which receive higher purchases as a percentage of market value on a given purchase date have higher returns and alphas both around that date as well as up to a month in the future. As for a short-term increase, a 1% increase in BOJ

[8] In robustness tests, we run five-factor regressions on portfolios formed on BOJ Ownership (%), and confirm that high BOJ Ownership (%) portfolios indeed have higher factor exposure.

ownership on a single BOJ purchase date would lead to an increase of average daily return of 1.78% and alpha of 0.29% in the window of (-1, 1) around the BOJ purchase date. Looking to the longer-term, a 1% increase in BOJ ownership on a single BOJ purchase date would lead to an increase of average daily return of 0.36% and alpha of 0.18% in the window of (1, 20) after the BOJ purchase date. Therefore, we actually observe a positive price drift after BOJ purchases. This may be due to additional purchase days within the event window.

IV.E Probability of BOJ Purchases

[Table 9 about here.]

Table 9 presents evidence on when the BOJ chooses to purchase shares.

Returns are calculated from Datastream by using Datastream's total return index, which includes the effect of share splits, repurchases, and dividends. Then, averages of returns for the different groups are calculated. BOJ Return represents the average of the returns for BOJ-held firms on a given date. Non-BOJ Return represents the average of the returns of the other firms. Mkt Return represents an average of all firms' returns on a given date. Then dates are assigned a one for Is BOJ Purchase Date if it was a day in which the BOJ reported purchases for the "Main ETF" series, and zero otherwise.

We show that the BOJ is purchasing in days on which the BOJ-held firms have negative returns, but that the BOJ is not paying attention to the other firms' returns. The logistic regressions in columns (1), (2), and (3) show that any of BOJ returns, non-BOJ returns, or market returns individually are useful for predicting whether the BOJ will purchase on a given date, though model (1) with BOJ returns produces the highest R^2. All three are useful predictors individually due to high correlations between each other (0.98 of BOJ with Mkt, 0.95 of non-BOJ with Mkt, and 0.85 of BOJ with non-BOJ).

To determine whether the purchases are related to one of the measures and not the others, models (4) and (6) add Non-BOJ Return and Mkt Return, respectively, to the BOJ Return regression. In both of these regressions, BOJ return still significantly predicts BOJ purchase dates, while Non-BOJ Return and Mkt Return do not. Models (5) and (7) also add lags of the explanatory variables as controls, but we do not find any of the lags significant and the results from models (4) and (6) hold. We find that a one percentage point increase in the BOJ Return on a given day is associated with between a 78.8% decrease and 82.3% decrease in the probability of the BOJ purchasing ETFs on that day, depending on the selected model.

V Conclusion

The BOJ is purchasing stock ETFs as part of its overall market intervention strategy. We sought to evaluate the effect of these purchases on the price performance of the underlying firms. During the sample period, the BOJ was also purchasing JGBs and corporate debt. From 2013, the BOJ only purchased enough corporate debt to replace its maturing debt, so that likely had few effects on the economy. The JGB purchases may have affected the prices of firms, but it should not have affected them differentially. As we observe cross-sectional differences in price impacts directly related to the level of BOJ ownership, it suggests that the ETF purchases may have caused the increases in prices.

We have identified unintended effects of the BOJ's ETF purchase program. By targeting the Nikkei 225 by its index weights, the BOJ has ended up with large differences in percentage ownership across different firms. We have introduced PVD as an ex-ante measure of which firms will receive the most purchases. Those firms with high PVD receive more purchases and have larger increases in price, which was not a stated objective of the policy.

The effects of the ETF purchase program likely go beyond share prices. We have explored theoretically how corporate governance may be affected. We also noted that corporate financing could be affected due to changes in the costs of debt and equity. With higher frequency stock information, the microstructure effects of individual BOJ purchases could be explored. All of these would be interesting directions for future research.

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Appendices

A Name Matching with Machine Learning

A.A Overview

The Morningstar ETF data used to determine weightings of each firm within each index was missing many identifiers. Often, the only available identifier was the name. Therefore it was necessary to match these names to another data source containing identifers. For the Nikkei 225, there were few enough firms that we followed a mostly manual process. The TOPIX contains roughly 2000 firms, so rather than classify everything manually, we trained a machine learning algorithm to classify them.

A.B Standardized Levenshtein Distance

The main metric used in the matching approaches is the Levenshtein (1966) distance, often known as edit distance. It is very commonly used in string comparison and text classification, and represents the number of edits that would need to be made to convert one string into another. We have then converted it into a 0 - 100 score by dividing by the maximum length of the two compared strings, then multipling by 100.

A.C Dataset

To construct the name matching dataset, first we selected comparison data sets. For each index, we collected the current members from the index website. Then we selected each unmatched name from the Morningstar data. In the TOPIX data, there were approximately 6,000 names to be matched, as there are several variations of many names. Then for each name for be matched, we calculated the scaled Levenshtein (1966) distance with each name in the comparison data set, and selected the three comparison names with the highest scores.

A.D Manual Name Matching

For the Nikkei 225, matching was only a manual process. For the TOPIX, we followed the manual process for 4,000 out of the approximately 19,000 name pairs, to create training, validation, and testing data sets for the machine learning algorithms. Collectively, we refer to these 4,000 manually classified observations as the "labeled data".

For each name to be matched, we reviewed the three selected comparison names, and selected the appropriate matches, creating a dummy variable for whether there is a match.

A.E Machine Learning Data

A.E.1 Text Standardization

Standardizing company names vastly improves the performance of the algorithms. First, all company names were converted to lowercase and punctuation was removed. Then, words with common abbreviations were converted to their abbreviations. Specifically, company was converted to co, limited was converted to ltd, corporation was converted to corp, and manufacturing was converted to mfg.

A.E.2 Creating Variables

Often called "Feature Extraction" or "Feature Engineering" in computer science, variables need to be created which can be used for machine learning. Numeric variables must be used, so they must be created from text data. We have used the standardized Levenshtein (1966) distance to construct all the variables used for name matching. Not only did we calculate a variable for the overall distance, but also the pairwise distances between each word in the company name. For example, "ABC Corp." vs. "ABC XYZ Corp." would compare "ABC" to "ABC", "ABC" to "XYZ", and so on. Out of the entire data set, the maximum number of words in a company name was 6. Therefore 37 variables were constructed with the distances, 36 from the pairwise distances and one from the overall distance. If either side of the company name pair does not have a word in a particular position, any pairwise distances variables referencing that position receive a score of zero.

A.F Model Selection

A.F.1 General Notes

There are many possible different models which can be used for text classification purposes. It is standard practice in computer science to try different models and variations of each model and select the best performing one. Careful attention is paid to which data is being used to avoid overfitting models to the sample. The process is referred to as cross-validation and involves splitting the labeled data into training, validation, and testing data sets.

For each model, coefficients are set by minimizing classification error on the training data. Then the model's performance is evaluated by creating predictions on the validation data set, and an accuracy score is calculated.

The model with the maximum accuracy will be selected. By only selecting models based on their validation accuracy, overfitting concerns are reduced as the model is evaluated on different data than was used to fit the coefficients. Further, in addition to each type of model, each model has external parameters which must be set by the user. In a process known as grid search, different combinations of parameters are used in the same process, selecting the parameters that yield the highest validation accuracy.

But as so many different models are fit in this process and they are selected based on their validation accuracy, there may still be concerns about overfitting to irregularities in the validation data. But during this process, the testing data is never used. After the final model has been selected, then its performance is evaluated on the testing data, and a final accuracy score is calculated. As there should be no overfitting concerns with the testing data, it can be considered a reasonable estimate of the accuracy actually obtained by the model.

A.F.2 Specific Implementation

We randomly partitioned the labeled data into 60% training, 20% validation, and 20% testing samples, yielding 2,400 training observations, 800 validation observations, and 800 testing observations. As an accuracy metric, we used percentage of observations classified correctly. For each model, we used a grid search procedure to vary the main parameters of each model. Each model tested, along with its highest validation accuracy are shown in 10.

[Table 10 about here.]

Overall, all of the models performed well for classification once the best parameters were selected. Ultimately, the Random Forests model was selected due to its highest validation performance. Then the performance of the Random Forests model was evaluated on the testing data, yielding an accuracy of 98.3%.

B Comparison of Calculated Factors to Ken French Factors

[Table 11 about here.]

We collected data on return factors for Japan from Ken French's website, but we found that it was not similar enough to our sample. Therefore, we calculated our own factors, following Fama and French (1992). The differences are likely due to different data sources, as Ken French calculated his factors using data from Bloomberg, while our sample is collected from Datastream. We hypothesize that individual firm returns are nearly identical across the data sets, but the included set of firms is different. Table 11 shows that the calculated SMB and HML factors are statistically significantly different across the two data sources, justifying the need for factors calculated from the sample.

C A Model of Price - Value Distortion

C.A Analytical Conclusions

Consider a two firm index with three time periods. At $t = 0$, firms are set at their initial values. Between $t = 0$ and $t = 1$, each firm earns a return, and again between $t = 1$ and $t = 2$.

- V_{it} is the value of firm i at time t
- P_{it} is the price of firm i at time t
- S_{it} is the number of shares outstanding for firm i at time t
- r_{it} is the gross return $(1 + return)$ for firm i between time $t - 1$ and time t
- w_{it}^P is the price weighting of firm i at time t

- w_{it}^{V} is the value weighting of firm i at time t
- V_{it}^{I} is the total market value of the index at time t
- P_{it}^{I} is the total price of the index at time t
- $NikkeiMVPriceWeightDistortion(PVD)_{it}$ is the Price - Value Distortion measure for firm i at time t

Solving backwards for the PVD measure yields:

1. $PVD_{1,2} = w^{P}{}_{1,2} - w^{V}{}_{1,2}$
2. $PVD_{1,2} = \frac{P_{1,2}}{P^{I}{}_{2}} - \frac{V_{1,2}}{V^{I}{}_{2}}$
3. $PVD_{1,2} = -\frac{P_{1,1}S_{1,2}r_{1,2}}{P_{1,1}S_{1,2}r_{1,2}+V_{2,2}} + \frac{P_{1,1}r_{1,2}}{P_{1,1}r_{1,2}+P_{2,2}}$
4. $PVD_{1,2} = -\frac{P_{1,0}S_{1,0}r_{1,1}r_{1,2}}{P_{1,0}S_{1,0}r_{1,1}r_{1,2}+P_{2,0}S_{2,0}r_{2,1}r_{2,2}} + \frac{P_{1,0}r_{1,1}r_{1,2}}{P_{1,0}r_{1,1}r_{1,2}+P_{2,0}r_{2,1}r_{2,2}}$

And for the earlier PVD values:

1. $PVD_{1,0} = \frac{P_{1,0}}{P_{1,0}+P_{2,0}} - \frac{P_{1,0}S_{1,0}}{P_{1,0}S_{1,0}+P_{2,0}S_{2,0}}$
2. $PVD_{1,1} = -\frac{P_{1,0}S_{1,0}r_{1,1}}{P_{1,0}S_{1,0}r_{1,1}+P_{2,0}S_{2,0}r_{2,1}} + \frac{P_{1,0}r_{1,1}}{P_{1,0}r_{1,1}+P_{2,0}r_{2,1}}$

Examining the effect of the second period return for firm 1 on the second period PVD measure for firm 1:

$$\frac{\partial PVD_{1,2}}{\partial r_{1,2}} = -\frac{P_{1,1}S_{1,2}V_{2,2}}{(P_{1,1}S_{1,2}r_{1,2}+V_{2,2})^2} + \frac{P_{1,1}P_{2,2}}{(P_{1,1}r_{1,2}+P_{2,2})^2} \tag{1}$$

$$\frac{\partial PVD_{1,2}}{\partial r_{1,2}} = -\frac{P_{1,0}P_{2,0}S_{1,0}S_{2,0}r_{1,1}r_{2,1}r_{2,2}}{(P_{1,0}S_{1,0}r_{1,1}r_{1,2}+P_{2,0}S_{2,0}r_{2,1}r_{2,2})^2} + \frac{P_{1,0}P_{2,0}r_{1,1}r_{2,1}r_{2,2}}{(P_{1,0}r_{1,1}r_{1,2}+P_{2,0}r_{2,1}r_{2,2})^2} \tag{2}$$

Overall, we find that the effect of the contemporaneous firm return on its PVD is ambiguous in both sign and magnitude, depending on the prior returns, prices, and number of shares outstanding for this firm, as well as other firms. Therefore, to examine the impact of PVD on returns, lagged PVD should be used to avoid endogeneity.

C.B An Example of Price - Value Distortion

An example is helpful to show how PVD is calculated. Again consider the same two firm, two period model. In this example, the two firms will also have the same market value. Firm 1 has a low price and high number of shares outstanding, while firm 2 has a high price and low number of shares outstanding. The values for prices, shares outstanding, and returns are as follows:

- $P_{1,0} = 100$
- $P_{2,0} = 200$
- $S_{1,0} = 2$
- $S_{2,0} = 1$
- $r_{1,1} = 1.1$
- $r_{1,2} = 1.2$
- $r_{2,1} = 1.3$
- $r_{2,2} = 0.9$

At period 1, firm 1 has a price of 110, while firm 2 has a price of 260. This leads to price weights of 29.7% and 70.3%, and value weights of 45.8% and 54.2%, respectively. Therefore $PVD_{1,1} = -0.16$ and $PVD_{2,1} = 0.16$.

By period 2, firm 1 has a price of 132, while firm 2 has a price of 234. This leads to price weights of 36.1% and 63.9%, and value weights of 53.0% and 47.0%, respectively. Therefore $PVD_{1,2} = -0.17$ and $PVD_{2,2} = 0.17$.

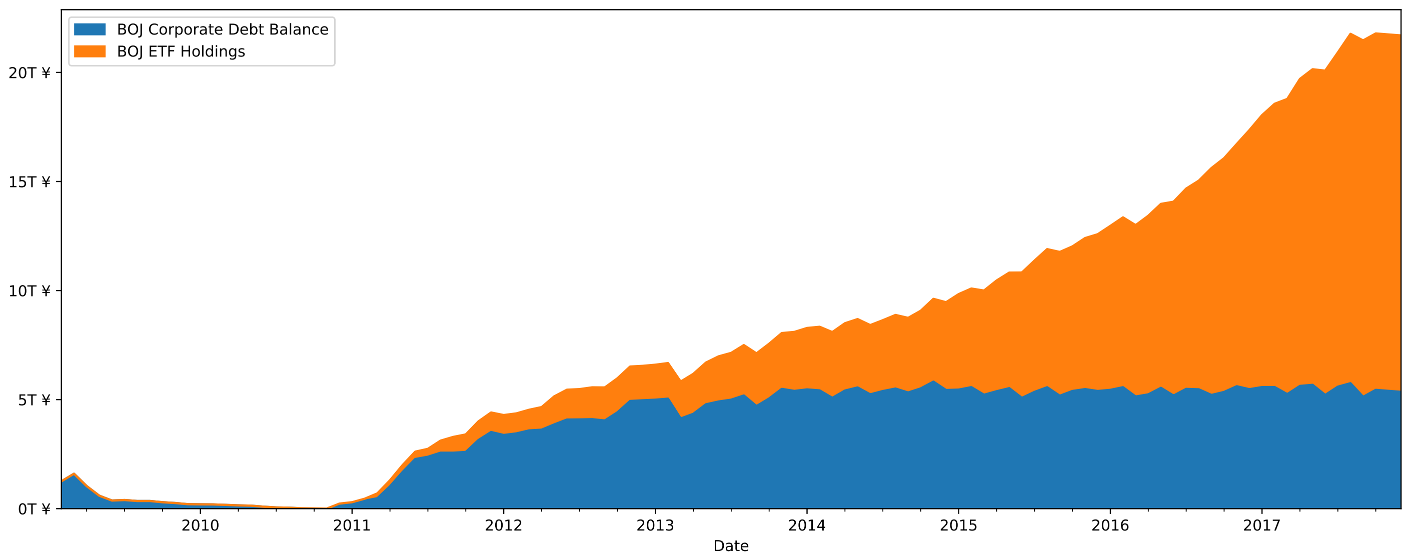


Figure 1: All BOJ Direct Intervention. This figure compares the total balances over time of the BOJ's corporate asset holdings. BOJ ETF Holdings and BOJ Corporate Debt balances are gathered from the BOJ's website at `http://www3.boj.or.jp/market/en/menu_etf.htm`. The sample period begins on 2010-01-01 and ends on 2017-12-31.

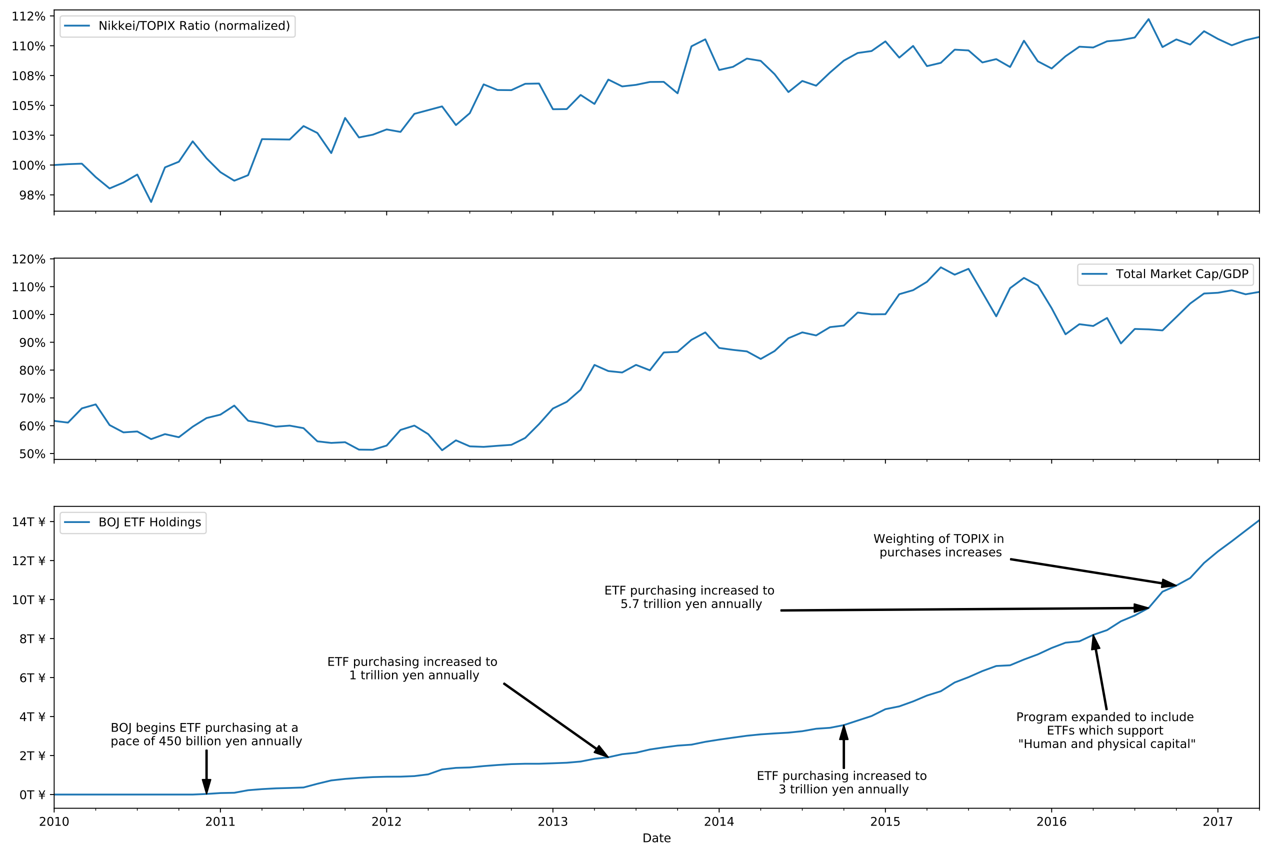


Figure 2: ETF Purchases and Market Valuations. The top series represents the ratio of the Nikkei 225 index value to the TOPIX index value, with both normalized to 1 at the beginning of the sample period. The middle series represents the ratio of the total market capitalization of Japanese firms to Japan GDP. The bottom series represents the total value of the BOJ's ETF holdings. BOJ ETF Holdings are gathered from the BOJ's website at `http://www3.boj.or.jp/market/en/menu_etf.htm`. We obtain the end of month values of the Nikkei 225 from the Nikkei Inc. website, and the end of month values for the TOPIX from the Japan Exchange Group website. The sample period begins on 2010-01-01 and ends on 2017-12-31.

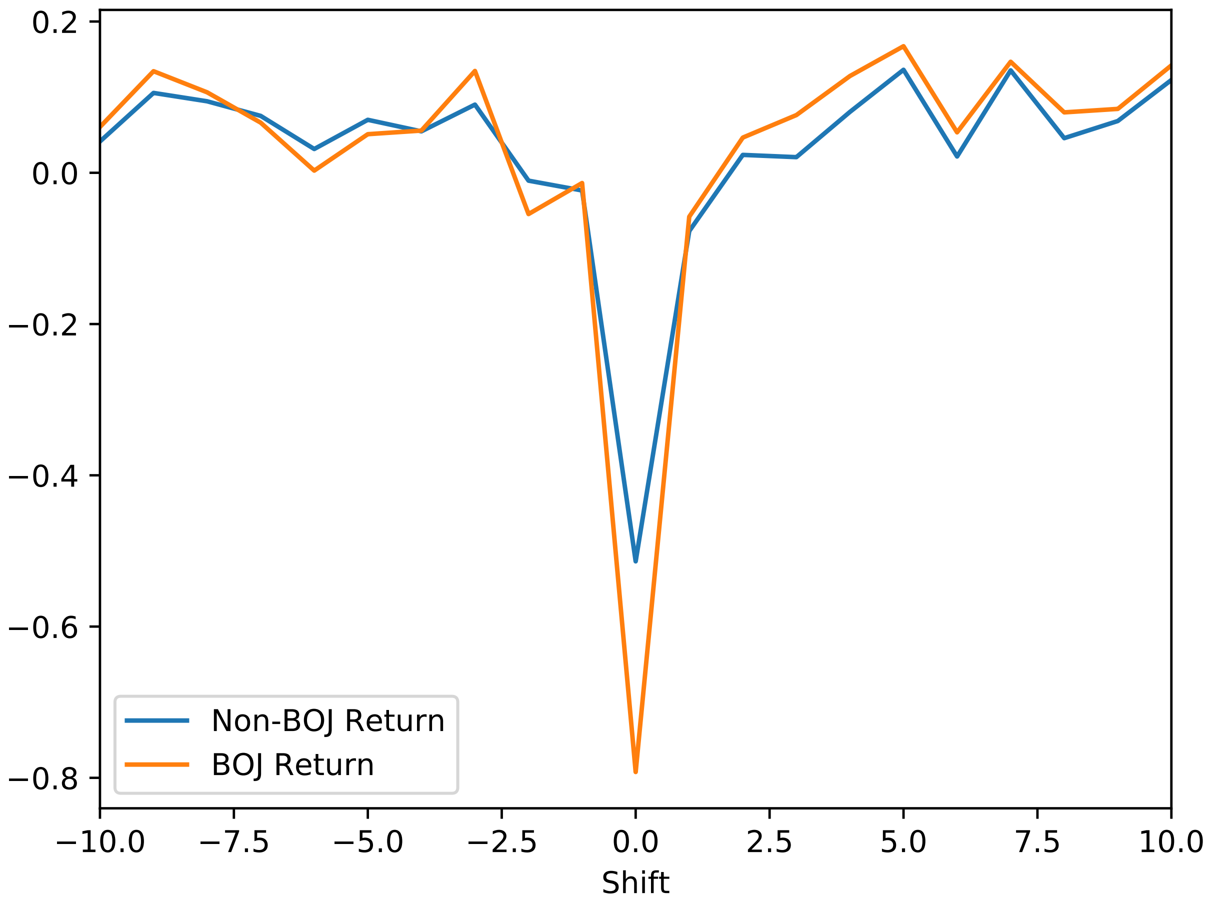
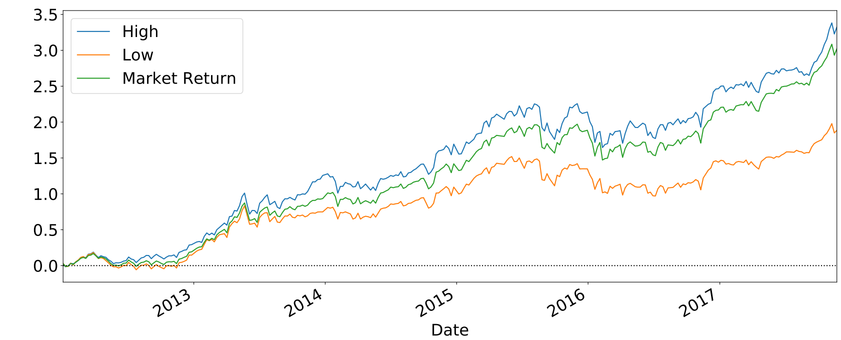
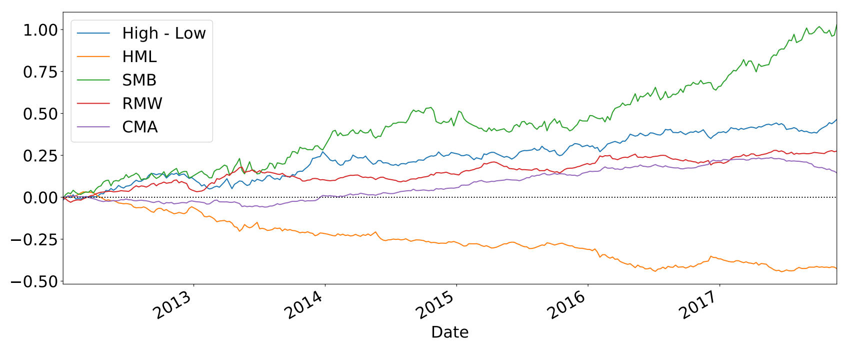


Figure 3: BOJ Purchases in Event Time. The mean of returns across firms relative to BOJ purchase days are presented. Non-BOJ Return represents the mean of returns for firms not in indexes tracked by the ETFs the BOJ is purchasing. BOJ Return represents the mean of returns for firms in the Nikkei 225 and TOPIX. First, BOJ purchase dates are selected as days in which the BOJ reported purchases for the "Main ETF" series. Then a data set of returns and alphas in windows around the purchase dates is constructed. From this data set, returns and alphas are cumulated across the windows, yielding a single observation per event day per firm with window returns and alphas.

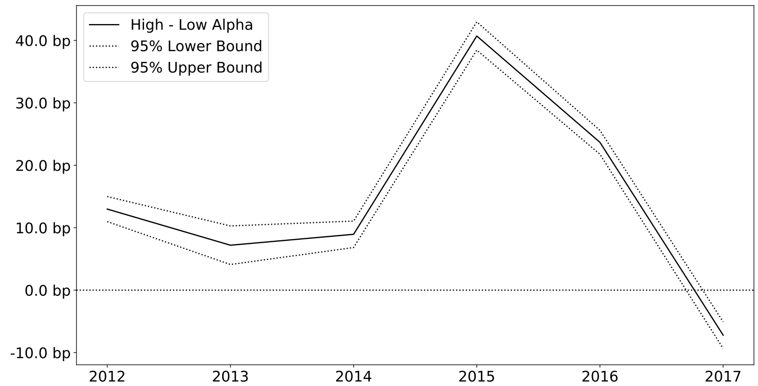


(i) Portfolio Levels

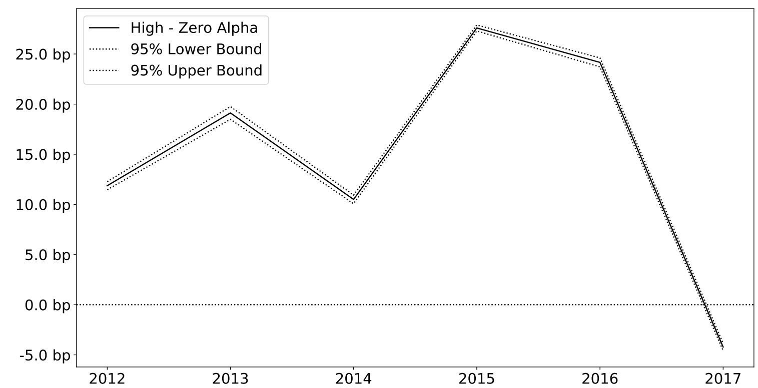


(ii) Long-Short Portfolios

Figure 4: Cumulative Portfolio Returns. At the end of every quarter, breakpoints are formed for portfolios by sorting observations in that quarter by PVD_{t-1} Port. Breakpoints are selected at every 1/3 of firms in that quarter, then firms are sorted into portfolios, where below the first breakpoint is considered the Low portfolio and above the highest breakpoint is considered the High portfolio. The Mid portfolio represents firms which are between the two breakpoints. The Zero portfolio represents only firms which have zero PVD_{t-1} Port. Equally and market-capitalization-weighted portfolio returns are then calculated by portfolio-week. Long-short portfolios are then formed by subtracting the short-side portfolio return from the long-side portfolio return in each week. Market returns, factors (SMB, HML, RMW, and CMA), and alphas are calculated following Fama and French (1992) and Fama and French (2015), using Datastream returns for the entire sample. Returns are calculated from Datastream by using Datastream's total return index, which includes the effect of share splits, repurchases, and dividends. For each portfolio, the average weighted by Market Value of the firms' returns for each week are calculated. Buy and hold returns (BHR) are calculated by taking the gross returns (1 + return) in each period and multiplying them together, subtracting 1 at the end. Panel I shows the cumulative returns of firms with High PVD_{t-1} Port, Low PVD_{t-1} Port, and all firms. Panel II shows the cumulative returns of market factors (HML, SMB, RMW, and CMA), as well as a long-short portfolio of High - Low.



(i) High - Low



(ii) High - Zero

Figure 5: Alphas by PVD_{t-1} Port Over Time. At the end of every quarter, breakpoints are formed for portfolios by sorting observations in that quarter by PVD_{t-1} Port. Breakpoints are selected at every 1/3 of firms in that quarter, then firms are sorted into portfolios, where below the first breakpoint is considered the Low portfolio and above the highest breakpoint is considered the High portfolio. The Mid portfolio represents firms which are between the two breakpoints. The Zero portfolio represents only firms which have zero PVD_{t-1} Port. Equally and market-capitalization-weighted portfolio returns are then calculated by portfolio-week. Long-short portfolios are then formed by subtracting the short-side portfolio return from the long-side portfolio return in each week. Market returns, factors (SMB, HML, RMW, and CMA), and alphas are calculated following Fama and French (1992) and Fama and French (2015), using Datastream returns for the entire sample. Returns are calculated from Datastream by using Datastream's total return index, which includes the effect of share splits, repurchases, and dividends. Then Fama and French (2015) regressions are run by portfolio over time. Finally, the alphas are averaged by year and presented, along with a 95% confidence interval for the estimate.

Table 1: Distortion of BOJ Ownership

	BOJ Float Ownership (%)	PVD_{t-1}	Market Value
Panel A: Highest BOJ Float Ownership (%)			
Fast Retailing Co., Ltd.	25.08	5.335	3,520,596
Mitsumi Electric Co., Ltd.	16.28	0.116	58,274
Hitachi Construction Machinery Co., Ltd.	16.01	0.391	603,828
Advantest Corporation	15.99	0.606	383,568
Konami Holdings Corporation	15.93	0.827	895,440
Panel B: Lowest BOJ Float Ownership (%)			
WAREHOUSE Co., Ltd.	0.02	0.000	2,575
Toho Acetylene Co., Ltd.	0.03	0.000	3,677
Aderans Company Limited	0.04	0.000	37,881
Yoshimura Food Holdings K.K.	0.04	0.000	12,849
Oomitsu Co., Ltd.	0.05	0.000	12,729

First, any observations with missing PVD_{t-1} are removed, then the maximum values of BOJ Float Ownership (%) by firm are calculated. Then, the firms with the highest and lowest values of BOJ Float Ownership (%) are selected. Firms with zero BOJ Float Ownership (%) are excluded. Other values are as of when the maximum BOJ Float Ownership (%) was observed. The market capitalization weighting of each firm in the Nikkei 225 at each time period was calculated as the market capitalization of the firm at that time divided by the total market capitalization of the Nikkei 225 at that time. The PVD measure is the price weighting of the firm minus the value weighting.

$$\text{PVD} = w_{it}^P - w_{it}^V \tag{3}$$

Where w_{it}^P is the price weighting of firm i at time t and w_{it}^V is the value weighting of firm i at time t. For any firm outside of the Nikkei 225, PVD will be zero as the firm is not being purchased according to a price weight.

Table 2: Portfolio Formation Summary for PVD_{t-1} Port

Portfolio	Mean	VW Mean	25%	Median	75%	Count
Panel A: PVD_{t-1}						
Low	-0.51	-1.41	-0.60	-0.31	-0.18	4,052
Mid	0.01	-0.01	-0.03	0.00	0.04	4,584
High	0.53	1.19	0.16	0.24	0.50	4,936
Panel B: BOJ Float Ownership (%)						
Zero	0.86	0.87	0.40	0.66	1.16	95,685
Low	1.33	1.42	0.60	1.03	1.88	4,052
Mid	2.32	2.29	0.95	1.72	3.18	4,584
High	4.28	4.49	1.68	3.22	6.09	4,936
Panel C: Return						
Zero	2.07	2.36	-3.29	0.88	5.87	179,200
Low	1.32	1.64	-3.57	1.05	5.81	4,052
Mid	1.92	2.28	-3.70	1.60	7.11	4,584
High	1.83	2.14	-3.53	1.83	6.82	4,936
Panel D: Market Value (billions of Yen)						
Zero	62.84	662.17	5.72	14.56	44.07	179,200
Low	2,371.09	6,429.30	840.05	1,342.25	2,864.03	4,052
Mid	401.68	930.57	132.53	235.76	506.58	4,584
High	1,062.22	2,967.02	287.62	535.81	1,195.74	4,936

Summary statistics are calculated by PVD_{t-1} Port value. Each panel represents a single variable summary, for the variable given in the panel name. Each row represents a PVD_{t-1} Port value. Each column represents a statistic. The sample period begins on 1/1/2012 and ends on 12/31/2017.

Table 3: Correlations of Portfolio Returns and Factors

Panel A: Correlations	Return High	Return Mid	Return Low	Return Zero	MKTRF	SMB	HML	RMW	CMA
Return High	1.00								
Return Mid	0.89	1.00							
Return Low	0.91	0.94	1.00						
Return Zero	0.90	0.90	0.92	1.00					
MKTRF	0.95	0.95	0.98	0.97	1.00				
SMB	-0.35	-0.29	-0.31	-0.10	-0.25	1.00			
HML	0.04	0.19	0.09	-0.09	0.02	-0.48	1.00		
RMW	0.12	-0.09	0.04	0.12	0.08	-0.03	-0.42	1.00	
CMA	-0.02	0.04	-0.01	-0.01	-0.01	-0.06	0.03	-0.13	1.00

Correlations are presented above. Returns were averaged by portfolio and by date, across firms in the portfolio, weighted by Market Value. Market returns, factors (SMB, HML, RMW, and CMA), and alphas are calculated following Fama and French (1992) and Fama and French (2015), using Datastream returns for the entire sample. Returns are calculated from Datastream by using Datastream's total return index, which includes the effect of share splits, repurchases, and dividends. Results are qualitatively similar with equally-weighted portfolio returns, though the correlation between SMB and the Zero portfolio becomes positive.

Table 4: Portfolios formed on PVD_{t-1}

	Alphas and five-factor loadings						Portfolio characteristics		
Portfolios	Alpha	MKTRF	SMB	HML	RMW	CMA	Market Value	Price	Count
Panel A: Monthly Returns - Equally Weighted									
Zero	-0.69***	0.97***	0.72***	0.07**	-0.16***	0.08	62841	3506	179200
	(-8.02)	(64.50)	(24.40)	(2.11)	(-4.34)	(0.93)			
Low	-0.94***	1.17***	0.07	0.22***	-0.20*	0.02	2371093	4218	4052
	(-4.65)	(40.30)	(1.00)	(3.52)	(-1.93)	(0.10)			
Mid	-0.19	1.16***	0.21***	0.46***	-0.47***	0.23	401676	1125	4584
	(-0.82)	(25.94)	(2.83)	(4.46)	(-3.29)	(1.24)			
High	-0.07	1.07***	-0.13	0.07	-0.13	-0.21*	1062220	3275	4936
	(-0.40)	(31.89)	(-1.64)	(0.83)	(-1.61)	(-1.77)			
High - Zero	0.60***	0.10***	-0.85***	0.00	0.03	-0.29*	89630	3499	184136
	(2.86)	(2.86)	(-9.46)	(0.01)	(0.37)	(-1.85)			
High - Low	0.85***	-0.10**	-0.20*	-0.15	0.07	-0.22	1652290	3700	8988
	(3.23)	(-2.07)	(-1.89)	(-1.19)	(0.49)	(-1.08)			
Panel B: Monthly Returns - Value Weighted									
Zero	0.06	0.94***	0.21***	-0.06*	0.07	0.05	662173	6107	179200
	(0.50)	(60.26)	(4.79)	(-1.73)	(1.40)	(0.54)			
Low	-0.38**	1.07***	-0.11*	0.08	-0.05	-0.02	6429297	6367	4052
	(-2.45)	(39.02)	(-1.83)	(1.18)	(-0.71)	(-0.24)			
Mid	0.38*	1.07***	0.01	0.25***	-0.32***	0.13	930575	1842	4584
	(1.75)	(26.78)	(0.27)	(3.26)	(-2.79)	(0.77)			
High	0.40*	0.97***	-0.25***	-0.07	0.08	-0.06	2967024	6716	4936
	(1.96)	(25.48)	(-2.97)	(-0.82)	(0.90)	(-0.49)			
High - Zero	0.32	0.03	-0.47***	-0.01	0.01	-0.10	1394387	6301	184136
	(1.31)	(0.81)	(-4.59)	(-0.09)	(0.10)	(-0.60)			
High - Low	0.76**	-0.09	-0.15	-0.15	0.14	-0.03	5206931	6490	8988
	(2.44)	(-1.54)	(-1.11)	(-1.06)	(0.90)	(-0.15)			

At the end of every quarter, breakpoints are formed for portfolios by sorting observations in that quarter by PVD_{t-1}. Breakpoints are selected at every 1/3 of firms in that quarter, then firms are sorted into portfolios, where below the first breakpoint is considered the Low portfolio and above the highest breakpoint is considered the High portfolio. The Mid portfolio represents firms which are between the two breakpoints. The Zero portfolio represents only firms which have zero PVD_{t-1}. Equally and market-capitalization-weighted portfolio returns are then calculated by portfolio-month. Long-short portfolios are then formed by subtracting the short-side portfolio return from the long-side portfolio return in each month. Market returns, factors (SMB, HML, RMW, and CMA), and alphas are calculated following Fama and French (1992) and Fama and French (2015), using Datastream returns for the entire sample. Returns are calculated from Datastream by using Datastream's total return index, which includes the effect of share splits, repurchases, and dividends. Then Fama and French (2015) regressions are run by portfolio over time. Alphas and factor loadings from the Fama and French (2015) regressions are presented. Both panels use monthly returns and factors. Panel A presents results with equally-weighted returns within portfolios, while Panel B presents results for market-capitalization-weighted returns within portfolios. The sample period is from 2012 to 2017.0. * signifies significance at the 90% level, ** at the 95% level, and *** at the 99% level. *t*-statistics are in parentheses.

Table 5: PVD_{t-1} Port Portfolio versus Market Value Port Portfolio Returns

Market Value Port	PVD_{t-1} Port					
	Zero	Low	Mid	High	High - Zero	High - Low
Panel A: Equally-Weighted Returns						
Low	1.76***	1.04	1.62**	1.54**	-0.22	0.51*
High	2.32***	1.65***	2.32***	2.14***	-0.17	0.49**
High - Low	0.56***	0.61**	0.71***	0.60**	0.04	-0.01
Panel B: Equally-Weighted 5-Factor Alphas						
Low	-1.24***	-1.34***	-0.84***	-0.42	0.81***	0.91**
High	-0.28**	-0.48***	0.56**	0.27	0.54**	0.74***
High - Low	0.95***	0.85**	1.38***	0.68**	-0.29	-0.19
Panel C: Value-Weighted Returns						
Low	1.97***	1.21*	1.81***	1.77***	-0.20	0.56*
High	2.38***	1.72***	2.44***	2.28***	-0.11	0.56**
High - Low	0.42**	0.51*	0.63**	0.51**	0.09	-0.01
Panel D: Value-Weighted 5-Factor Alphas						
Low	-1.00***	-1.09***	-0.63*	-0.25	0.73**	0.82**
High	0.10	-0.22	0.62***	0.51***	0.39	0.71***
High - Low	1.08***	0.85**	1.24***	0.74**	-0.35	-0.13

At the end of every quarter, breakpoints are formed for portfolios by sorting observations in that quarter by Market Value Port. Breakpoints are selected at every 1/3 of firms in that quarter, then firms are sorted into portfolios, where below the first breakpoint is considered the Low portfolio and above the highest breakpoint is considered the High portfolio. The Mid portfolio represents firms which are between the two breakpoints. The Zero portfolio represents only firms which have zero Market Value Port. Then within each portfolio formed on Market Value Port, a second set of breakpoints is calculated, for every 1/3 of PVD_{t-1} Port within the original portfolio. Observations are sorted into PVD_{t-1} Port portfolios by these breakpoints. Equally and market-capitalization-weighted portfolio returns are then calculated by portfolio-month. Long-short portfolios are then formed by subtracting the short-side portfolio return from the long-side portfolio return in each month. Then Fama and French (2015) regressions are run by portfolio over time. Rows represent Market Value Port portfolios while columns represent PVD_{t-1} Port portfolios. Values represent annualized average returns and five-factor alphas within the combination of the portfolio given by the row and the portfolio given by the column. * signifies significance at the 90% level, ** at the 95% level, and *** at the 99% level.

Table 6: Regressions of Return and Alpha on PVD_{t-1} Port and Characteristics - Nikkei 225 Firms Only

Panel A: OLS

	Return			Alpha		
	(1)	(2)	(3)	(1)	(2)	(3)
Low_{t-1}	-0.52	-0.60***	-0.66***	-0.55**	-1.08***	-1.14***
		(-2.80)	(-3.48)	(-2.38)	(-4.40)	(-3.98)
BOJ Purchase Date $Count_{t-1}$	-0.12	-0.05	-0.05	0.00	-0.02	-0.02
	(-0.58)	(-0.26)	(-0.25)	(0.01)	(-0.45)	(-0.45)
Ln(Market $Value)_{t-1}$		-0.04	-0.08		0.35**	0.34*
		(-0.28)	(-0.54)		(2.06)	(1.85)
Ln(Market to Book $Equity)_{t-1}$		-1.01*	-1.23**		-0.38	-0.50
		(-1.92)	(-2.26)		(-0.56)	(-0.72)
Institutional $Ownership_{t-1}$		0.09***	0.07***		0.07***	0.06***
		(3.92)	(2.71)		(3.51)	(3.00)
Controls	No	Yes	Yes	No	Yes	Yes
Cluster by Date	Yes	Yes	Yes	Yes	Yes	Yes
Cluster by Datastream Industry Code	Yes	Yes	Yes	Yes	Yes	Yes
N	13365	13158	13158	13352	13149	13149
Adj-R2	0.00	0.00	0.00	0.00	0.00	0.01

Panel B: Fama-Macbeth

	Return			Alpha		
	(1)	(2)	(3)	(1)	(2)	(3)
Low_{t-1}	-1.04***	-0.85	-1.15**	-0.44**	-0.82***	-1.07***
	(-3.59)	(-1.63)	(-2.42)	(-2.33)	(-2.75)	(-3.24)
BOJ Purchase Date $Count_{t-1}$	0.01	0.01	-0.44	-0.68*	-0.62	-0.52
	(0.01)	(0.02)	(-0.49)	(-1.65)	(-1.51)	(-1.19)
Ln(Market $Value)_{t-1}$		-0.03	0.01		0.36***	0.40***
		(-0.10)	(0.03)		(2.92)	(3.07)
Ln(Market to Book $Equity)_{t-1}$		0.38	0.03		0.52	0.22
		(0.43)	(0.03)		(1.02)	(0.43)
Institutional $Ownership_{t-1}$		-0.05	-0.06		0.35	0.36
		(-0.08)	(-0.09)		(0.80)	(0.78)
Controls	No	Yes	Yes	No	Yes	Yes
N	13365	13158	13158	13352	13149	13149

OLS and Fama-Macbeth regressions of returns on PVD_{t-1} Port and other characteristics are presented. Controls for model 2 include $Return_{t-1}$. Controls for model 3 include $Return_{t-1}$, Book Debt to Assets, Operating Margin, and CAPEX/Total Assets. At the end of every quarter, breakpoints are formed for portfolios by sorting observations in that quarter by PVD_{t-1} Port. Breakpoints are selected at every 1/3 of firms in that quarter, then firms are sorted into portfolios, where below the first breakpoint is considered the Low portfolio and above the highest breakpoint is considered the High portfolio. The Mid portfolio represents firms which are between the two breakpoints. The Zero portfolio represents only firms which have zero PVD_{t-1} Port. Equally and market-capitalization-weighted portfolio returns are then calculated by portfolio-month. Long-short portfolios are then formed by subtracting the short-side portfolio return from the long-side portfolio return in each month. Market returns, factors (SMB, HML, RMW, and CMA), and alphas are calculated following Fama and French (1992) and Fama and French (2015), using Datastream returns for the entire sample. Returns are calculated from Datastream by using Datastream's total return index, which includes the effect of share splits, repurchases, and dividends. Then Fama and French (2015) regressions are run by portfolio over time. * signifies significance at the 90% level, ** at the 95% level, and *** at the 99% level. t-statistics are in parentheses.

Table 7: Regressions of Return and Alpha on PVD_{t-1} Port and BOJ Float Ownership $(\%)_{t-1}$ Port and Characteristics

Panel A: PVD	Return			Alpha		
	(1)	(2)	(3)	(1)	(2)	(3)
PVD_{t-2}	0.00	0.17*	0.17*	0.29**	0.33**	0.33**
	(0.00)	(1.94)	(1.85)	(2.05)	(2.29)	(2.20)
Ln(Market Value)$_{t-1}$		-0.20**	-0.22***		0.15***	0.13***
		(-2.35)	(-2.61)		(3.35)	(2.88)
Ln(Market to Book Equity)$_{t-1}$		-0.60*	-0.62*		-0.92***	-0.93***
		(-1.77)	(-1.73)		(-3.57)	(-3.54)
Institutional Ownership$_{t-1}$		0.14*	0.14*		0.02	0.02
		(1.93)	(1.85)		(0.78)	(0.58)
Controls	No	Yes	Yes	No	Yes	Yes
Datastream Industry Code Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Cluster by Datastream Industry Code	Yes	Yes	Yes	Yes	Yes	Yes
Cluster by Date	Yes	Yes	Yes	Yes	Yes	Yes
N	189609	186453	186453	188897	185909	185909

Panel B: BOJ Ownership (%)	Return			Alpha		
	(1)	(2)	(3)	(1)	(2)	(3)
BOJ Float Ownership $(\%)_{t-2}$	-0.00	0.75***	0.76***	0.15	0.41***	0.41***
	(-0.01)	(2.95)	(2.98)	(1.35)	(3.62)	(3.65)
Ln(Market Value)$_{t-1}$		-3.36**	-3.33**		-1.62***	-1.54***
		(-2.56)	(-2.52)		(-3.87)	(-3.03)
Ln(Market to Book Equity)$_{t-1}$		-2.23**	-2.38**		-0.31	-0.48
		(-2.19)	(-2.18)		(-0.33)	(-0.42)
Institutional Ownership$_{t-1}$		0.01	0.01		-0.02	-0.02
		(0.22)	(0.14)		(-0.60)	(-0.61)
Controls	No	Yes	Yes	No	Yes	Yes
Issuer ISIN Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Cluster by Datastream Industry Code	Yes	Yes	Yes	Yes	Yes	Yes
Cluster by Date	Yes	Yes	Yes	Yes	Yes	Yes
N	189609	186453	186453	188897	185909	185909

OLS regressions of returns on PVD_{t-1} Port and BOJ Float Ownership $(\%)_{t-1}$ Port and other characteristics are presented. Controls include Operating Margin, Book Debt to Assets, CAPEX/Total Assets, and Return$_{t-1}$. Returns are calculated from Datastream by using Datastream's total return index, which includes the effect of share splits, repurchases, and dividends. Market returns, factors (SMB, HML, RMW, and CMA), and alphas are calculated following Fama and French (1992) and Fama and French (2015), using Datastream returns for the entire sample. Returns are calculated from Datastream by using Datastream's total return index, which includes the effect of share splits, repurchases, and dividends. * signifies significance at the 90% level, ** at the 95% level, and *** at the 99% level. t-statistics are in parentheses.

Table 8: Event-Time Regressions of Return and Alpha on BOJ Ownership Changes and Characteristics

Panel A: (-1, 1) Window	BHR			BHAR		
	(1)	(2)	(3)	(1)	(2)	(3)
BOJ Ownership (%) Change$_{t-1}$	3.56**	3.10**	3.08**	0.58***	0.46**	0.45**
	(2.30)	(2.17)	(2.16)	(2.73)	(2.30)	(2.26)
Ln(Market Value)$_{t-1}$		0.04	0.06		-0.01	-0.02
		(0.12)	(0.18)		(-0.16)	(-0.24)
Ln(Market to Book Equity)$_{t-1}$		1.38***	1.32***		0.81***	0.81***
		(2.81)	(2.64)		(5.77)	(5.48)
Institutional Ownership$_{t-1}$		0.03***	0.03***		0.01***	0.01***
		(3.27)	(3.24)		(2.86)	(2.72)
Controls	No	Yes	Yes	No	Yes	Yes
Issuer ISIN Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Cluster by Date	Yes	Yes	Yes	Yes	Yes	Yes
Cluster by Datastream Industry Code	Yes	Yes	Yes	Yes	Yes	Yes
N	583084	583063	583063	583084	583063	583063

Panel B: (1, 20) Window	BHR			BHAR		
	(1)	(2)	(3)	(1)	(2)	(3)
BOJ Ownership (%) Change$_{t-1}$	3.60	6.85*	6.75*	2.55**	3.38***	3.28**
	(1.10)	(1.83)	(1.81)	(2.45)	(2.59)	(2.54)
Ln(Market Value)$_{t-1}$		-4.07***	-3.78***		-0.68**	-0.42
		(-3.78)	(-3.45)		(-2.35)	(-1.20)
Ln(Market to Book Equity)$_{t-1}$		4.28***	3.59**		-1.07	-1.68**
		(2.98)	(2.44)		(-1.57)	(-2.13)
Institutional Ownership$_{t-1}$		0.06**	0.06**		0.02	0.02
		(1.99)	(1.98)		(0.91)	(0.86)
Controls	No	Yes	Yes	No	Yes	Yes
Issuer ISIN Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Cluster by Date	Yes	Yes	Yes	Yes	Yes	Yes
Cluster by Datastream Industry Code	Yes	Yes	Yes	Yes	Yes	Yes
N	582997	582977	582977	582997	582977	582977

OLS regressions of returns on BOJ Ownership (%) Change$_{t-1}$ and other characteristics are presented. Controls for model 2 include Return$_{t-1}$. Controls for model 3 include Return$_{t-1}$, Book Debt to Assets, Operating Margin, and CAPEX/Total Assets. First, BOJ purchase dates are selected as days in which the BOJ reported purchases for the "Main ETF" series. Then a data set of returns and alphas in windows around the purchase dates is constructed. From this data set, returns and alphas are cumulated across the windows, yielding a single observation per event day per firm with window returns and alphas. Then financial and stock information is merged to the event-day-firm observations. Returns are calculated from Datastream by using Datastream's total return index, which includes the effect of share splits, repurchases, and dividends. Buy and hold returns (BHR) are calculated by taking the gross returns (1 + return) in each period and multiplying them together, subtracting 1 at the end. Buy and hold abnormal returns (BHAR) are calculated by first calculating the abnormal returns as the residual from Fama and French (2015) regressions. Then the gross abnormal returns (1 + abnormal return) are multiplied together, subtracting 1 at the end. * signifies significance at the 90% level, ** at the 95% level, and *** at the 99% level. t-statistics are in parentheses.

Table 9: Logit Regressions Predicting BOJ Purchase Days

Panel A: Is BOJ Purchase Date

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
BOJ Return	-1.55***			-1.58***	-1.59***	-1.67***	-1.73***
	(-16.51)			(-13.11)	(-13.03)	(-7.72)	(-8.10)
Non-BOJ Return		-1.62***		0.05	0.09		
		(-7.88)		(0.47)	(0.89)		
Mkt Return			-1.69***			0.15	0.23
			(-13.44)			(0.65)	(1.06)
Controls	No	No	No	No	Yes	No	Yes
N	1663	1616	1616	1616	1488	1616	1488
Pseudo-R2	0.26	0.19	0.24	0.26	0.26	0.26	0.26

Returns are calculated from Datastream by using Datastream's total return index, which includes the effect of share splits, repurchases, and dividends. Then, averages of returns for the different groups are calculated. BOJ Return represents the average of the returns for BOJ-held firms on a given date. Non-BOJ Return represents the average of the returns of the other firms. Mkt Return represents an average of all firms' returns on a given date. Then dates are assigned a one for Is BOJ Purchase Date if it was a day in which the BOJ reported purchases for the "Main ETF" series, and zero otherwise. Logit regressions of returns on None and other characteristics are presented. Controls for model 5 include BOJ Return$_{t-1}$, BOJ Return$_{t-2}$, BOJ Return$_{t-3}$, Non-BOJ Return$_{t-1}$, Non-BOJ Return$_{t-2}$, and Non-BOJ Return$_{t-3}$. Controls for model 7 include BOJ Return$_{t-1}$, BOJ Return$_{t-2}$, BOJ Return$_{t-3}$, Mkt Return$_{t-1}$, Mkt Return$_{t-2}$, and Mkt Return$_{t-3}$. * signifies significance at the 90% level, ** at the 95% level, and *** at the 99% level. t-statistics are in parentheses.

Table 10: A Comparison of Machine Learning Models for Company Name Matching

Model	Validation Accuracy
Random Forests	98.75%
Deep Learning - Multi-layer Perception	97.75%
SVM	96.25%
Stochastic Gradient Descent SVM	96.00%
K-Nearest Neighbors	96.63%
Gaussian Process	96.50%

A cross-validation process is used to split the labeled data into training, validation, and testing data sets. For each model, coefficients are set by minimizing classification error on the training data. Then the model's performance is evaluated by creating predictions on the validation data set, and an accuracy score is calculated. In a process known as grid search, different combinations of parameters are used in the same process, selecting the parameters that yield the highest validation accuracy. After the final model has been selected, then its performance is evaluated on the testing data, and a final accuracy score is calculated. The model with the maximum accuracy will be selected.

Table 11: Comparisons of Calculated Sample Factors to Ken French Factors

Variables	Mean			Median			Stdev		10%		90%		Correl
	Calc	FF	t-stat	Calc	FF	chi2-stat	Calc	FF	Calc	FF	Calc	FF	
Panel A: Daily Factor Comparisons													
mktrf	0.11	0.06	1.09	0.13	0.07	1.59	1.19	1.16	-1.18	-1.25	1.42	1.37	0.87
smb	0.06	0.02	1.77	0.09	0.05	3.59	0.66	0.56	-0.75	-0.63	0.85	0.66	0.89
hml	-0.05	-0.01	-2.13	-0.05	-0.03	1.08	0.48	0.51	-0.58	-0.58	0.49	0.58	0.80
rmw	0.02	0.01	0.86	0.03	0.02	0.61	0.27	0.31	-0.29	-0.35	0.34	0.37	0.34
cma	0.01	0.00	0.79	0.01	0.00	0.86	0.23	0.28	-0.27	-0.32	0.28	0.33	0.25
Panel B: Monthly Factor Comparisons													
mktrf	2.07	0.99	1.62	2.40	1.11	1.01	4.43	3.53	-4.23	-2.53	6.79	5.13	0.79
smb	1.17	0.46	1.81	1.11	0.46	2.82	2.53	2.10	-1.88	-2.11	4.68	2.79	0.90
hml	-0.82	-0.15	-1.61	-1.11	-0.21	2.28	2.45	2.51	-3.02	-3.16	2.14	2.17	0.78
rmw	0.43	0.24	0.71	0.59	0.18	0.11	1.66	1.39	-1.48	-1.57	2.46	1.90	0.41
cma	0.23	0.01	1.18	0.14	0.02	0.25	1.02	1.22	-1.14	-1.70	1.46	1.42	0.40

This table presents comparisons of Fama-French 5 Factors calculated from sample data, versus those downloaded from Ken French's website. Market returns, factors (SMB, HML, RMW, and CMA), and alphas are calculated following Fama and French (1992) and Fama and French (2015), using Datastream returns for the entire sample. Returns are calculated from Datastream by using Datastream's total return index, which includes the effect of share splits, repurchases, and dividends.