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Naïve *Buying* Diversification and Narrow Framing by Individual Investors

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ABSTRACT

We provide the first tests to distinguish whether individual investors equally balance their overall portfolios (naïve portfolio diversification, NPD) or, in contrast, equally balance the values of same-day purchases of multiple assets (naïve *buying* diversification, NBD). We find NBD in purchases of multiple stocks, and in mixed purchases of individual stocks and funds. In contrast, there is little evidence of NPD. Evidence suggests that NBD arises due to stock picking behavior and neglect of diversification. These findings suggest that behavioral finance theory should incorporate transaction, as well as portfolio, framing.

PEOPLE OFTEN APPLY SIMPLE AND imperfect heuristics to their financial decisions, guiding their choices, such as setting saving to be a constant fraction of income. We investigate here how investors approach a very fundamental financial choice: how to allocate funds for investment across multiple stocks.

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Portfolio theory offers standard recommendations for diversifying optimally across stocks (Markowitz (1952)). However, individual investors deviate substantially from what theory recommends (Goetzmann and Kumar (2008)).[1]

One of the major explanations that have been proposed to explain this failure is narrow framing—the propensity to evaluate choices in isolation (Gilovich and Griffin (2010)). For example, investors may evaluate whether to buy a stock without regard to the characteristics of other assets available to the investor or in the investor's current portfolio. This contrasts with the recommendation of portfolio theory to integrate information about the characteristics of all available assets. One proposed consequence of narrow framing is the reluctance of investors to include new assets in their portfolios. This provides a possible explanation for limited stock market participation and portfolio underdiversification (Barberis, Huang, and Thaler (2006), Barberis and Huang (2008)).

Another possible aspect of narrow framing has received little attention. This involves the neglect of something even more basic—the benefit of coordinating the amounts of new purchases of an asset with the investor's current holding of that asset. Specifically, it seems obvious that in making a purchase of an asset, investors should have in mind some target level of holdings that they are trying to achieve. For example, portfolio theory recommends mean-variance optimal holdings. A simpler target would prescribe allocating equal investment across stocks in the portfolio. Both can be achieved by moving from the endowment position with appropriate purchases and sales to achieve the target position.

In this paper, we examine the trading choices of a sample of retail investors provided by Barclays Stockbroking in the United Kingdom and reveal new insights into how investors weight different stocks in their buying decisions. We first show that when investors buy stocks, they often group several trades together on the same day; one-third of the total amount invested in our sample can be accounted for by multiple-stock buy day purchases. We then show that, when allocating their buy day investment across multiple stocks, investors commonly split their investments evenly, that is, they use the $1/N$ heuristic. This raises the question of whether, when making a purchase, investors seek to bring their *overall portfolios* into balance, or whether they apply $1/N$ only to their *new purchases*. We show that the latter is much more common. We find little evidence of investors balancing their portfolios, either via multiple stock purchases on single days, or through successions of purchases spread across trading intervals of weeks or months. Instead, where investors use $1/N$, they use it as a buying weight heuristic.

We therefore show that investors act *very* narrowly, naïvely diversifying among what they buy on a particular day, not what they hold. We call this behavior *Naïve Buying Diversification* (NBD). The main contribution of this

[1] Investors typically hold only a few stocks and exhibit biases such as overtrading (Barber and Odean (2000)), sensitivity to gains compared with losses (Odean (1998)) and rank effects (Hartzmark (2015)). See also the reviews of behavioral finance of Hirshleifer (2015) and Barberis (2018) and the review of investor behavior of Barber and Odean (2013).

paper is to show that investors engage in NBD and do not engage in *Naïve Portfolio Diversification* (NPD), defined as equal weighting of securities in their portfolios. In other words, many investors split their buys according to the $1/N$ heuristic, but very few allocate buy amounts so as to achieve $1/N$ portfolio shares.

We show that this behavior is not limited to stock purchases. We find NBD among investors when buying stocks and funds on the same day, even when buying index-tracking exchange traded funds (ETFs) on the same day as individual stocks. This behavior also results in portfolios that are heavily tilted toward a few stocks, which is *inconsistent* with NPD.[2] This result is surprising, given that individual stocks and funds are very different categories of investment, so that under rational balancing of risk and return, there is no presumption that investments across these categories, either in new purchases or in overall portfolios, should be at all close to equally weighted.

Why do investors use the NBD heuristic? We consider two main hypotheses. The first is that the investor is not making an active choice to diversify, but instead picks a combination of attractive stocks for reasons unrelated to diversification, and arrives at an NBD allocation based on the simple heuristic of equal weighting (without any inherent motive of holding more stocks in the portfolio in order to reduce risk). We call this the *stock-picking hypothesis*.

If stock-picking investors choose multiple stocks to buy on a day in this way, they will hold riskier portfolios than if they attempted to diversify. As shown in previous studies, stock-picking investors tend to choose stocks with similar risk and return profiles, such as those that have received salient news coverage and/or strong recent returns (Barber and Odean (2008)). Stock-picking investors often choose stocks from the same geography or industry (Massa and Simonov (2006)), particularly the industry in which they work (Døskeland and Hvide (2011)).

The second hypothesis is that the investor, who might otherwise have purchased only a few stocks (possibly just one), makes an active choice to diversify by adding additional stocks to the purchase. We call this the *diversification motive hypothesis*. The difference between these hypotheses is that, under the stock-picking hypothesis, NBD occurs without any consideration by investors of the risk benefits of having more stocks in the portfolio, while under the second hypothesis investors have a diversification motive.

These two hypotheses about how NBD arises yield distinct testable implications. Under the stock-picking hypothesis, NBD should be more common when investors buy stocks that are similar in their "attractiveness," as reflected by their news coverage or risk and return profiles (as investors are drawn to a set of similar stocks). Under the diversification-motivated hypothesis, NBD should be more common when investors buy dissimilar or low-correlation stocks (as they seek to diversify through stock buying choices).

[2] Investors who have private information may have good reasons to choose portfolios heavily tilted toward particular stocks. But this does not provide a sensible reason to tilt heavily toward a stock in order to equalize the amount invested in a stock and a fund on a given buy day.

We implement this test using standard measures of stock similarity based upon recent performance or idiosyncratic risk, and also nontraditional measures of news sentiment for individual stocks at the daily level sourced from the Thomson Reuters MarketPsych Index (TRMI). Our analysis conditions on portfolio size and characteristics, together with other controls for investor heterogeneity such as age and gender. We find evidence consistent with *stock-picking* NBD, suggesting that NBD is a result of investors picking stocks, focusing on stock characteristics over and above concerns about portfolio diversification.

We consider the implications of NBD for portfolio performance. NBD investors with a stock-picking focus may indeed not be targeting risk-adjusted returns, yet analysis of simple returns shows that on average NBD investors perform worse than non-NBD investors. For risk-adjusted returns, a normative literature provides evidence suggesting that NPD is the best diversification rule investors can implement in practice.[3] We extend the simulation model used in DeMiguel, Garlappi, and Uppal (2009) to analyze the effectiveness of NBD, and find that NPD outperforms NBD, with the extent of the performance gap increasing as idiosyncratic risks and time period increase. In our sample, NBD is no less common when idiosyncratic risk is high (measured by either proportion of trades, or average value of trades), indicating that NBD investors do not mitigate risk. Taken together, our findings of NBD in stock portfolios and stock-and-fund portfolios, together with the existing evidence for $1/N$ behavior over longer time horizons in retirement savings schemes (as in Benartzi and Thaler (2001)), suggests that the use of NBD is substantially detrimental to investor earnings.[4]

In additional analysis, we suggest that investors prefer NBD because it simplifies the buying decision problem. The way in which investors implement NBD suggests a strong preference for simplicity. Specifically, many investors choose their trades so that the amount invested is evenly divisible by the number of stocks purchased.[5]

[3] DeMiguel, Garlappi, and Uppal (2009) evaluate the out-of-sample performance of a suite of models against NPD, including the sample-based mean-variance model, and find that none is consistently better than NPD over reasonable time horizons. The reason it is hard to beat this simple heuristic is that there is high estimation error for portfolio weights estimated from the relatively short-time-period samples available, given the fact that means and covariances are not entirely stable over time. Simulations in DeMiguel, Garlappi, and Uppal (2009) show that the estimation window needed for the sample-based mean-variance strategy to outperform NPD is approximately 3,000 months for a portfolio with 25 assets and approximately 6,000 months for a portfolio of 50 assets.

[4] The inferior portfolio performance of investors in our sample is further exacerbated by the typical portfolio holding only a few stocks (median 5). Goetzmann and Kumar (2008) show that U.S. equity investors on average also hold underdiversified portfolios. Calvet, Campbell, and Sodini (2007) use comprehensive data from Sweden and show that, while a few households are very poorly diversified, most Swedish households outperform the Sharpe ratio of their domestic stock index through some degree of international diversification.

[5] Other studies on the role of round numbers in financial markets include Aggarwal and Lucey (2007) and Johnson, Johnson, and Shanthikumar (2007).

Our paper contributes to the literature on investor behavior by demonstrating new evidence of individual investor portfolio-weighting strategies that mark a departure from the approach of both rational models and many existing behavioral finance models. In many psychology-based models of investment choices, even though investors do not behave rationally, they engage in portfolio framing, that is, they seek to optimize an overall portfolio in order to achieve an attractive probability distribution of consumption (Daniel, Hirshleifer, and Subrahmanyam (2001), Grinblatt and Han (2005), Li and Yang (2013), Barberis, Mukherjee, and Wang (2016)). Our findings provide a new type of empirical support for the hypothesis that investors narrowly frame on incremental purchases (as in Barberis and Huang (2001)).

Our findings also present field data evidence for very narrow framing. The tendency of individuals to narrowly frame, or "bracket," their choices has been demonstrated in laboratory experiments (Read et al. (1999)), with studies showing that narrow framing leads to dominated choices (Rabin and Weizsäcker (2009)). In laboratory choices over a series of gambles, Imas (2016) shows that individuals tend to bracket on incremental gambles, and that this narrow bracketing creates excess sensitivity to losses. Our finding that investors often diversify with equal weighting within the new stocks being acquired provides a new kind of test for and confirmation of narrow framing on new gambles. This new kind of test focuses on relative weights within the day's transactions rather than on the decision of whether to invest. We refer to the investor's narrow focus on the day's transactions as *transaction framing*.[6]

We are not the first to study the use by investors of naïve diversification heuristics. Our findings differ in two key ways. First, our study resolves a debate in the literature as to whether individuals actually use $1/N$ as a heuristic for investing. Previous studies provide evidence that employees make $1/N$ allocations in establishing their regular contribution rates to retirement savings plans (Benartzi and Thaler (2001), Huberman and Jiang (2006)). The debate centers on whether such $1/N$ allocations result from a $1/N$ choice heuristic or arise from a framing effect associated with the number of options, N, in the choice set. Our findings provide evidence that individuals actually do use $1/N$ as a heuristic, since we examine a general stock investment setting in which there is no plan-ordained number of available assets "N" in the menu of options available to investors.

The second key way in which our findings differ derives from the fact that we examine an empirical setting that permits a sharp distinction between NBD

[6] Previous studies suggest that investors act narrowly across other aspects of their asset allocation, such as retirement saving funds (Choi, Laibson, and Madrian (2009)). Hence, the narrow framing we observe is most likely a lower bound on the extent of narrow framing in the investor's overall portfolio of assets. There is also evidence that institutional traders act narrowly. Coval and Shumway (2005) show that proprietary traders bracket their performance at the daily level, regularly assuming above-average afternoon risk to recover from morning losses. Akepanidtaworn et al. (2019) show that institutional investors differ in their buy side framing compared with their sell side framing finding, in contrast with our results: that investors engage in transaction framing on the sell side but not the buy side.

and NPD. We document that NBD is present, whereas NPD is not. In the Benartzi and Thaler (2001) and Huberman and Jiang (2006) retirement saving plan testing context, it is not possible to distinguish between NBD and NPD because investors choose buying weights for allocating their monthly contributions once, usually at origination, instead of making a series of buying weight decisions. This one-time decision very strongly links specific purchase transactions weights to overall portfolio weights. This is especially the case given very strong evidence of inertia in retirement investing (Madrian and Shea (2001)). This distinction is important since findings of naïve diversification from past literature are often described as a bias toward NPD.[7]

Overall, these results suggest that the behavior of individual investors is far from optimal. However, the investors in our sample are purchasing multiple stocks and de facto achieving some degree of diversification of their portfolios, albeit in a crude manner. Naïve diversification may be an improvement on no diversification at all; many studies find most investors hold underdiversified portfolios (Barber and Odean (2013)). Nevertheless, our results indicate that investors apply the naïve diversification strategy in an extremely narrow way.

The paper proceeds as follows. Section I introduces the brokerage data. Section II documents NBD in the brokerage data set. Section III presents tests that distinguish NBD from NPD. Section IV explores tests competing hypotheses for why investors use the NBD heuristic. Section V examines the implications of NBD for portfolio performance. Section VI examines selling behavior. Section VII explores whether investors jointly choose the investment amount and number of stocks. Section VIII concludes the paper.

I. Data

A. *Brokerage Account Data*

We use data from Barclays Wealth, a large mainstream U.K.-based broker. The data consist of transaction histories of 182,569 accounts held with the broker between April 2012 and June 2016. The panel data are unbalanced, with accounts opening during the period. Dropping accounts with no activity during the data period, we define the baseline sample as 118,169 accounts that have at least one buy transaction within the data period. The data include stock identification numbers (Stock Exchange Daily Official List (SEDOL) numbers, a list of security identifiers used in the United Kingdom and Ireland for clearing purposes), transaction dates, transaction types (e.g., buy, sell), transaction quantities, and transaction prices. We use SEDOL numbers to match additional data on individual stock product and performance information via Datastream.

[7] For example, in their review paper, Benartzi and Thaler (2007) define the $1/N$ rule in NPD terms as "when faced with 'N' options, divide asset shares evenly across the options" (p. 86). We do not rule out the possibility that the Benartzi and Thaler (2001) results derive from the use of an NPD heuristic in addition to (or even instead of) an NBD heuristic—the empirical context they examine does not disentangle these possibilities. What we can conclude is that in our setting, in which the two types of heuristics can be sharply distinguished, there is evidence of NBD but not NPD.

B. Sample

Our interest lies in how individuals choose to allocate funds invested when purchasing multiple stocks. Our analysis focuses on two samples.

First is a sample of all accounts. In this sample, we observe all stock purchases undertaken during the sample period. From this sample, we draw samples based upon the interval between stock purchases. Our main analysis focuses on a sample of multiple-stock buy days, which we define as a day on which the investor makes a purchase of two or more common stocks (denominated in GBP), via either opening a position in new stocks or adding additional shares to an existing position.[8] Multiple-stock buy days account for 30.8% of the total amount invested over the data period in the sample of all accounts. We also draw samples of multiple-stock buy weeks and multiple-stock buy months.

Second, we draw a subsample that includes all new accounts that open within the data period. For this subsample of new accounts we have richer data, allowing us to observe the complete portfolio position of the account from opening date onward, including for accounts that are transferred in from another broker service. This sample restriction provides 8,982 accounts (43.1% of new accounts in the baseline sample). In this subsample, we observe 25,507 multiple-stock buy days (16.3% of buy days in the baseline sample of new accounts). We also draw samples of multiple-stock buy weeks and multiple-stock buy months from the sample of new accounts.

Approximately 68% of multiple-stock buy days involve purchases of two stocks. Among the all accounts sample, 70.4% of account holders are male. The average age of the account is four years. Account holders make on average 1.8 trades per month, with an average investment amount of over £16,500 on a multiple-stock buy day (median value is close to £7,000). Among the sample of new accounts, for which we have additional information, investor portfolios are worth on average £61,000, with an average investment amount on a multiple-stock buy day of £11,500. On average, portfolios contain eight individual stocks and investors engage in 1.5 trades per month.[9]

The low number of individual stocks we see investors in our sample hold in their portfolios is consistent with existing studies that document a lack of diversification among individual investors in the individual stock component of the portfolio (Goetzmann and Kumar (2008), Barber and Odean (2013)). Purchases of diversified investment products, such as mutual funds or ETFs are rare in the sample—fewer than 6% of purchases are of mutual funds or ETFs. In addition, while the benefits of diversification increase with the variance in market prices, among the sample of all buy days (including single-stock buy days), the average number of stocks purchased per day does not depend on

[8] We restrict to buy events involving the choice of an investment amount on the part of the investor on the buy day. Hence we exclude, for example, automatic dividend reinvestments.

[9] Summary statistics are provided in Tables I and II in the Internet Appendix. The Internet Appendix may be found in the online version of this article.

market volatility and does not vary over the sample period. Further details are provided in the Internet Appendix.[10]

II. Naïve Buying Diversification

A. Allocations on Multiple-Stock Buy Days

We first examine whether investors engage in NBD. We begin by showing allocations across purchased stocks on multiple-stock buy days in which the investor bought N stocks. We calculate the percentage of the total buy day investment (in pounds sterling and net of fees) that is allocated to each stock.[11] Choosing one of the N stocks at random to be "Stock A," Figure 1 plots the proportion of the buy day investment allocated to Stock A among all N-stock buy days in the sample, with panels showing different values of N. The width of each bin is 0.01. We focus on allocation to one randomly chosen stock to avoid the dependence of observations that naturally arises because the sum of weights across stocks must be equal to one.

Strikingly, Figure 1 shows large heaping in the frequencies of portfolio weights around $1/N$. In Panel A, 29.7% of two-stock buy days involve allocations of monies invested on the day in the 49 to 51 interval. This suggests that, as seen in Panel A, many trades are made with allocations that are close to 50:50 and investors may be using that heuristic to guide their allocation choices. In Panels C to D, we also see heaping around $1/N$. On three-stock buy days, investors often spend one-third of their money on each stock. On four-stock buy days, investors often spend one quarter of their money on each stock. And so on.[12]

When measuring NBD, we should not restrict the definition to a precise $1/N$ allocation of funds across N stocks. This is because the indivisibility of individual stocks implies that investors could not in all cases make precise NBD allocations (even if they wanted to). Given the total amount invested and the prices of individual stocks, investors may only be able to achieve an allocation close to $1/N$. As with most investment platforms, on the Barclays platform investors can input the amount of money they would like to invest in a stock and the platform calculates the maximum number of shares (in integers) at the

[10] See Figures 1 and 2 in the Internet Appendix for further details.

[11] Fees are low as they are a proportion of the average amount invested. Hence, our results are not sensitive to the inclusion of fees in the allocation calculations.

[12] Figure 3 in the Internet Appendix illustrates the proportion of observations for which the allocation of monies invested on the day is in the 49 to 51 interval for a range of values of N. In additional analyses, we also investigated whether investors might naïvely equate the number of shares purchased across multiple stocks. Additional analysis presented in the Internet Appendix demonstrates that this is not the case. Figure 4, Panel A, illustrates that allocations in which the number of shares purchased are equalized only occurs when the unit price of the shares is very close. When the unit price of the shares is further apart, we do not see equal allocation of the number of shares, but we do see equal allocation of the money amount (shown in Panel B).

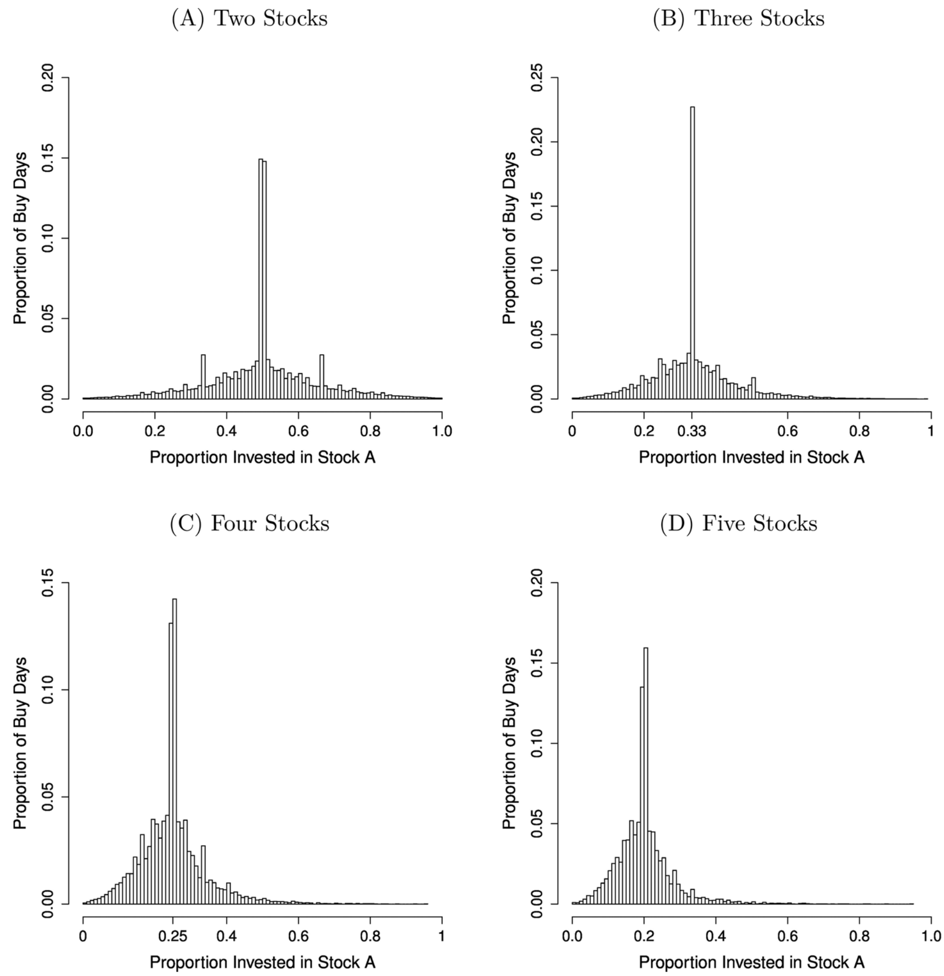


Figure 1. Proportion of buy day investment allocated to each stock on multiple-stock buy days. This figure shows a histogram of the proportion of the total buy day investment (in pounds) that is invested in Stock A, where Stock A is a randomly chosen stock from the group of stocks purchased. Bin width is 0.01. The sample is restricted to multiple-stock buy days. See Section I for details on the sample construction.

time-limited quoted price (in local currency) that can be purchased with that amount at the market price.[13]

[13] For example, consider the case in which an investor intends to invest £1,000 to buy two stocks, Stocks A and B, and the price of Stock A is £4.50 per unit and Stock B £100.50 per unit. Were the investor to aim for NBD, the precise stock split generating an equal cost split would be: Stock A = £500/£4.50 = 111.11 units, Stock B £500/£100.50 = 4.96 units. Purchases of common stock must be made in indivisible single units. Due to this indivisibility, the investor cannot invest £500 for each stock, so might instead decide to buy 111 shares of Stock A with a cost of 111 × £4.50 = £499.50 and five shares of Stock B with a cost of 5 × £100.50 = £502.50. Thus, the

Table I

NBD Allocations on Multiple-Stock Buy Days

This table shows summary data for multiple-stock buy days. Each row reports the percentage of buy days involving N stocks in which the proportion invested in each stock falls within the $1/N$ range for differing the number of stocks bought on the day (N). See Section II for details. Lower and upper limit values of 95% confidence intervals from bootstrap mean estimates are reported in LL and UL columns. The standard errors were corrected for clustering by accounts. The sample is restricted to multiple-stock buy days. See Section I for details on the sample construction.

Panel A: (£$P/N \times (1 \pm 0.02)$)

N	$1/N$ Buying (%)	LL	UL	Buy Days
2	29.7	29.1	30.3	177,193
3	20.3	19.4	21.1	48,896
4	18.6	17.6	19.7	17,672
5	17.5	16.0	19.0	7,925
6+	15.2	13.1	17.3	9,899
All	26.3	25.6	26.9	261,585

Panel B: (£$P/N \times (1 \pm 0.05)$)

N	$1/N$ Buying (%)	LL	UL	Buy Days
2	36.5	36.0	37.1	177,193
3	23.3	22.4	24.2	48,896
4	20.9	19.7	22.1	17,672
5	20.1	18.6	21.7	7,925
6+	18.0	15.3	20.6	9,899
All	31.8	31.1	32.5	261,585

Panel C: (£$P/N \times (1 \pm 0.1)$)

N	$1/N$ Buying (%)	LL	UL	Buy Days
2	45.6	45.1	46.2	177,193
3	27.8	26.8	28.7	48,896
4	23.9	22.6	25.2	17,672
5	22.4	20.7	24.0	7,925
6+	20.0	17.2	22.8	9,899
All	39.1	38.4	39.9	261,585

We therefore present bandwidth measures of NBD. Table I reports the proportion of multiple-stock buy days on which a buy day investment of £P is split such that the monetary value of stock purchases is divided in the intervals £$P/N \times (1 \pm X)$, where X takes values of 0.02, 0.05, and 0.1 in Panels A to C. This range of values of X allows for the indivisibility of individual stocks. In the two-stock case, these intervals translate to a proportion of the total buy day investment invested in Stock A of 49 to 51 (Panel A), 47.5 to

allocation of the investment to Stock A is £499.50 ÷ (£499.50 + £502.50) = 0.498 and that to Stock B is 0.502.

52.5 (Panel B), and 45 to 55 (Panel C). We report 95% bootstrapped confidence intervals clustered by accounts.

The estimates in Table I show that, for two-stock buy days, allocations fall in the NBD interval in between one-quarter and one-half of cases, depending on bandwidth. As the number of stocks bought on the multiple-stock buy day increases, the proportion of allocations falling within the range decreases. This will be in part due to a mechanical effect, as the indivisibility of individual stocks resulting in $1/N$ allocations becomes less likely as the number of stocks bought rises. Across all buy days involving multiple-stock purchases, 49.6% of investors exhibit at least one buy day on which they make an allocation in the interval $£P/N \times (1 \pm X)$ with $X = 0.02$.

Our findings raise the question of whether NBD has a mechanical source or is limited to particular market conditions or time periods. For example, if the investment platform uses an interface in which an NBD allocation is presented as an on-screen default, this might lead investors to accept an NBD allocation. However, the platform used by the brokerage did not automatically default to, or suggest, equal money investments across multiple stocks. Investors were required to key in their investment amount for each stock separately and each transaction required a separate multiple-screen journey, with no default allocation or recommended allocation shown on screen or in investment guidance.[14] We also find that NBD is not limited to particular market conditions or time periods. NBD is invariant to market volatility and does not vary over the sample period, an issue we return to later in our analysis when considering the relation between NBD and portfolio performance in Section V.

B. Stock-and-Fund Buy Days

We also explore whether investors use NBD when buying individual stocks and funds in combination. In standard portfolio theory, there is no rationale for equal portfolio weights, or equal new purchase weights, for combinations of stocks and funds. We focus on buy days on which the investor purchased at least one fund and at least one common stock, either by opening a new position or adding to an existing position(s). We further restrict our analysis to ETFs, as orders for other types of funds (such as Unit Trusts) are commonly executed with a delay of a few days.[15] Purchases of funds (of any type) are relatively

[14] A video showing the Barclays Stockbroking user interface and screen display journey involved in making a purchase can be viewed at https://youtu.be/M1HGgKp6p6k. The video explains that the buy/sell screen display shows only information about the stocks to be purchased/sold and does not allow for multiple purchase or sale events in a way that would encourage NBD, or show portfolio information (such as illustration of portfolio positions before or after a purchase/sale) on the same screen.

[15] Orders of other types of funds are queued and batch-processed by the platform every few trading days in order to reduce trading costs. This poses a challenge for our analysis, which focuses on buy day allocations. This is because in the data we observe the executed price and quantity, which will differ from the order price and quantity placed by the investor a few days previously. We therefore restrict our analysis to ETFs, orders that are processed in real time, as is the case for orders of common stocks.

uncommon in the Barclays data. As a result, the sample for this analysis is much smaller than that for the analysis of multiple-stock buy days.

We adopt the same approach to the calculation of allocations on stock-and-fund buy days as for multiple-stock buy days (see the Internet Appendix for details). We calculate the percentage of the total buy day investment (in pounds sterling and net of fees) that is allocated to each security. Results reveal that, depending on bandwidth, between one-fifth and one-third of trades involving stock-and-fund combinations have allocations within the $1/N$ range.

We also explore whether investors use this weighting approach for mixes of asset categories when investing in index-ETFs, a category specifically designed to use market weights. We therefore further restrict the sample to FTSE100 ETFs (the two most popular FTSE100 ETFs in the sample by total holdings are the ISHARES Core FTSE100 and the Vanguard FTSE100). Results reveal that allocations in the $1/N$ range are only slightly less common in this subsample: in the two-security case, the percentage of index-ETF-and-stock buy days in the $1/N$ range is 21.7% (bandwidth 0.02), 26.8% (bandwidth 0.05), and 33.2% (bandwidth 0.10), compared with 23.0%, 29.1%, and 36.3% in the ETF-and-stock buy day sample. Hence, even among investors who are partly engaged in low-cost index investing, we see similar levels of $1/N$ allocations compared with those in the multiple-stock and ETF-and-stock buy day samples. The use of the $1/N$ heuristic for allocations on stock-and-fund buy days is particularly striking, as it implies, in the two-security example, that the single common stock receives a far higher weighting than the individual holdings within the fund.[16]

C. Allocations in Multiple-Stock Buy Weeks and Buy Months

Multiple-stock buy days are empirically important, accounting for approximately 31% of the total amount invested over the sample period, and 36% of total trades. However, it is still possible that investors sometimes psychologically bracket their buying episodes at wider intervals than a day. If investors perceive buying episodes as longer periods, such as weeks or months, and combine a series of purchases to create a portfolio position, our tests might miss important elements of NBD or NPD.

We therefore examine multiple-stock buying behavior over intervals of multiple-stock buy weeks and multiple-stock buy months. These longer intervals include combinations of single-stock buy days and multiple-stock buy days, over various numbers of days. In total, approximately 67% of the total amount invested and 69% of total trades are accounted for by multiple-stock buy months.[17]

[16] For example, the highest weight of any individual stock within an FTSE ETF is approximately 7%. This implies, in the two-security example, that the individual stock would have a weight more than 14 times higher than the largest stockholding within the ETF.

[17] The remainder consists of trades of single stocks that are separated from other trades by intervals of greater than one month.

Table II

NBD Allocations on Multiple-Stock Buy Weeks and Buy Months

This table shows summary data for multiple-stock buy weeks (Panel A) and multiple-stock buy months (Panel B). Each row reports the percentage of buy weeks involving N stocks in which the proportion invested in each stock falls within the $1/N$ range (£$P/N \times (1 \pm 0.02)$), for differing the number of stocks bought in the week or month (N). A week is defined as five business days from Monday to Friday. Multiple-stock buy weeks consisting of a single buy day were excluded. A month is defined as a calendar month. Multiple-stock buy months consisting of a single buy week were excluded. Lower and upper limit values of 95% confidence intervals from bootstrap mean estimates are reported in the LL and UL columns. The standard errors were corrected for clustering by accounts.

Panel A: Multiple-Stock Buy Weeks

N	$1/N$ Buying (%)	LL	UL	Buy Weeks
2	19.5	19.1	20.0	91,158
3	10.2	9.7	10.7	39,693
4	8.3	7.6	8.9	18,546
5	7.3	6.5	8.2	9,447
6+	5.3	4.5	6.3	14,889
All	14.3	13.9	14.8	173,733

Panel B: Multiple-Stock Buy Months

N	$1/N$ Buying (%)	LL	UL	Buy Months
2	15.7	15.4	16.0	86,875
3	8.0	7.7	8.4	48,386
4	6.1	5.7	6.5	26,636
5	5.1	4.7	5.6	15,538
6+	3.3	3.0	3.7	32,491
All	10.0	9.8	10.3	209,926

We analyze $1/N$ allocation behavior on multiple-stock buy weeks and multiple-stock buy months using the same methodology as in the previous section. The results, reported in Table II, indicate that $1/N$ allocations become less common at wider intervals, accounting for 14.3% of all multiple-stock buy weeks and 10% of all multiple-stock buy months.[18] This suggests that NBD is related to the narrower buying interval of a day and that investors often psychologically bracket trades made within a given day.

D. Other 1/*N Allocations*

In additional analyses, we investigate whether investors might use related heuristics such as making allocations with 2/3:1/3 weights. Figure 1 shows small peaks at 1/3:2/3 and 2/3:1/3 allocation in the two-stock case, with some evidence of peaks at other simple fractions in the three- and four-stock cases.

[18] The calculations in this table use a bandwidth of $0.0X$. Sample sizes for multiple-stock buy weeks and multiple-stock buy months are shown in Table III in the Internet Appendix.

These indicate that some investors might use these alternative simple weights. In additional analysis, we test whether the peaks at these weights are due to (i) investors using different weights for each trade, or (ii) investors making multiple trades of the sample stock, for example, an investor making equally valued purchases of Stocks A and B, then subsequently making another purchase of Stock A or B of the same value. The analysis shows that investors appear to use different weights, suggesting that some investors choose related allocation weight in the family of simple fractions, among which $1/N$ is the most common choice. Additional results are provided in the Internet Appendix.

III. NBD or NPD?

A key contribution of our paper is that it performs tests that distinguish whether investors engage in NPD (targeting equal weights in the portfolio) or NBD (targeting equal weights in a given purchase). This distinction is important because, as a target portfolio-balancing heuristic, NPD arguably performs well for investors in practice. From a normative perspective, DeMiguel, Garlappi, and Uppal (2009) compare the performance of NPD against 14 alternative models and find that none is consistently better than NPD in achieving a Sharpe ratio, certainty-equivalent return, or turnover.

A. *Evidence from Top-Up Buy Days*

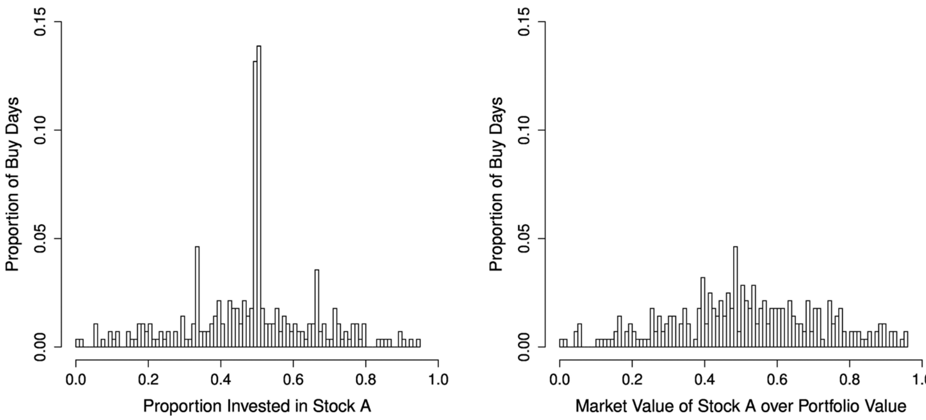
The cleanest setting in which to distinguish between NBD and NPD is when investors top up multiple stocks already held in their portfolio. We examine whether they split the top-up investment $1/N$ across new funds invested (i.e., NBD), or instead top up such that the portfolio is balanced $1/N$ as a result of the trades (i.e., NPD). For this analysis, we draw on the sample of new accounts, for which we can recreate the complete portfolio of holdings at any day.

First, we show results for top-up buy days involving two stocks. Panel A of Figure 2 shows the proportion of the buy day investment allocated to (randomly chosen) Stock A. The right-side figure shows the market value of Stock A over the total end-of-day portfolio value (of holdings of Stocks A and B). There is clear heaping around $1/N$ in the left-side figure, which is absent in the right-side figure. Hence, in this sample we see NBD, not NPD, on top-up buy days.

Investors may fail to achieve NPD simply because the level of total investment on the buy day is not large enough to bring their portfolio into balance. In that case, an investor could only achieve NPD if they increased the total amount invested on the buy day, or reduced their holdings of one position. In Panel B of Figure 2, we restrict the sample to top-up buy days on which the investor could achieve NPD, given the total buy day investment amount, without requiring any sell activity. Again, there is clear heaping around $1/N$ in the left-side figure, which is absent in the right-side figure.[19]

[19] Results from this restricted sample are summarized in Table VI in the Internet Appendix.

(A) Whole Sample



(B) Restricted Sample

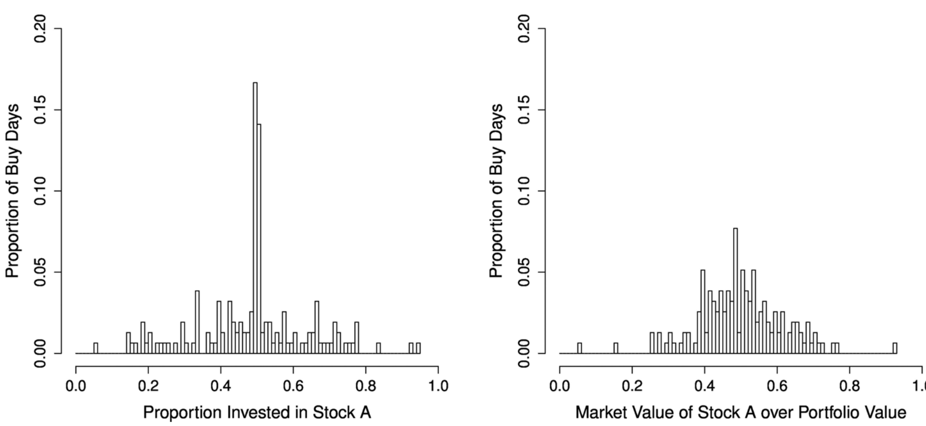


Figure 2. Naïve buying diversification versus naïve portfolio diversification investors topping-up two-stock portfolios. Panel A shows a histogram of the proportion of the total buy day investment (in pounds) in Stock A, where Stock A is randomly chosen from the pair of stocks purchased. Bin width is 0.01. Panel B shows a histogram of the proportion of the end-of-day investment in the portfolio that is allocated to Stock A, where Stock A is randomly chosen from the pair of stocks purchased. The sample is restricted to two-stock buy days in the sample of new accounts. See Section I for details on the sample construction. Bin width is 0.01.

Next, we extend our analysis to all top-up buy days involving multiple stocks. Results are shown in Table III, which presents a breakdown of the starting positions, buying allocations, and ending positions of all buy day episodes with at least two existing positions in the portfolio. In each panel, the rows summarize eight mutually exclusive scenarios for account positions at the start of the day and activity during the day.

Table III

Starting and Ending Portfolio Positions on Multiple-Stock Buy Days

This table shows summary data for multiple-stock buy days. Each row reports the percentage of buy days by combinations of existing positions at the beginning of the day, buying split, and resulting positions in the 1/N range for differing ranges. Lower and upper limit values of 95% confidence intervals from bootstrap mean estimates are reported in the LL and UL columns. The sample is restricted to multiple-stock buy days in the new accounts data. See Section I for details on the sample construction.

Panel A: (£$P/N \times (1 \pm 0.02)$)

1/N Existing Positions	1/N Buying	1/N Resulting Positions	Proportion of Buy Days	LL	UL
Yes	Yes	Yes	0.5	0.4	0.7
Yes	Yes	No	0.6	0.4	0.7
Yes	No	Yes	0.0	0.0	0.0
Yes	No	No	1.1	0.9	1.3
No	Yes	Yes	0.1	0.0	0.1
No	Yes	No	28.5	27.3	29.8
No	No	Yes	0.1	0.0	0.1
No	No	No	69.2	67.8	70.4

Panel B: (£$P/N \times (1 \pm 0.05)$)

1/N Existing Positions	1/N Buying	1/N Resulting Positions	Proportion of Buy Days	LL	UL
Yes	Yes	Yes	1.5	1.3	1.7
Yes	Yes	No	1.3	1.1	1.5
Yes	No	Yes	0.1	0.0	0.1
Yes	No	No	1.9	1.6	2.1
No	Yes	Yes	0.1	0.1	0.2
No	Yes	No	32.7	31.5	34.0
No	No	Yes	0.2	0.1	0.3
No	No	No	62.2	60.9	63.5

Panel C (£$P/N \times (1 \pm 0.1)$)

1/N Existing Positions	1/N Buying	1/N Resulting Positions	Proportion of Buy Days	LL	UL
Yes	Yes	Yes	2.7	2.4	3.1
Yes	Yes	No	2.2	2.0	2.5
Yes	No	Yes	0.2	0.1	0.2
Yes	No	No	2.7	2.4	3.0
No	Yes	Yes	0.2	0.2	0.3
No	Yes	No	37.2	36.0	38.3
No	No	Yes	0.3	0.2	0.4
No	No	No	54.5	53.3	55.8

The first four rows in each panel show accounts that begin the buy day with NPD (2.2% of observations). Of these, 1.1% engage in NBD and 1.1% in non-NBD. At the day end, in 0.5% of cases the portfolio is balanced by NPD; in 1.7% of cases the portfolio is not balanced by NPD. The bottom four rows in each panel show accounts that begin the buy day away from NPD (97.8% of observations). Of these, in 28.6% of the cases investors use NBD and in 69.3% they choose some other allocation. In only 0.2% of the cases, the portfolio shows NPD. Panels B and C show similar results. Table IA.VI in the Internet Appendix shows the proportion of buy days resulting in NPD in the restricted sample. Across all multiple-stock buy days in the restricted sample, only 2% result in NPD.

B. Evidence from Top-Up Buy Weeks and Buy Months

NPD may be uncommon on multiple-stock buy days because investors balance their portfolios of longer time periods, such as a week or a month. By focusing on buy days, we may miss NPD that investors implement through a series of trades over a period of days spread out, for example, across the period of a week or a month. Neglecting this behavior would cause us to underestimate the extent of NPD in the data.

We therefore examine NPD over longer time intervals, using the samples of multiple-stock buy weeks and multiple-stock buy months, as defined in the previous section, but drawing again on new accounts. We adopt the same methodology as above for determining whether investors achieve NPD over these longer intervals. Results, reported in Table IV, reveal that NPD is uncommon over these longer multiple-stock buying intervals, occurring on only 0.8% of multiple-stock buy weeks or buy months.

C. Evidence from All Buy Days

To verify whether this finding of NBD generalizes to the full sample of new accounts, we now extend the analysis to examine purchases without restricting the number of stocks currently held, the set of stocks purchased on the buy day, or the interval between stock purchases. The advantage of this analysis is that it draws upon 100% of buy trades. The majority of buy days are single-stock buy days. One might have thought that investors would intermittently trade several stocks of interest at the same time. But most trades are of a single stock, which is suggestive of narrow framing. The 100% sample therefore combines any number of existing positions, top-up trades, and portfolio positions in which NPD is more or less feasible given the size of investment on the buy day.

This analysis shows that in this broadest sample NBD is common, while NPD is extremely rare across all combinations of numbers of stocks held and numbers of stocks purchased. The panels in Figure 3 describe the proportion of observations of NBD and NPD for different combinations of the numbers of positions in the investor's existing portfolios at the beginning of the buy day

Table IV

NPD Allocations on Multiple-Stock Buy Weeks and Buy Months

This table shows summary data for multiple-stock buy weeks and buy months. Each row reports the percentage of buy weeks or buy months resulting positions in the $1/N$ range (£$P/N \times (1 \pm 0.02)$), for different number of stocks in the portfolio at the end of the week or month. In Panel A, a week is defined as five business days from Monday to Friday. Multiple-stock buy weeks consisting of a single buy day were excluded. The sample was restricted to multiple-stock buy weeks with an existing position at the beginning of the week. In Panel B, a month is defined as a calendar month. Multiple-stock buy months consisting of a single buy week were excluded. The sample was restricted to multiple-stock buy weeks with an existing position at the beginning of the month. Lower and upper limit values of 95% confidence intervals from bootstrap mean estimates are reported in the LL and UL columns. The standard errors were corrected for clustering by accounts.

Panel A: Multiple-Stock Buy Weeks

N	$1/N$ Portfolios (%)	LL	UL	Buy Weeks
2	5.3	4.1	6.5	1,343
3	1.4	0.8	1.9	1,768
4	0.4	0.1	0.7	1,548
5	0.2	0.0	0.6	1,202
6+	0.0	0.0	0.1	7,106
All	0.8	0.7	1.0	12,967

Panel B: Multiple-Stock Buy Months

N	$1/N$ Portfolios (%)	LL	UL	Buy Months
2	5.1	4.1	6.1	1,741
3	1.0	0.6	1.5	2,089
4	0.2	0.1	0.4	1,847
5	0.2	0.0	0.4	1,592
6+	0.0	0.0	0.1	8,285
All	0.8	0.6	0.9	15,554

and the number of stocks purchased. Within each panel, the horizontal axis denotes the number of stocks bought on the day. The bandwidth used to define NBD and NPD is (£$P/N \times (1 \pm 0.02)$). The red bars and whiskers illustrate 95% confidence intervals for the proportion of buy days within the cell that show NBD. The blue bars and whiskers illustrate 95% confidence intervals for the proportion of buy days that show NPD.

Strikingly, NBD is consistently high on buy days in which, at the beginning of the day, there are multiple stocks in the portfolio. In contrast, NPD is rare across all combinations of existing positions and numbers of stocks bought on the day (with the exception of empty accounts with no existing positions at the beginning of the day for which, by construction, NBD = NPD). Tables V and VI report the mean values and bootstrapped 95% confidence interval bounds within each cell. This analysis makes clear that NPD is extremely rare, whether investors are topping up their portfolios or adding new positions.

Table V

Naïve Portfolio Diversification by N Stocks Purchased and N Positions: All Buy Days

This table shows data for all buy days. Each cell reports the percentage of buy days that end in $1/N$ allocations (£$P/N \times (1 \pm 0.02)$) by the number of existing positions at the start of the buy day and number stocks purchased on the day. Cell [0,1] is empty as it takes a value of 100% by construction. Values in square brackets report lower and upper limit values of 95% confidence intervals from bootstrap mean estimates. The sample is restricted to multiple-stock buy days in the new accounts data. See Section I for details on the sample construction. The numbers in the first row slightly differ from those in Table VI due to intraday price movement.

	Single-Stock Purchase	2-Stock Purchase	3-Stock Purchase	4-Stock Purchase	5-Stock Purchase	6-Stock Purchase
0 Existing Position	NA	36.5	24.9	22.4	25.0	14.1
		[34.8,38.3]	[22.0,27.5]	[19.0,25.8]	[19.5,30.6]	[10.6,17.8]
1 Existing Position	8.6	7.3	4.7	4.8	10.0	4.5
	[8.1, 9.2]	[6.0, 8.5]	[2.6, 7.1]	[1.6, 8.7]	[2.3,18.9]	[0.0,10.5]
2 Existing Positions	2.3	3.9	2.9	0.0	2.8	4.8
	[2.0, 2.5]	[3.0, 5.0]	[1.2, 4.5]	[0.0, 0.0]	[0.0, 9.7]	[0.0,11.9]
3 Existing Positions	0.6	0.9	2.2	1.2	0.0	0.0
	[0.5, 0.7]	[0.5, 1.4]	[0.8, 4.0]	[0.0, 3.8]	[0.0, 0.0]	[0.0, 0.0]
4 Existing Positions	0.3	0.5	0.3	1.1	0.0	0.0
	[0.2, 0.4]	[0.2, 0.9]	[0.0, 0.9]	[0.0, 3.6]	[0.0, 0.0]	[0.0, 0.0]
5 Existing Positions	0.1	0.2	0.0	0.0	8.1	0.0
	[0.0, 0.1]	[0.0, 0.4]	[0.0, 0.0]	[0.0, 0.0]	[0.0,18.8]	[0.0, 0.0]
6+ Existing Positions	0.0	0.0	0.0	0.0	0.0	0.3
	[0.0, 0.0]	[0.0, 0.0]	[0.0, 0.0]	[0.0, 0.0]	[0.0, 0.0]	[0.0, 0.8]

Table VI

Naïve Buying Diversification by N Stocks Purchased and N Positions: All Buy Days

This table shows data for all buy days. Each cell reports the percentage of buy days on which the investor splits the buy day investment $1/N$ (£$P/N \times (1 \pm 0.02)$), by the number of existing positions at the start of the buy day and the number of stocks purchased on that day. Values in square brackets report lower and upper limit values of 95% confidence intervals from bootstrap mean estimates. The sample is restricted to multiple-stock buy days in the new accounts data. The numbers in the first row slightly differ from those in Table V due to intraday price movement.

	2-Stock Purchase	3-Stock Purchase	4-Stock Purchase	5-Stock Purchase	6-Stock Purchase
0 Existing Position	39.5	28.4	26.4	29.9	19.4
	[37.7,41.4]	[25.7,31.3]	[22.8,30.5]	[24.3,35.5]	[15.5,23.6]
1 Existing Position	31.5	27.0	19.0	30.0	19.7
	[29.4,33.7]	[22.6,31.7]	[12.5,26.6]	[17.5,42.2]	[10.3,29.4]
2 Existing Positions	32.9	19.8	25.6	19.4	14.3
	[30.6,35.0]	[15.9,24.1]	[16.5,34.9]	[7.1,34.1]	[4.8,25.6]
3 Existing Positions	29.2	19.4	16.7	20.6	21.1
	[26.9,31.6]	[15.4,23.5]	[9.0,24.4]	[8.3,35.0]	[8.3,34.1]
4 Existing Positions	29.5	17.5	29.3	12.2	7.9
	[26.7,32.4]	[13.6,21.8]	[20.8,38.9]	[4.2,23.4]	[0.0,17.6]
5 Existing Positions	30.6	17.8	20.9	35.1	17.2
	[27.6,33.8]	[13.4,22.5]	[13.3,29.5]	[16.7,53.1]	[5.3,33.3]
6+ Existing Positions	30.4	18.9	18.0	15.2	13.9
	[28.2,32.6]	[16.1,21.6]	[14.4,21.7]	[11.4,19.4]	[9.2,19.1]

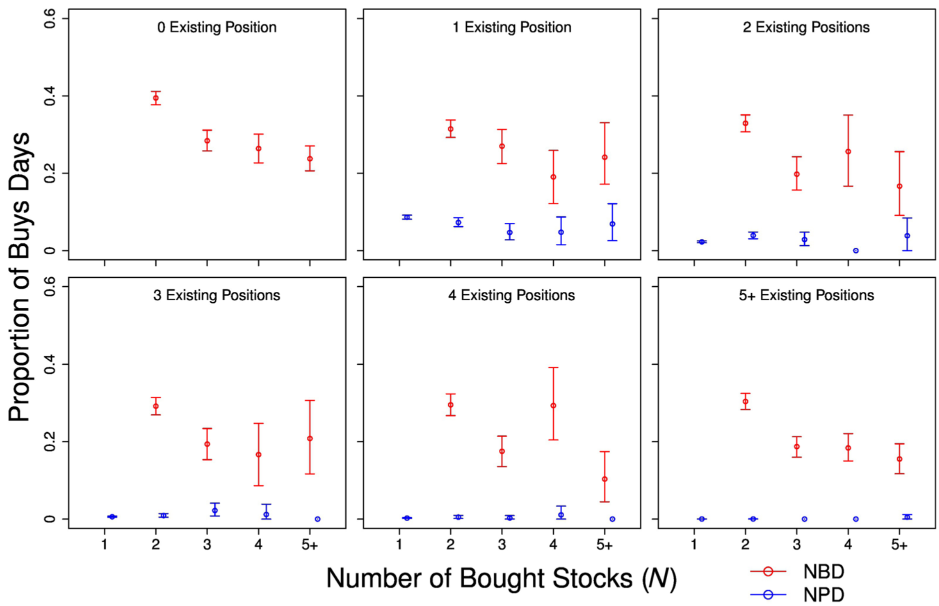


Figure 3. Naïve buying diversification versus naïve portfolio diversification: all buy days. These plots illustrate the proportion of buy days on which multiple-stock purchases are split across stocks $1/N$ (in red) and on which the end-of-day portfolio positions are split $1/N$ (in blue). Separate panels for the number of existing positions within the portfolio at the start of the day, with the number of stocks purchased on the day are shown on the x-axis of each panel. The bandwidth used to define NBD and NPD is $(£P/N \times (1 \pm 0.02))$. The sample is restricted to multiple-stock buy days in the new accounts, data. See Section I for details on the sample construction. (Color figure can be viewed at wileyonlinelibrary.com)

IV. Why Do Investors Use the NBD Heuristic?

We next examine competing hypotheses for the NBD heuristic. We consider two main hypotheses as to why investors use this heuristic, which we refer to as *stock-picking* NBD and *diversification-motivated* NBD. The stock-picking NBD hypothesis is that investors are drawn to multiple attractive stocks, possibly due to strong performance in recent returns or salient news about those stocks (in the spirit of Barber and Odean (2008)) and choose to invest an equal amount in each stock based on a naïve equal-weighting heuristic without regard to the risk benefits of including more stocks in the portfolio. The diversification-motivated hypothesis is that investors who might only have purchased fewer stocks, motivated by the risk-reduction benefit of diversification, purchase additional stocks. Doing so offers them perceived diversification benefits, albeit using equal weights. Under the first hypothesis, NBD is the result of investors paying little attention to diversification; under the second hypothesis, NBD is diversification-driven and is an improvement on a counterfactual in which the investor would have made a less diversified buying decision.

While we cannot directly measure what investors are thinking, these alternative hypotheses offer a testable implication: Under the stock-picking hypothesis, NBD should be more common when investors buy stocks that are similar, particularly in terms of their perceived "attractiveness," the result of news coverage or risk and return profiles (as they are drawn to a set of similar stocks). Under the diversification-motivated hypothesis, NBD should be more common when investors buy dissimilar or low-correlation stocks (as they seek to diversify through stock-buying choices).

We test between these hypotheses by drawing upon measures of the similarity of the stocks purchased by investors on multiple-stock buy days, and then relating these measures of similarity to the likelihood that the allocation across stocks is NBD. We draw upon four measures of stock similarity in this analysis.

First, we apply three measures of stock similarity based upon stock characteristics and recent stock performance, measuring absolute differences in (i) idiosyncratic returns, (ii) past 60 days returns, and (iii) forward 60 days returns. The idiosyncratic return is calculated by estimating daily excess returns of ordinary shares listed in the London Stock Exchange from a single-index model.[20]

Second, we measure the similarity of stocks in their news salience to the investor on the day. To do so, we merge into our data daily-level indices of positive coverage of the stock on news and social media using the TRMI "Buzz" measure. The TRMI aggregates data from worldwide traditional news media and social news media sites to measure the volume of positive sentiment toward individual securities in real time. This is achieved using natural language processing techniques, from which quantitative measures of sentiment toward stocks are derived. On a given day, a single stock may register many tens of thousands of positive sentiment events, while on other days a single stock may attract few or no sentiment events.[21] On any given day, a small number of stocks account for a large proportion of TRMI Buzz, those being the stocks "in the news" on that day.[22]

We calculate the absolute difference in TRMI Buzz between the purchased stocks. As the volume of TRMI Buzz varies by day, we measure the difference in Buzz between stocks as the absolute difference in the proportion of total TRMI Buzz attributable to the stock. We then calculate a three-day moving average of the proportion of TRMI Buzz received by the stock. A larger absolute

[20] For this analysis, we used the 200 stocks that were traded throughout the data period and were most frequently traded in the data. Stocks having a zero daily return for more than 25% of trading days were excluded. As a risk-free rate, we used the U.K. government liability one-year spot rate retrieved from https://www.bankofengland.co.uk/statistics/yield-curves.

[21] MarketPsych's natural-language processing software employs grammatical templates customized to extract meanings from financial news, social media, and other data. Further details are available at https://www.marketpsych.com/.

[22] Figure 8 in the Internet Appendix illustrates a cumulative density function of TRMI Buzz, showing that, on average, a handful of stocks account for half of the total measured Buzz on a given day.

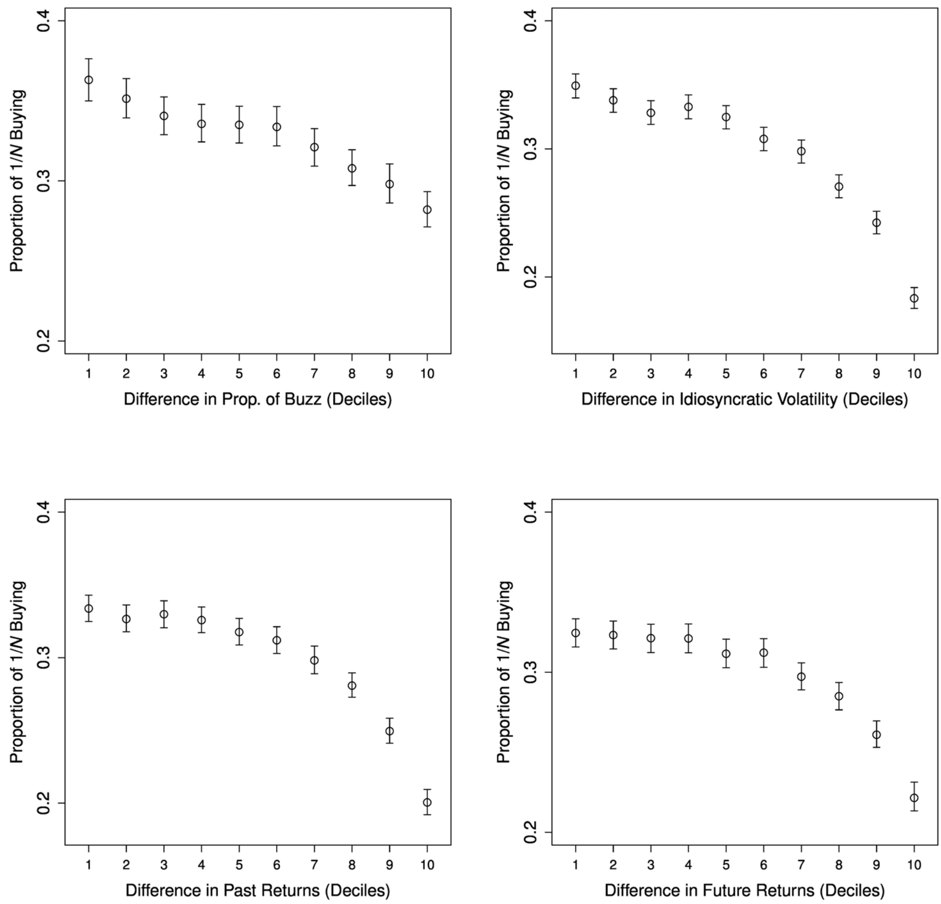


Figure 4. NBD and stock similarity: Two-stock buy days. This figure shows the proportion of all two-stock buy days on which the buy day investments are split equally (in pounds) across the two stocks. "Equal" is defined in the range from 49% to 51%. The sample is restricted to two-stock buy days. See Section I for details on the sample construction. Ninety-five percent confidence intervals are illustrated in error bars.

difference in Buzz between two stocks means that one stock has a higher volume of positive market sentiment on that day, compared with the other stock(s) purchased by the investor.

Figure 4 illustrates the relation between these measures of stock similarity and NBD. The figure plots the proportion of two-stock buy days resulting in NBD by deciles of the measures of stock similarity. Note that the four measures of similarity are weakly correlated with each other.[23]

Each panel of Figure 4 shows a clear negative relation between stock similarity and NBD shown in each panel. We quantify the relations observed in

[23] See correlation matrix shown in Table VIII in the Internet Appendix.

Figure 4 using a cross-section multivariate regression model. In the linear probability model (shown for ease of interpretation; very similar results are obtained from Probit and Logit models), the dependent variable is a dummy variable indicating whether the two-stock buy day allocation is NBD. The model is estimated on the sample of all multiple-stock buy days.

We report results from three specifications. A first specification includes the three measures of stock similarity based upon stock returns. A second specification adds the TRMI Buzz measure. A third specification adds a set of control variables that might explain NBD behavior. The set of control variables included in the model are:

- Gender and age: Previous studies show that gender is important (Barber and Odean (2001), Choi et al. (2002), Agnew, Balduzzi, and Sundén (2003), Dorn and Huberman (2005), Mitchell et al. (2006)). Studies also show age is important (Korniotis and Kumar (2013)).
- Portfolio size and characteristics: These are controls for limited attention.[24] They may be important if investors face fixed costs for calculating the investment share of each stock in an optimal portfolio (such as time or psychic costs of portfolio calculations); then, for investment choices with low economic stakes, investors might optimally choose the simple naïve diversification heuristic. In models with fixed optimization costs, it is worth paying the optimization cost (e.g., time cost) only when stakes are sufficiently high. Also, investors may be inattentive to their investment choices when distractions are present (as in Hirshleifer, Lim, and Teoh (2011)). This is a feature that DellaVigna and Pollet (2009) refer to as "behavioral inattention"; they provide evidence of reduced market reaction to earnings announcements made on Fridays.
- Trading frequency: Studies have found that investors learn to avoid the disposition effect as they gain more trading experience (Feng and Seasholes (2005) Seru, Shumway, and Stoffman (2010)), while, in the case of investing in initial public offerings, investors appear not to learn from their mistakes (Kaustia and Knüpfer (2008), Chiang et al. (2011)). There is evidence that individuals learn from previous experience when using financial products (Agarwal et al. (2008), Ater and Landsman (2013), Miravete and Palacios-Huerta (2014)). We control for trading frequency, following Barber and Odean (2001).[25]

[24] Theoretical models have suggested that limited investor attention affects trading and asset prices (Hirshleifer and Teoh (2003), Peng and Xiong (2006), Hirshleifer, Lim, and Teoh (2011)). A considerable body of empirical research finds evidence consistent with attention effects in asset markets. Examples include DellaVigna and Pollet (2009), Hirshleifer, Lim, and Teoh (2009), Hou, Peng, and Xiong (2009), Cohen, Diether, and Malloy (2013), and Huang (2015). Models of rational inattention explain quasirational behaviors as arising due to opportunity costs in allocating attention, as in Sims (2003). Recent studies present mixed evidence as to whether individuals behave in a way that is consistent with rational inattention (DellaVigna (2009); Chetty et al. (2014), Taubinsky and Rees-Jones (2018), Gathergood et al. (2019)).

[25] The unconditional relations between these control variables and NBD are illustrated in the Internet Appendix Figures 9 to 20 and Tables IX to XI.

The first specification draws upon all two-stock buy days in the all accounts sample; the second specification restricts to two-stock buy days involving stocks in the FTSE100 index; the third specification further restricts to the new accounts sample, in which the full set of covariates included in the model is available.[26]

Results are shown in Table VII. The coefficients on similarity measures in predicting NBD are negative, which in most models is statistically significant at the 1% level or lower. Evaluating the coefficients in Model 3, a one-standard-deviation increase in the difference in past 60-days returns lowers the likelihood of NBD by one-quarter of a standard deviation, while the equivalent effect sizes are a one-eighth of a standard deviation for a standard deviation increase in the difference in idiosyncratic return, and approximately two-thirds of a standard deviation for the difference increase in the difference in Buzz. Coefficient estimates also indicate that NBD is less likely at a high trading frequency, when the number of stocks purchased on the day is larger, and when the investor makes a sale on the same day.

In summary, the empirical analysis provides support for the stock-picking explanation for NBD. The analysis shows that NBD is more common when investors buy similar stocks, as defined by recent stock return characteristics and current market sentiment. This is consistent with investors being drawn to similarly attractive stocks and using a naïve heuristic of investing an equal amount in each stock.

V. NBD and Portfolio Performance

Our main result, that investors often use NBD, whereas there is no evidence that they use NPD, raises the question of whether, and how much, NBD damages portfolio performance. For individual investors who may not have access to sophisticated portfolio optimization tools, the $1/N$ rule may be a feasible second-best portfolio allocation strategy.[27]

In this section, we evaluate the portfolio performance of NBD. We consider both a standard sophisticated measure of performance, the risk-adjusted returns of a portfolio, and the less sophisticated measure of unadjusted returns that might appeal to investors who are not focused upon portfolio diversification.

We first evaluate the portfolio performance of NBD investors (compared with non-NBD investors) by average unadjusted returns. While this measure of returns is simple and arguably unsophisticated, it may be the one that stock-picking NBD investors value most highly. We classify investors in our sample into three groups by intensity of NBD: "50% or More NBD," "At Least One NBD," and "Never NBD" investors. A total of 50% or More NBD investors had two or more multiple-stock buy days of which 50% were NBD. At-Least-One

[26] Summary statistics for the set of controls are reported in the Internet Appendix Table VII.

[27] This is not to say that the $1/N$ rule is not beatable by sophisticated investors (e.g., for discussion, see Pedersen, Babu, and Levine (2021)).

Table VII
Linear Regression Coefficients: 1/N Buying on Multiple-Stock Buy Days

This table reports coefficients from linear regression model estimates. Standard errors shown in parentheses. The dependent variable is a 1/0 dummy indicating whether the buy day investment falls within the $1/N$ range, defined as £$P/N \times (1 \pm 0.02)$. Gender and decade of birth are included in all models and month-of-year dummies are included in Models 3 and 4, but are not shown. The sample is restricted to multiple-stock buy days. Some independent variables are available only for a part of accounts. For example, *Portfolio Value*, *Number of Stocks in the Portfolio*, and *Existing Position Dummy* are available only for new accounts. Statistics of dependent and independent variables are reported in Table IA.VII in the Internet Appendix. * denotes statistical significance at the 5% level, ** at the 1% level, and *** at the 0.1% level. The standard errors were corrected for clustering by accounts and buy dates.

IV	(1)	(2)	(3)
Diff in Past 60-Days Return	−0.0002	−0.058***	−0.093***
	(0.003)	(0.013)	(0.022)
Diff in Next 60-Days Return	−0.107***	−0.108***	−0.059
	(0.007)	(0.011)	(0.034)
Diff in Idiosyncratic Return (60-days)	−0.034^***	−0.110^***	−0.076**
	(0.003)	(0.011)	(0.026)
Diff in Proportion of Buzz (3-Days MA)		−0.381***	−0.456^***
		(0.036)	(0.085)
Ave Num of Trades Per Month			−0.002**
			(0.001)
Portfolio Value (/ 10,000)			−0.001*
			(0.0004)
Num of Stocks in the Portfolio			0.002*
			(0.001)
Inv Amount on the Day (/ 10,000)			0.002
			(0.003)
N (Num of Bought Stocks)			−0.043***
			(0.006)
Existing Position Dummy			−0.060***
			(0.013)
Same-Day Sale Dummy			−0.081***
			(0.015)
(intercept)	0.312***	0.498***	0.606***
	(0.087)	(0.125)	(0.093)
Observations	201,009	86,932	10,314
R^2	0.011	0.012	0.031
Adjusted R^2	0.011	0.012	0.029

NBD investors exhibited NBD at least once in the data period. Never NBD investors at no point exhibited NBD in the data period. 50%-or-More NBD investors are a subset of At-Least-One NBD investors, while Never NBD investors are exclusive of the other two types of investors. We then compare the unadjusted returns of these three groups over the sample period. Returns are calculated at a monthly frequency and include dividend payments (and dividend reinvestments as observed in the data), and are calculated net of fees.

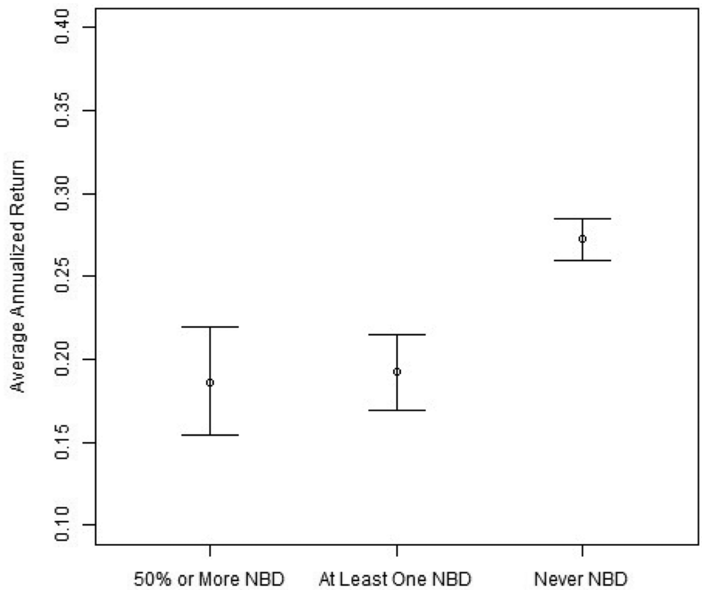


Figure 5. Annualized total returns for NBD and non-NBD investors. This figure shows mean annual returns for 50% or More NBD, At Least One NBD, and Never NBD investors. 50% or More NBD investors had two or more multiple-stock buy days of which 50% or more were NBD. At least One NBD investors exhibited NBD at least once in the data period. Never NBD investors never exhibited NBD in the data period. The first two groups are not mutually exclusive. Mean annual returns are calculated as an average of monthly returns including dividend receipts and are net of fees. See Section I for details on the sample construction.

Mean annualized returns for NBD and non-NBD investors are shown in Figure 5. Never NBD investors, on average, earn annualized returns approximately one-third higher than investors who with 50% or more NBD, or At-Least-One NBD (these groups have very similar returns). The difference in mean returns between non-NBD and the other groups is statistically significant at the 1% level. These results indicate that NBD investors do not, on average, outperform non-NBD investors over the time horizon of the sample period. Even though NBD investors appear focused on stock picking, and possibly devote cognitive resources to their choice of stocks, this does not pay off in superior performance. This is broadly consistent with evidence of investors underperforming the market through their trading activity, at least on average (Barber and Odean (2013)).

The lower mean annualized returns of NBD investors might be compounded by the shortcomings of NBD as a diversification strategy. To evaluate this possibility, given the relatively short time window over which we can track the risk-return performance of investors, we draw upon simulation methods. Specifically, we simulate portfolio performance when adopting an NBD strategy, in comparison with an NPD strategy. We choose an NPD strategy not only because it is the natural counterpart to NBD, but because it is simple to implement in practice. As mentioned earlier, DeMiguel, Garlappi, and

Uppal (2009) evaluate the out-of-sample performance of 14 different portfolio estimation and formation models against NPD, and find that none perform consistently better than NPD over reasonable time horizons.

To conduct this exercise, simulated asset returns are generated according to the single-factor model used in DeMiguel, Garlappi, and Uppal (2009). We assume that an investor i holds a portfolio consisting of N_i risky assets, one of which is the factor. Annualized excess returns of the factor, $R_{b,t}$, are drawn from the normal distribution $R_{b,t} \sim N(\mu_b, \sigma_b^2)$. Annualized excess returns of the remaining $N_i - 1$ risky assets, $R_{a,t}$, follow $R_{a,t} = BR_{b,t} + \epsilon_t$, where B is the factor loading and ϵ_t is an error term drawn from the normal distribution $\epsilon_t \sim N(0, \Sigma_t)$ and Σ_t is a diagonal variance-covariance matrix, where the squared root of the diagonal elements represent the idiosyncratic volatility.

We implement the NBD and NPD rules over a time horizon T (months) with a regular contribution into the portfolio at each time step. Under the NPD rule, assets are sold and purchased at each time step to rebalance the portfolio to $1/N_i$ weights. Under the NBD rule, the monthly contribution is simply split equally over the N_i assets. We evaluate portfolio performance using the Sharpe ratio based on 1,000 simulations.

A key parameter for calibration analysis is idiosyncratic volatility. This is where the NBD and NPD strategies diverge. At the limit, with no idiosyncratic volatility, these strategies are identical, as the stocks have perfectly correlated risks, and hence stock weights are irrelevant. Based on historical data, we therefore present two calibrations, one with low and one with high idiosyncratic volatility (the squared root of the diagonal elements of Σ_t). These are calibrated to the interquartile range (25% to 75%) of estimated annualized idiosyncratic volatilities of stocks in the data (other parameter values used in the simulation are the same as those in DeMiguel, Garlappi, and Uppal (2009): $\mu_b = 0.08$ and $\sigma_b = 0.16$; B are evenly spread from 0.5 to 1.5.) In the low-idiosyncratic risk simulation, the idiosyncratic components are drawn from a $U[0.10, 0.30]$, which is shifted to $U[0.40, 0.60]$ in the high-idiosyncratic risk simulation. We conduct simulations for each pairwise combination of $N_i \in \{5, 10, 20\}$ and $T \in \{120, 360\}$.

We fit daily excess returns of ordinary shares listed in the London Stock Exchange to the single-index model where the index is FTSE 500 index. (Note that we used 200 stocks that were traded throughout the data period and were most frequently traded in the data. Stocks having a zero daily return for more than 25% of trading days were excluded. As a risk-free rate, we used the U.K. government liability one-year spot rate retrieved from https://www.bankofengland.co.uk/statistics/yield-curves.) The interquartile range (25% to 75%) of the estimated annualized idiosyncratic volatilities is approximately 0.20 (the average in the low-idiosyncratic risk simulation) and 0.50 (the average in the high-idiosyncratic risk simulation), respectively. Idiosyncratic volatilities of 56% of stocks are within the parameter value range in the low-idiosyncratic risk simulation (0.10 to 0.30) and those of 17% of stocks are within the parameter value range in the high-idiosyncratic risk simulation (0.40 to 0.60).

Table VIII

Sharpe Ratio Simulations for NPD versus NBD

This table shows Sharpe ratios from simulations based upon a one-factor model. Values in parentheses are the p-values from a t-test for the differences in the Sharpe ratios between NPD and NBD strategies.

Panel A: Low Idiosyncratic Risk

	$N_i = 5$		$N_i = 10$		$N_i = 20$	
Strategy	$T = 120$	$T = 360$	$T = 120$	$T = 360$	$T = 120$	$T = 360$
NPD	0.127	0.128	0.136	0.139	0.134	0.140
NBD	0.125	0.124	0.135	0.135	0.133	0.136
	(0.661)	(0.111)	(0.736)	(0.161)	(0.791)	(0.151)

Panel B: High Idiosyncratic Risk

	$N_i = 5$		$N_i = 10$		$N_i = 20$	
Strategy	$T = 120$	$T = 360$	$T = 120$	$T = 360$	$T = 120$	$T = 360$
NPD	0.091	0.091	0.109	0.107	0.126	0.119
NBD	0.081	0.079	0.097	0.084	0.116	0.092
	(0.015)	(0.000)	(0.004)	(0.000)	(0.014)	(0.000)

Table VIII summarizes results from the simulation exercise. In the low-idiosyncratic risk simulations, shown in Panel A, a t-test fails to reject the null hypothesis that the average Sharpe ratios of the NBD and NPD strategies are equal. The NPD simulations in Panel A are consistent with those in table 6 of DeMiguel, Garlappi, and Uppal (2009).

In contrast, in the high-idiosyncratic risk simulations, shown in Panel B, NBD substantially reduces Sharpe ratios relative to NPD, and the t-test rejects the null hypothesis of equality in the Sharpe ratios at the 1% level in the majority of cases. The difference in Sharpe ratio increases with both N_i and T. The reduction in the Sharpe ratio under the NBD rule compared with the NPD ranges from 11.0% (with $N_i = 5$ and $T = 120$) to 22.7% (with $N_i = 20$ and $T = 360$).

A key question that arises from this result, that NBD performs significantly worse under high idiosyncratic risk is whether higher idiosyncratic risk, is associated with a weaker propensity of investors to engage in NBD. In additional analyses, we examine the relation between idiosyncratic risk (measured by the volatility of the FTSE100, over a 10-day horizon) and the proportion of trades that are NBD, and also the average value of NBD trades. If NBD investors are responsive to the downside of using NBD in the presence of heightened idiosyncratic risk, we would expect either the prevalence and/or value of NBD trades to decrease when idiosyncratic risk is high. However, the additional analysis shows that NBD is no less common when idiosyncratic risk increases (and there is some indication that NBD is more common when idiosyncratic risk is at its highest). [28] There is also no reduction in the average value of NBD trades when idiosyncratic risk increases. Hence, investors appear unaware of the downside of using NBD when idiosyncratic risk is high, reinforcing our main result: that these investors appear not to focus on diversification when using NBD.

To understand the shortcoming of NBD as a diversification strategy intuitively, consider how NBD tends to induce arbitrary disparities in portfolio weights, so we do not expect it to do as good a job as NPD in evenly balancing the portfolio and diversifying risk.[29] Such an imbalance tends to increase portfolio risk more when there is greater idiosyncratic risk to be diversified. The investors in our data show no reduction in NBD when such risks are high .

Furthermore, portfolio weights tend to diverge as random return realizations shift relative to asset values, T, and this random divergence is stronger when return correlations are low (i.e., idiosyncratic risk is high). Such divergence can create especially large nondiversification for portfolios that are already imbalanced, as arises under NBD, because random divergence in the weights in the few stocks that are most heavily held has a larger effect on portfolio volatility. In contrast, NPD adjusts portfolio weights to offset random divergence. These adverse effects for NBD are increasing with both T and N_i, with higher T allowing further random divergence from initial weights and higher N_i generating a lower correlation in returns. Our analysis of trading patterns shows that, in practice, investors do not reduce their use of NBD to mitigate these risks.

This test therefore provides no evidence that NBD investors are even thinking about risk reduction as a motivation for NBD. A caveat to this conclusion is that Sharpe ratios, which are based on mean and variance, are insufficient to describe the welfare of investors who care about skewness. Moreover, Sharpe ratios are not, in general, sufficient to describe welfare in a dynamic lifetime consumption/investment portfolio choice setting.

VI. 1/*N* Selling

Investors could employ a naïve selling diversification (NSD) heuristic when selling multiple stocks. However, if NBD is due to narrow framing, then NSD might be less likely, as, for example, when making selling decisions, investors are confronted with information on their portfolio. Previous research, including the well-known disposition effect (Barber and Odean (2013)) and rank effects (Hartzmark (2015)) suggests that investor selling behavior is related to the framing of the portfolio. By these heuristics, investors tend to pick out stocks from the distribution within their portfolio. Indeed, in our data the vast majority of sell days involve single stocks. We observe 1,108,080 sell days, among

[28] See Figure 5 in the Internet Appendix for this additional analysis.

[29] For example, in general, an asset that happens to be purchased on a day when few other assets are purchased or on a day when a greater number of funds are invested will tend to have a higher portfolio weight. An asset that happens to be bought on multiple days will also tend to have a higher portfolio weight.

which 84% involve a single-stock sale. The majority of sell trades are liquidating sales (62%) and the remainder partial sales. (Another category is short-selling, which is uncommon in our data, affecting only 7% of sell trades.)

A. 1/*N Selling on Multiple-Stock Sell Days*

Additional analysis in the Internet Appendix illustrates the proportion of selling proceeds from a randomly chosen stock, Stock A, on two-stock sell days. The peak at $1/N$ accounts for approximately 10% of sell days in the 49% to 51% interval. In total, only 6.2% of all multiple-stock sell days involve investors choosing NSD. Overall, NSD accounts for fewer than 1.5% of all sell days in the data.

B. Selling to Achieve 1/*N Portfolios*

Alternatively, investors might sell positions such that they achieve NPD. Again, this might be more likely than NPD when buying because selling stocks necessarily involves looking at the values of existing positions. We calculated the percentage of sell days that result in NPD by combinations of the number of existing positions in the portfolio at the start of the day, number of positions sold (either partially or fully liquidated), and number of resulting positions. Results show that NSD is a very rare outcome.[30]

VII. Do Investors Jointly Choose Investment Amounts and *N*?

A possible motivation for using the NBD heuristic is that it simplifies the decision problem. If so, we would expect that investors who use the NBD heuristic would implement it in a simple way. To investigate this, we analyze how investors choose the total amount to invest on a given day and the number of stocks bought (N). We find that their choice is driven by the desire to make the division calculation simpler, say, choosing to invest approximately £15,000 in three stocks or £10,000 in two stocks. This is consistent with NBD investors having a preference for simplicity.

In Figure 6, we plot the investment amount on multiple-stock buy days on which individuals split their purchases $1/N$, for different values of N. The striking feature of the plot is the heaping of investment amounts around simple round number multiples of N. Beginning at Panel A with $N = 2$, one observes heaping at values of £1,000, £2,000, £4,000, £10,000, and £20,000. By contrast, in Panel B, with $N = 3$, we see investment amounts dominated by numbers that are simple multiples of 3, £1,500, £3,000, £6,000,

[30] When we restrict the sample to sell days on which the investor can achieve NSD without requiring any purchases of stocks, we find that NSD is achieved on only 7.2% of sell days (see the Internet Appendix Table XIV). When we restrict the sample to days with both buy and sell trades on which the investor can achieve NSD by reallocating the total sales and total investment on the day without requiring any additional purchase or sale, we find that NSD is achieved on only 1.6% of sell days (see Table XV).

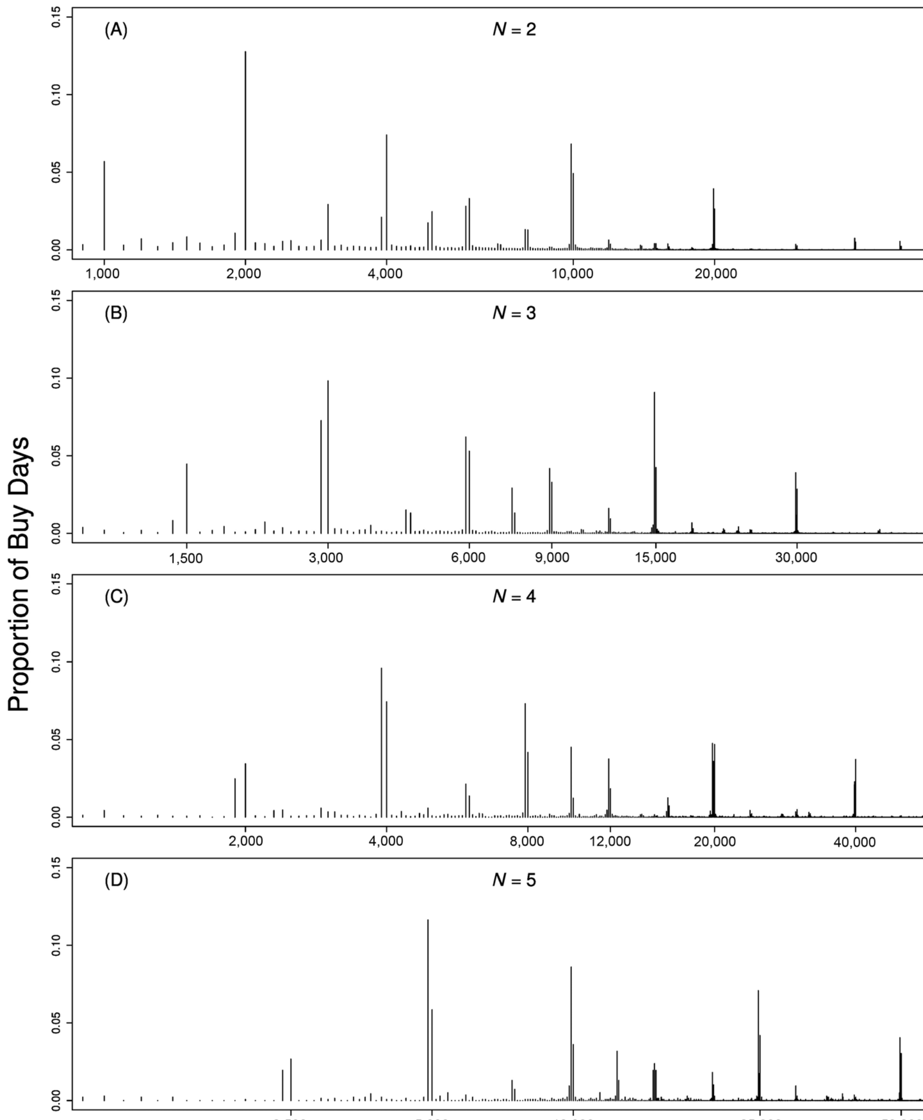


Figure 6. Distribution of total buy day investment (in £) by number of stocks bought. These panels illustrate the distribution of monies invested on the buy day (in pounds) for multiple-stock buy days involving two to five stocks. The sample is restricted to multiple-stock buy days. See Section I for details on the sample construction.

£9.000,£15,000, and £30,000. We further see this patterns when $N = 4$ and when $N = 5$. In Panel C, showing $N = 4$, we see heaping at £2,000, £4,000, £8,000, £10,000, £12,000, £20,000, and £40,000. In Panel D, showing $N = 5$, we see heaping at £2,500, £5,000, £10,000, £25,000, and £50,000. It is further striking that the modal investment bin is £2,000 when $N = 2$, £3,000 when $N = 3$, £4,000 when $N = 4$ and £5,000 when $N = 5$. One outcome of this behavior is that it gives rise to nearly identical distributions of investment amounts *per stock* across multiple-stock buy days involving two to five stocks. The distribution of investment amount per stock across five-stock buy days appears nearly-identical to that across two-stock buy days. Hence, the total amount invested on the buy day rises monotonically with the number of stocks bought, while the average amount invested in each stock remains constant. However, while the average amount invested in each stock remains constant with the number of stocks in the sample, this is not true at the investor level. Restricting to the sample of investors who make at least one multiple-stock buy trade and one single-stock buy trade within the sample period, only 2.3% of investors spend approximately the same amount on every trade (allowing a 10% bandwidth). Therefore, we can rule out the hypothesis that NBD arises due to a coincidence of investors always investing a constant amount per stock and sometimes buying multiple stocks on the same day.

An example of a compelling pattern pointing in this direction is the observation that investors tend to buy two not three stocks with a spend of £2,000, three not two stocks with a spend of £3,000; but then often two not three stocks with a spend of £4,000. This suggests that the total sum of money available for investment may be determining the number of stocks bought in a very non-monotonic way. An interpretation of these results is that investors are not only utilizing $1/N$ as a simple heuristic for allocating across N stocks, but that they are choosing a total investment amount to be allocated such that $1/N$ becomes a simple calculation. Unfortunately, we do not have experimental or natural sources of exogenous variation in either the total investment amount or N within or across investors.

VIII. Conclusion

We investigate how investors go about approaching a common financial choice: how to allocate invested funds across multiple stocks bought on the same day. Previous research on retirement savings fund allocation has proposed that investors use an $1/N$ heuristic, but has not disentangled whether individuals use $1/N$ as a rule for dividing the amount invested across funds, or as a target portfolio allocation. We disentangle these, showing that a common approach among investors is to simplify this problem by applying an $1/N$ heuristic to their buy day purchases, approximately equalizing the amount invested across several stocks purchased on a given day or across a mixture of stocks and funds, a behavior that we term NBD. In contrast, investors almost never invest approximately equal amounts in each stock, an outcome we term NPD.

The propensity to use the NBD heuristic decreases with investor experience and financial stakes, consistent with models of learning and attention allocation. Nevertheless, even when investor experience is high and financial stakes are large, the proportion of investments made with NBD is above 20%. Hence, NBD is only modestly sensitive to investor experience and economic stakes of investing. Investors may use the NBD heuristic because of an attraction to simplicity. Consistent with this notion, investors implement NBD in a simple way, appearing to choose both margins in order to make the $1/N$ task mathematically simple.

Use of the NBD heuristic results in the creation of portfolio shares for individual stocks that do not closely approach equalizing weights in the investor's overall portfolio (NPD). This behavior is consistent with narrow framing, whereby investors appear to approach the buy day task of allocating funds across stocks in isolation from their existing portfolio positions. In other words, they engage in *transactional* framing instead of *portfolio* framing.

Barberis and Huang (2001) argue that when an investor contemplates adding an incremental gamble to their portfolio, the investor narrowly frames on the increment rather than on the overall portfolio, and that this offers an explanation for otherwise puzzling phenomena, such as the rejection of small independent gambles and the stock market participation puzzle. We show that the tracks of such narrow framing are also evident in the incremental purchases of assets already in the portfolio. The resulting $1/N$ behavior makes it especially clear that investors are engaged in narrow framing on the incremental purchase. Even conditional on making an asset purchase, narrow framing on the transaction results in bad choices in the *relative weights* allocated to the different securities in the transaction. So, we document that narrow framing extends to incremental portfolios of gambles, not just single ones. This suggests that behavioral models of investment decisions should incorporate the effects of transactional framing by investors.

Our findings also have implications for the design of contribution-based savings plans, such as pension schemes. Such schemes typically ask investors to select buying weights across funds for continuing monthly *contributions*. This can have the adverse side effect of encouraging investors to use the NBD heuristic without integrated consideration of the current portfolio allocation. Our findings suggest that a different scheme may help investors achieve better diversified overall portfolios. Such a scheme could offer them a choice over the overall portfolio target. The scheme would then automatically provide the investor simultaneously with (i) a recommended portfolio reallocation, and (ii) monthly contribution weights consistent with this target. An interesting topic for future research is whether such a scheme improves investor diversification and portfolio performance.

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Supporting Information

Additional Supporting Information may be found in the online version of this article at the publisher's website:

Appendix S1: Internet Appendix.
Replication Code.