Learning From Luck: Evidence From Mutual Fund Managers

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Abstract

Confident managers may have been born this way to some extent, but they may also have enjoyed success, which led to them to become confident. This is especially interesting to consider when success is due to something beyond a manager's control, as is so often the case. In this paper, I use data on mutual fund managers to examine whether success breeds confidence. I find that the better a manager performs in a given year, the bolder the investments he tends to make in the following year. This is true whether boldness is measured based on the historical returns of a managers' holdings, or based on realized returns. In addition, I find that the more experience a manager possesses, the less his investment decisions tend to react to his recent performance. These results are plausibly consistent with a Bayesian framework in which managers learn about their own ability over time. Next, I investigate whether observably lucky success breeds confidence as well, which would be a clear departure from the Bayesian framework. I isolate lucky success in two ways. First, I estimate success that is due to market-timing and not stock-picking. Second, I estimate success that is due to the market shock that followed September 11th. In both cases, I find evidence that lucky managers indeed become more confident in themselves, apparently attributing some of their good fortune to their own ability.

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1 Introduction

In trying to explain across-firm variation in corporate practices, economic research has traditionally focused on firm-, industry- and market-level factors. While managers are directly responsible for choosing the actions of firms, much of the literature has, to some extent, assumed that different managers, when faced with the same circumstances, would make similar decisions. Recent work, however, has drawn attention to the importance of individual managers in determining firm behavior. Indeed, evidence has been found that a significant amount of the heterogeneity in the investment, financial, and organizational practices of firms can be explained by the presence of manager fix-effects (Bertrand and Schoar, 2003). Moreover, some of these differences in management style seem to be related to manager confidence. In particular, there is evidence that more confident managers have higher investment to cash flow sensitivity and are also more prone to make acquisitions, especially when internal funds are available (Malmendier and Tate, 2005, 2007).

This suggests that confidence may, to some extent, be a determinant of managerial boldness. It is then natural to ask: why are some managers more confident than others? This question has received little attention in the literature thus far. Of course, the answer can be broken down in terms of the familiar nature-nurture dichotomy. That is, confident managers may have been born confident, or they may have become confident over the course of their lives as a result of their experiences. In this paper the latter case will be investigated. In particular, it is plausible that managers who have enjoyed much success, may, as a result if that success, be those who are most confident in themselves. For example, a manager who has made several successful acquisitions may have a high propensity to make further acquisitions, whereas a manager who has made several poor acquisitions may be more hesitant going forward. If self-confidence reflects beliefs about unknown ability, such behavior could be in keeping with the canonical models in which workers learn about their talent over time (e.g. Holmstrom, 1982). In many instances, however, success is due to factors clearly outside of a manager's control, which can therefore be regarded as luck. To the extent that such

luck is observable, no updating about ability should result from it.

Thus, the questions that this paper seeks to address are two-fold. First, does success lead to increased confidence, which in turn leads to increased boldness in decision-making? Second, does this process solely reflect rational learning about ability, or does misattribution appear to take place? In particular, do observably lucky managers attribute some of their good fortune to themselves and subsequently become overconfident and overly-aggressive?

I examine these questions in the context of mutual fund managers. There are several advantages in choosing this domain. First, standard measures of success and boldness are available for fund managers. Moreover, these measures can be observed at fairly high frequencies, which is useful in examining of the dynamics of managerial confidence. In addition, the job of a mutual fund manager is narrowly defined relative to that of a firm manager, which reduces the number of confounding factors one must worry about in interpreting results. For example, if it were found that after a good year, firms tend to behave more boldly, it would be difficult to interpret this as relating to changing manager confidence per se. The size of most firms makes it unclear who is primarily responsible for particular actions. Moreover, the complexity of firms and the environments in which they operate, makes many other explanations plausible. For instance, capital market imperfections, or changing investment opportunities, could also lead firms to become more aggressive following periods of high performance. In the context of mutual funds, there are fewer such concerns. Of course, the disadvantage in studying fund managers is that doing so can only provide indirect evidence on the behavior of other types of managers. It is my hope, however, that this domain will provide a fairly clean laboratory for understanding the dynamics of managerial confidence more broadly.

I begin by examining whether success appears to breed confidence for mutual fund managers. I gather data on a sample of 1,723 managers from 1980-2004. Performance is measured annually as a manager's return relative to the market. Boldness, also measured annually, is represented by idiosyncratic risk. Using these measures, I find that high performance in

the previous year is indeed strongly associated with increased boldness in the current year. Moreover, inexperienced managers tend to react more to their previous year performance than do experienced managers. It should be noted that these results hold whether idiosyncratic risk is computed ex-post (from realized fund returns) or ex-ante (from the historical returns of the assets held in a manager's portfolio). The latter, holdings-based, approach helps assure that these findings are indeed driven by active changes in the nature of managers' portfolios, and not by more passive or mechanical forces such as under-rebalancing, or general patterns in asset returns and volatility.

The idiosyncratic risk of a portfolio can be increased in three ways: by holding a more concentrated portfolio, by holding more volatile stocks, or by holding more correlated stocks. Using the ex-ante (holdings-based) measure of idiosyncratic risk, I attempt to determine the relative importance of these three factors in explaining the observed increase in risk that follows a successful year. Interestingly, I find that the risk increase is due to an increase in the volatility and correlation of stocks in managers' portfolios. Somewhat surprisingly, however, portfolio concentration appears to *decrease* with performance.

The fact that success seems to increase manager confidence—especially for inexperienced managers—is perhaps not entirely surprising. Indeed, this is potentially consistent with a Bayesian framework in which managers learn about their ability over time by observing their performance. If this were the primary explanation for the above findings, they would still be of interest, as little evidence regarding employee learning of this kind has been uncovered thus far. I will argue, however, that these findings are even more interesting in that they seem to, at least partially, reflect a departure from a Bayesian framework. Specifically, I find evidence suggesting that not only does general success breeds confidence, but lucky success does so as well.

To capture the notion of luck, I take two approaches. First, I examine performance that is due primarily to the performance of the market as a whole. To the extent that a manager achieves high relative returns because he has a high loading on the market factor when the

market does well, he should not directly learn anything about his stock-picking ability. I find evidence, however, that managers strongly react to relative returns that are due to such market-timing. It is, of course, possible that stock-picking ability and market-timing ability are correlated, in which case managers may indirectly learn about stock-picking ability from market-timing performance. Still, I argue that such indirect updating should be of lesser magnitude than direct updating based a stock-picking performance measure. In fact, the opposite appears to be true. I find that managers react more strongly to market-timing performance than they do to stock-picking performance.

The second approach I take in examining lucky performance is less general, but perhaps more clean. I focus on differences in performance that can be attributed to the market shock which followed the terrorist attacks of September 11, 2001. I assume that the attacks were uniformly unforeseen by mutual fund managers. As a result, managers whose portfolios performed relatively well on September 11, perhaps because they had little invested in airline stocks and/or much invested in defense stocks, can be considered to have had lucky success. I find that managers who performed well in 2001 because they were lucky in this way indeed took on bolder positions in 2002, apparently attributing some of their lucky performance to themselves.

This paper relates to several strands of the literature. As mentioned earlier, Bertrand and Schoar (2003)find evidence of differences in style across managers, and Malmendier and Tate (2005, 2007) link some of these style differences to manager confidence. While those papers view manager style and confidence as fixed attributes, however, this paper explores their dynamics by studying how they relate to managers' past experiences.

Because of the dynamic approach taken here, and also because I study mutual fund managers rather than firm managers, this paper is also related to Gervais and Odean (2001) and DANIEL, Hirshleifer, and Subrahmanyam (1998), both of which model investor overconfidence in a dynamic framework. In Gervais and Odean's model, investors are not initially overconfident, but rather "learn to be overconfident" over time due to self-serving attribu-

tion. That is, investors tend to attribute success to themselves, but not failure. Evidence that mutual fund managers suffer from such self-serving biases has recently been found by Choi and Lou. They find that, holding performance constant, managers with more volatile past monthly returns (and therefore more extreme highs and lows), tend to increase their trading activity, as measured by active share and turnover ratio, more than those with less volatile returns. Here I do not focus on asymmetries between learning from success versus failure–although I do touch on these issues; rather, my main interest is in investigating the extent to which managers learn from luck.

In this sense, this paper also relates to Bertrand and Mullainathan's (2001) work on CEO pay. They find evidence that CEOs are rewarded for lucky performance, particularly when corporate governance is poor, which is interpreted as a form of cream skimming. In the context this paper, an interesting question would be whether those CEOs that Bertrand and Mullainathan identify as observably lucky, would agree in their own minds that they are being overpaid. Indeed it is plausible that those CEOs would in fact believe that their pay was justified, and that the good performance of their firms was due to themselves, despite evidence to the contrary. To the extent that CEOs think in this way, they may become overconfident and begin to make unduly bold decisions.

Finally, this paper also relates to the literature on career concerns begun by Holmstrom (1982) and applied empirically to fund managers by Chevalier and Ellison (1999). Chevalier and Ellison find that a manager's probability of retaining or improving his current position is increasing in the risk-adjusted return he achieves, and that managerial termination is more performance-sensitive for younger managers. Moreover, the probability of termination decreases steeply with performance when managers have negative excess returns, but it is fairly insensitive to differences at positive excess return levels. Consistent with these incentives, Chevalier and Ellison find that inexperienced managers tend to avoid idiosyncratic risk and also tend to hold more conventional portfolios. In contrast, I find that while inexperienced managers may generally take on less idiosyncratic risk, they alter their risk more in response

to past performance than experienced managers do. Although Chevalier and Ellison do not examine such within-manager changes in risk, this too could be attributed to a form of career concerns; After a good year, a manager may feel that he has built up reputational capital, and therefore can afford to make bolder investments. I will provide some evidence, however, suggesting that this is not the case.

The rest of the paper is organized as follows. Section 2 describes the data. Section 3 investigates whether general success breeds confidence. Section 4 then looks at the effects of lucky success. Section 5 explores alternative explanations for the results of sections 3 and 4, and finally section 6 Concludes.

2 Data

The data used in this study are collected from several sources. As described above, fund holdings data are used to examine year-to-year changes in portfolio characteristics such as portfolio concentration, sector weights, and historical idiosyncratic risk (this will be referred to also as "ex-ante" risk). The holdings data used in this paper are obtained from the Thomson Financial Network (TFN) S12 database, which in turn is compiled primarily from the SEC N-30D filings. These filings were required quarterly prior to 1985 and have been required semi-annually subsequently. TFN also uses prospectuses and contacts management companies to increase update frequency. Thus, fund portfolios are generally observed 2-4 times per year, usually at the end of a quarter, but often at other dates as well. The S12 holdings database covers almost all historical domestic mutual funds that have been in existence since 1980 and is largely free of survivor-bias as a result. For each stock held by a fund on a given report date, the S12 database provides the number of shares held in addition to the price per share. Unfortunately, problems have been reported with these price data, so I choose not to use them in this study. Instead, I obtain individual stock price data from The Center for Research in Security Prices (CRSP). Specifically, I use the CRSP historical names

file to link stocks in the TFN data to the CRSP permanent identifier variable, *PERMNO*. Stocks are linked primarily by CUSIP, but when this fails, the ticker-exchange combination is used. This process binds virtually all of the holdings in the TFN data to a CRSP *PERMNO*. Using this identifier, I am then able to link each stock in a portfolio to the price per share (on the S12 report date) from the CRSP daily stock file. These prices are then used to compute portfolio weights.

In order to examine the historical riskiness of a portfolio, I also require historical return data for the individual stocks in the portfolios. These data are also obtained from the CRSP monthly stock file and, as before, stocks are linked by *PERMNO*. These historical monthly stock returns are then used to generate historical monthly portfolio returns, using the portfolio weights computed above. In some cases, the historical returns for a stock are not available before a certain date, usually because the company had not yet made its initial public offering. To account for this, portfolio weights are recalculated, excluding the missing stock for the months it is missing.

While TFN has excellent fund holdings data, it provides little information regarding fund characteristics (such as fees, expenses, and date of first offer) and it has no data on realized fund returns. For this I use the CRSP mutual fund database, the source of which is primarily Standard and Poor's Fund Services, now owned by Morningstar. Funds in TFN and CRSP are linked using the MFLINKS file, which has been developed for this purpose by Russ Wermers in conjunction with Wharton Research Data Services. In this process, funds in both databases are bound to a Wharton Financial Institution Center Number (*WFICN*), which serves as a common identifying variable. It is important to note that a fund in the TFN data can correspond to multiple funds in the CRSP data. This is due to the widespread presence of multi-class funds, which offer investors different types of shares for the same underlying investment portfolio. Classes differ in terms of fees, expenses, and shareholder services; as a result they also differ in terms of net returns. Each class of a multi-class fund is considered a separate entity in CRSP, but all map to the the same holdings in TFN. This

paper investigates the dynamics of portfolio decisions, therefore a fund portfolio is a more logical unit of observation in this context than a fund class. In general, to collapse multiple classes down to one fund/portfolio, I compute the variable of interest separately for each class and then take the mean. For example, to compute the annual gross return for a multi-class fund, I take the annual net return for each class and gross it up by the class's expense ratio for the year. In principle, the gross return for all classes should be the same, as they all share the same underlying portfolio. In practice, however, following this procedure leaves a small amount of within-class variation. To resolve this, I average across classes. Similarly, to compute the idiosyncratic risk of a multi-class fund, I use the monthly net returns for each class to compute risk separately and then average across classes.

Because this paper seeks to examine the dynamics of manager confidence, it is also necessary to ascertain the identities of the fund managers. This is important as it helps assure that year-to-year changes in boldness do not reflect changes in management. In addition, knowing the identities of the fund managers allows me to test whether the effects that I find vary with manager characteristics, particularly experience. Manager data are obtained from Morningstar Inc. via the *Principia* CD-ROMs, which are released monthly. Each monthly CD contains a file with a complete management history for all funds active at the time of release. I collect data from CDs released on December 31 of each year from 1996-2004. For each record on each CD, I attempt to bind a *WFICN* both to identify multi-class funds, and to allow the Morningstar Data to be merged with the TFN/CRSP data. The process by which I link records to *WFICN*s is described in detail in the next paragraph. In principle, different classes of a multi-class fund should have identical management histories on a given CD. In the rare cases in which this does not hold, I merge the histories together. Specifically, a history initially consists of several observations of the form *MstarFundCode-ManagerName-StartDate-StopDate*. The *MstarFundCode* will differ across classes of the same fund, so I replace it with *WFICN* and then keep all distinct observations. Thus if classes have identical fund histories, only one set will be kept, but if there are conflicts, additional

observations will result. For each *WFICN* I then keep the most recent management history available. Therefore, when management histories conflict across CDs, precedent is given to the most recent release; this is done to account for data corrections. I use multiple CDs, as opposed to only the most recent, in order to avoid inducing survivor-bias. It should be noted, however, that at this point there is some survivor bias induced, as I only have Morningstar CDs going back to December 31, 1996. As a result, if a fund ceased to exist prior to this date, I do not currently observe its management history. An additional difficulty is that Morningstar does not assign managers unique identification codes. When a unique identifier is needed, I am thus force to use my own manager code, which is generated from the $ManagerName$ variable. Fortunately $ManagerName$ usually includes middle name or initial, and is therefore reasonably unique. In addition to fund management histories, the Morningstar CDs contain biographical information about many managers. This includes the managers' educational background as well as their work history. I eventually use these data to construct a measure of management experience.

Linking Morningstar observations to *WFICN*s is somewhat difficult. Morningstar primarily identifies mutual funds by their ticker symbol until 1999, when it starts to include fund cusips as well. Unfortunately, CRSP only has ticker symbols for funds listed on NASDAQ, and TFN has ticker symbols for all exchanges, but only starting in 1999. CRSP does, however, have fund cusips for all years. Therefore I adopt the following procedure in trying to bind a *WFICN* to a fund in the Morningstar data. First, I try to link by cusip, which is only possible after 1999. Second, I try to link by the ticker variable in CRSP, which is only possible for NASDAQ listed funds. Third, I try to link by the ticker symbol in TNF, which is only possible after 1999. At this point a observation is very likely to have been linked if it came from a CD released during 1999 or after, but prior to 1999 only NASDAQ listed funds will have been matched. For each observation in a Morningstar CD, however, I have several pieces of identifying information which are largely internally consistent (that is, they remain the same across CDs for a given fund). These 1) The (internal) Morningstar fund

code, *MstarFundCode*, which is used in the back-end database files on the CDs, 2) the full fund name, 3) the fund ticker, and 4) the fund cusip, which again is only available on CDs starting in 1999. If a observation is not yet bound to a *WFICN,* but it has 2 or more of the above identifiers in common with another observation (from another CD) that has been linked, and all linked observations with which the observation has common identifiers have the same *WFICN*, then the observation is assigned that *WFICN*. This process successfully binds a *WFICN* to most observations on the Morningstar CDs, but it should be noted that for some funds, in particular those that ceased to exist prior to 1999 and those that are not listed on NASDAQ, it will not be possible to assign a *WFICN* without further data. This, however, does appear to be a major concern. Before imposing restrictions (explained below), there are 50,169 fund-year observations in CRSP for this time period. Of these 45,190, or approximately 90%, are match to funds in Morningstar.

I wish to limit the data to actively managed domestic equity funds having a single manager; therefore, I exclude funds that are characterized as index funds or enhanced index funds by Morningstar. In addition, I keep only funds with an investment objective of aggressive growth, growth, or growth and income, according to TFN. This eliminates international, municipal bond, bond & preferred, balanced, metal, and unclassified funds. After these restrictions, I am left with data on 1,723 managers over the the period from 1980-2004. Table 1 shows the number of funds observed each year. As is apparent, there was tremendous growth in the mutual fund industry over this period, with a six fold increase in the number of funds in existence. In Table 1, funds are also broken down into single-manager funds, multiple-manager funds and funds for which no manager was found in the Morningstar data. A fund is considered to have had multiple managers in a given year if 1) the manager is listed as "Management Team" 2) there are multiple names listed as managers, or 3) the manager changed mid-year. In a given year, it appears that between 35 and 60 percent of funds have single manager for the entire year. Because I am interested in studying how the styles of individual managers evolve over time, I keep only these single manager observations. Fi-

nally, since the dependent variable in many of my regression will be across-year changes in boldness, a fund-year will often be excluded if the fund did not have the same manager for the entire previous year as well.

[Table 1 about here.]

3 Does General Success Breed Confidence?

3.1 The Effect of Past Performance on Risk-Taking

I first examine whether good performance leads to increased confidence, which in turn leads to increases boldness. I analyze this relationship at a yearly frequency, because at higher frequencies "window dressing" motives may introduce a confounding factor, especially in the later months of the year (Chevalier and Ellison, 1997). For example, toward the end of a good year, a manager may reduce the riskiness of his portfolio to lock in gains. Conversely, toward the end of a bad year, a manager may increase the riskiness of his portfolio to try to make up for losses. In either case, one would not want to interpret these changes in risk-taking behavior as reflecting changes in confidence. My basic empirical approach is thus simply to estimate equations of the form,

$$\Delta Boldness_{i,t} = \delta_0 + \delta_1 Performance_{i,t-1} + \mathbf{x_{i,t}}\gamma + u_{i,t},$$

where i indexes managers, t indexes years, and $\mathbf{x_{i,t}}$ is a vector of controls. To implement this approach, $Performance$ and $Boldness$ must first be defined.

For the purpose of this paper, I want to measure fund performance in roughly the same way that fund managers do, because as long as a manager considers his own performance to be good, it might increase his confidence and boldness. Therefore, I choose to focus primarily

on relative returns. Specifically, I define performance as,

$$Performance_{i,t} = r_{i,t} - r_{mkt,t},$$

where $r_{i,t}$ is the annual gross return (net return plus expense ratio) of manager i in year t and $r_{mkt,t}$ is the return on the market. Alternatively, I could have followed the common practice of risk-adjusting performance by using some form of Jensen's *alpha*, or I could have used benchmarks based on the characteristics of the manager's holdings, as in DANIEL, Grinblatt, TITMAN, and Wermers (1997). While such methods may indeed provide better measures of manager skill, it seems implausible that managers evaluate their own performance in such ways. Indeed, fund managers interviewed in Daniel et al., did not like the characteristics-based benchmarking methodology proposed in that paper, as it gave a manager no credit for picking stocks with characteristics that generally performed well that year. Specifically, to evaluate a manager, Daniel et al. form passive portfolios with characteristics (size, book-to-market, momentum) similar to those of the manager's portfolio. The manager then only receives credit for stock picking ability to the extent that he beats the characteristic-matched passive portfolio. The negative reaction to this methodology among managers would seem to support the notion that they generally prefer to evaluate their performance relative to a fixed benchmark index i.e. on that does not change in response to changes in their portfolio. It should be noted that performance relative to a fixed index is also frequently used in determining manager compensation, which likely further serves to encourage managers to think of their performance in these terms.[1]

My primary measure of *Boldness* is idiosyncratic risk, which is computed both ex-post (from realized fund returns) and ex-ante (from the historical returns of the assets held in a manager's portfolio). Summary statistics are shown in Table 2. In the following subsections, I will describe these variables in more detail, and discuss results.

[1]For example, according to the Fidelity Magellan fund's Statement of Additional Information, a manager's bonus is determined by performance relative to the S&P 500 Index and also performance relative to a peer group (funds in the 6 Morningstar large- and mid-cap categories).

[Table 2 about here.]

3.1.1 Ex-Post Measures of Risk

Ex-post idiosyncratic risk, $\sigma_{i,t}^{post}$, is defined as the standard deviation of the residual from the CAPM regression. For each manager i in year t, there are 12 monthly observations of fund returns, $\{r_{i,m,t}\}_{m=1...12}$, where the subscript m indexes months. I use these observations to estimate CAPM equations for each fund-year:

$$r_{i,m,t}^{e} = \alpha_{i,t} + \beta_{i,t}^{post}(r_{mkt,m,t}^{e}) + \varepsilon_{i,m,t}^{post}; \quad m = 1..12$$

The superscript, e, indicates that the return is in excess of the risk free rate, which here is represented by the one-month Treasury bill rate provided by Ibbotson Associates via The Fama and French Data Library. While 12 observations per regression is admittedly low, I choose an annual frequency to allow for yearly changes in risk-taking. In addition, it seems plausible that annual risk and performance are most salient to managers. Having estimated the CAPM parameters, I compute ex-post idiosyncratic risk as,

$$\sigma_{i,t}^{post} = SD(\{\widehat{\varepsilon}_{i,m,t}^{post}\}_{m=1..12}) = SD(\{r_{i,m,t}^{e} - \widehat{\beta}_{i,t}^{post} r_{mkt,m,t}^{e}\}_{m=1..12}).$$

Finally, because I am examining changes in boldness across years, I subtract the risk level of the previous year to obtain $\Delta\sigma_{i,t}^{post}$.

As a robustness check, I also occasionally use tracking error as an additional measure of risk. Tracking error is defined as the standard deviation of the difference between the fund return and the market return. That is,

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$$\begin{aligned} te_{i,t}^{post} &= SD(\{r_{i,m,t} - r_{mkt,m,t}\}_{m=1..12}) \\ &= \sqrt{VAR(\{r_{i,m,t}^{e} - \widehat{\beta}_{i,t}^{post} r_{mkt,m,t}^{e}\}_{m=1..12}) + (\widehat{\beta}_{i,t}^{post} - 1)^2 VAR(\{r_{mkt,m,t}^{e}\}_{m=1..12})}. \end{aligned}$$

This is a rawer measure of risk in that it is β-free. Thus, using tracking error assures that results are not somehow driven by issues in estimating β from small samples. Note that tracking error would be equivalent to idiosyncratic risk if β were unity. Otherwise, tracking error can be decomposed into two parts, as shown in the second equality. The first term represents idiosyncratic risk, and the second term represents additional risk arising from deviations of β from unity; these can be thought of as implicit bets with or against the market.

Table 3 shows baseline results obtained using these ex-post measures of risk. In the first column, I begin by estimating the simple univariate regression of $\Delta\sigma_{i,t}^{post}$ on $r_{i,t-1} - r_{mkt,t-1}$. In this univariate regression, the coefficient on lagged relative return is estimated to be approximately 0.032 and is highly statistically significant. To interpret this magnitude, consider a manager who goes from matching the market for the year to beating it by 10%. This would imply that monthly σ would increase by .32%, and that annualized σ would increase by 1.12%. The median manager in this sample has an annualized σ of 6.92%, so for him this would represent a percentage increase of 16.2. Thus, the magnitude of this relationship is economically significant, especially considering the yearly frequency of analysis.

There are several possible concerns with this univariate regression. One possibility is that there may be mean reversion in risk-taking. This could arise due to conscious effort by managers to achieve a target volatility, or it could more literally represent reversion toward the mean. Note, however, that mean reversion alone could not explain the above result. Indeed, mean reversion would predict that high relative returns in the previous year would be associated with decreased risk in the current year, as high relative returns would likely be generated by high risk. Nonetheless, it may be important to control for mean reversion, as this could play an major role in determining year-to-year changes in σ. To account for mean reversion, the previous level of risk is included as a control in the regression. The results, shown in the second column Table 3, suggests mean reversion is indeed very strongly present.

After a year of high (low) volatility, managers' portfolios tend to become less (more) volatile, all else equal. Controlling for mean reversion, however, does not diminish the estimated effect of lagged performance. In fact, this is actually strengthened, both in terms of magnitude and statistical significance.

In columns three and four, year fixed effects and manager fixed effects are added to the specification. These fixed effects are included to allow for years/managers which generally tend to be associated with increases or decreases in risk. Neither set of fixed effects change the primary qualitative results. Finally, columns 5-8 replicate columns 1-4, using ex-post tracking error as the measure of boldness. Although the strength of the effect appears to be diminished under this specification, the qualitative results again remain the unaltered.

[Table 3 about here.]

One other possible concern is that capital inflows may be playing a role in determining idiosyncratic risk. Chevalier and Ellison (1997) show that flow is positively related to lagged relative returns, especially for younger funds. In light of this, controlling for flows may be important in the context of this paper, as flows are likely correlated with the lagged performance, which is the independent variable of primary interest. If anything, however, one would expect the estimated effect of lagged performance to be strengthened by the inclusion of flows in the regression. This is because after a good year, a fund may tend to get more capital inflows, but to invest these inflows the manager may have to put them into more liquid stocks, which tend also to be less risky. Somewhat surprisingly, however, preliminary regressions suggest flows do not appear to be a significant determinant of risk-changes.

3.1.2 Ex-Ante Measures of Risk

The fact that $\sigma_{i,t}^{post}$ is computed from realized fund returns has both advantages and disadvantage. Using fund returns takes into account changes in the fund portfolio over the year, as well as changes in the riskiness of assets over time. On the other hand, changes in

realized idiosyncratic risk could be driven by factors unrelated to confidence. For example, it may be the case that assets that perform well generally become more volatile. Another possibility is that under-rebalancing could lead to similar results. Specifically, high relative returns in year $t-1$ are likely associated with risky assets paying off. Failure to rebalance would then lead these assets to have increased portfolio weight, which in turn would lead to increased idiosyncratic risk realized in year t. To assure that such mechanical/passive forces are not driving the results found in the previous sub-section, I use ex-ante idiosyncratic risk as an additional measure of boldness. Ex-ante idiosyncratic risk, $\sigma_{i,t}^{ante}$, is defined similarly to ex-post idiosyncratic risk except that historical asset returns are used rather than realized fund returns. Thus, an observation in which $\Delta\sigma_{i,t}^{ante}$ is positive indicates that manager i has shifted to a portfolio that is historically riskier than the one he held in year $t-1$. To compute $\sigma_{i,t}^{ante}$, I take the first observed portfolio of manager i in year t to be representative for that year (as long as that portfolio is from before July). [2] Then, holding portfolio weights fixed, I compute the historical idiosyncratic risk of the portfolio, based on 3 years of previous returns. Specifically, allow the subscript $i(t)$ to indicate that the subscripted variable represents manager i's portfolio for year t, so that $r_{i(t),m,\tau}$ is the return of manager i's year t portfolio in month m of year τ. Then, for each manager i and year t, I estimate the following two equations:

$$\begin{aligned} r^e_{i(t),m,\tau} &= \alpha_{i(t)} + \beta^{ante}_{i(t)}(r^e_{mkt,m,\tau}) + \varepsilon^{ante}_{i(t),m,\tau} \\ r^e_{i(t-1),,m,\tau} &= \alpha_{i(t-1)} + \beta^{ante}_{i(t-1)}(r^e_{mkt,m,\tau}) + \varepsilon^{ante}_{i(t-1),m,\tau} \end{aligned}$$

Where $m = 1...12$ and $\tau = t-5...t-2$. The residuals from these regressions are then use to obtain,

$$\Delta\sigma^{ante}_{i,t} = SD(\{\widehat{\varepsilon}^{ante}_{i(t),m,\tau}\}_{\tau=t-5...t-2;m=1..12}) - SD(\{\widehat{\varepsilon}^{ante}_{i(t-1),m,\tau}\}_{\tau=t-5...t-2;m=1..12}).$$

[2] Because some funds do not report holdings in the first half of the year for two consecutive years, the number of observations in the sample is decreased slightly by the use of the holdings-based dependent variables

$\Delta te_{i,t}^{ante}$ is defined analogously. The important point here is that when $\Delta\sigma_{i,t}^{ante}$ is being computed, the same estimation period is used to estimate the historical riskiness of the year t portfolio as the year $t-1$ portfolio; in both cases, the estimation period is years $t-5$ to $t-2$. This methodology is illustrated by the timeline shown in Figure 1. If instead the immediately preceding three years were used for both portfolios, this would mean that the estimation window would shift. As a result, $\Delta\sigma_{i,t}^{ante}$ would partially reflect changes in the *measured* riskiness of the portfolio. In contrast, I would like $\Delta\sigma_{i,t}^{ante}$ to represent only changes in risk that arise from changes in the actual holdings. Put another way, if the estimation period were allowed to shift, $\Delta\sigma_{i,t}^{ante}$ would likely be nonzero, even if the manager held a portfolio with the same weights on the same stocks in both years.

[Figure 1 about here.]

In Table 4 , I repeat the baseline regressions of Table 3 , using the analogous ex-ante measures of boldness. In general, the estimated effect of lagged performance appears to be somewhat diminished by the use of ex-ante measures. In particular, the magnitude of the estimated effect in Table 4 is roughly a one-third of that estimated in Table 3 . Nonetheless, the basic qualitative results remain unchanged. In all specifications, $Boldness_{i,t}^{ante}$ is found to be strongly mean reverting, and the relationship between $\Delta Boldness_{i,t}^{ante}$ and $Performance_{i,t-1}$ is estimated to be positive and economically/statistically significant. Thus, after a good year, it appears that managers indeed choose portfolios that have historically been riskier.

[Table 4 about here.]

3.2 Decomposition of Risk

Because the ex-ante measures of risk are holdings-based, they can be decomposed as in Calvet, Campbell, and Sodini (2007). Suppose that all stocks in manager i's portfolio were to have CAPM residuals with the same variance, $\bar{\sigma}_{i,t}^2$, and the same pair-wise correlation,

$\overline{\rho}_{i,t}$, with one another. In this special case, idiosyncratic risk would satisfy,

$$\sigma_{i,t} = \bar{\sigma}_{i,t} \left[C_{i,t} + (1 - C_{i,t}) \bar{\rho}_{i,t} \right]^{\frac{1}{2}},$$

where $C_{i,t} = \sum_{n=1}^{N_i} \omega_{n,i,t}^2$, or the sum of squared portfolio weights, which can be interpreted as a measure of portfolio concentration between zero and one. According to this identity $\sigma_{i,t}$ is increasing in $\bar{\sigma}_{i,t}$, $C_{i,t}$, and $\overline{\rho}_{i,t}$. This makes it clear that observed changes in idiosyncratic risk may be due to (1) changes in the volatility of assets, (2) changes in the concentration of the portfolio, or (3) changes in the correlation of assets. Because it is not actually the case that all stocks in a manager's portfolio have the same residual variance and correlation, the above identity can only be used as an approximation. I do the natural thing and approximate $\bar{\sigma}_{i,t}^2$ and $\overline{\rho}_{i,t}$ using equal-weighted means. An untabulated regression of actual ex-ante idiosyncratic risk on predicted ex-ante idiosyncratic risk (as predicted by the above equation along with the approximations), produces a coefficient of 1.05, and an R-squared of 0.96. Thus, the approximation suggested by the above identity fits the data remarkably well.

In Table 5, the baseline regressions are repeated yet again, but now with $\Delta C_{i,t}$, $\Delta \bar{\sigma}_{i,t}$, and $\Delta \overline{\rho}_{i,t}$ as the dependent variables. Note that if a manager executed zero trades between year $t-1$ and year t, and thus held the same numbers of shares of the same stocks, $\Delta \bar{\sigma}_{i,t}$ and $\Delta \overline{\rho}_{i,t}$ would be exactly zero. This is because they are equal-weighted means, so changes in portfolio weights (e.g. due to price changes) are irrelevant. In other words, only changes in the *identities* of the stocks in the portfolio matter for $\Delta \bar{\sigma}_{i,t}$ and $\Delta \overline{\rho}_{i,t}$. In contrast, $\Delta C_{i,t}$ would likely be non-zero in the above scenario because price changes would lead to changes the portfolio weights, which in turn would lead to a passive change in $C_{i,t}$, the the sum of squared weights. To isolate *active* changes in weights, I form an additional dependent variable, $\Delta \widetilde{C}_{i,t}$, which uses year t portfolio weights calculated at year $t-1$ prices.

In the first four columns of Table 5 , I examine how portfolio concentration responds to lagged performance. One might have expected that after a good year, a manager with

increased confidence would hold a more concentrated portfolio. Somewhat surprisingly, the opposite appears to be the case. This holds both for overall changes in concentration as well as active changes. From Table 4 , however, we know that total ex-ante risk is positively related to lagged performance. Therefore, to the extent that the above approximation holds, a decrease in concentration must be offset by an increase in the volatility and/or correlation of assets. Indeed, this is confirmed by columns 5-8, which show that $r_{i,t-1} - r_{mkt,t-1}$ has a strong positive effect of on both $\Delta\overline{\sigma}_{i,t}$ and $\Delta\overline{\rho}_{i,t}$. Unfortunately, because the role of confidence in the manager's portfolio choice problem has not been explicitly modeled here, there is no theoretical basis upon which to judge whether these results are consistent with increased manager confidence following high performance. One intuitive interpretation, however, is that after a good year, funds tend to get capital inflows, which are largely invested in new stocks, but due to increased manager confidence these stocks tend to be more volatile and/or in the same sector as stocks in the existing portfolio. On the whole, this leads to an increase in the riskiness of the manager's portfolio.

[Table 5 about here.]

3.3 Experience As a Mitigating Factor

Next, I examine whether inexperienced managers appear to react to lagged performance more than experienced managers. This would be consistent with a Bayesian-type framework in which managers learn about their talent over time; experienced managers should not update their beliefs as much based on an addition year of performance data, since they have observed their own performance for many years already. To investigate this, I create an experience variable from the Morningstar database. For each manager, Morningstar provides a complete employment history. I use the year of their first reported mutual fund management job to create the variable

$$Experience_{i,t} = t - FirstYear_i.$$

I then interact experience with lagged relative return. Results are show In Table 6. In the first column I use the change in ex-post risk as the dependent variable. In the second column, the change in ex-ante risk is used. Finally, in the third and fourth columns, I use the change in (equal-weighted) average ex-ante risk and correlation, which were found to respond positively to lagged performance in the previous section. In all four specifications, the coefficient on the interaction term is estimated to be negative and statistically significant at the 5% level. This is consistent with the notion that experience might diminish the effect of performance on risk-taking. To give a sense of the magnitudes, the results of the first column imply that a manager with 18 years of experience will be approximately half as sensitive to lagged performance as a manager with no experience. Similarly, the estimates in the second column imply a manager with 20 years of experience will be half as sensitive.

[Table 6 about here.]

4 Does Lucky Success Breed Confidence?

In Section 3, evidence was presented that success breeds confidence, especially among inexperienced managers. As was noted before, these findings alone may not be entirely surprising. Indeed, if managers are uncertain of their own ability, a Bayesian-type learning model may predict similar results. Even if rational learning were the primary explanation, evidence of employee learning of this kind would still be of interest. In this section, however, I examine the extent to which the findings presented in Section 3 appear to represent a departure from the Bayesian framework. In particular, I investigate whether success breeds confidence, even when it is observably lucky. It is clear that the standard rational model would not predict this type of behavior.

To investigate whether managers learn from luck I take two approaches. First, I examine performance that is due primarily to the performance of the market as a whole. To the extent that a manager achieves high relative returns because he has a high loading on the

market factor and the market does well, he should not directly learn anything about his stock-picking ability. Second, I examine performance that is due to the terrorist attacks of September 11th, which was an unforeseen shock that had a differential impact across mutual funds. To the extent that some managers' portfolios fared better than others', this too could be considered luck, and no learning should have resulted from it.

4.1 Stock-Picking vs. Market-Timing Performance

To isolate relative returns that are due to market-timing, I create a monthly benchmark return, based on the CAPM,

$$r_{i,m.t}^{capm} = r_{f,m,t} + \widehat{\beta}_{i,t}^{post}(r_{mkt,m,t} - r_{f,m,t}).$$

$r_{i,m,t}^{capm}$ represents the expected return for manager i, in month m, of year t, given his loading on the market factor for the year, $\widehat{\beta}_{i,t}^{post}$, and the realized excess return of the market, $r_{mkt,m,t} - r_{f,m,t}$. From these monthly benchmark returns I the compute the cumulative benchmark return for the year, $r_{i,t}^{capm}$ with compounding. I use this to decompose annual relative returns as,

$$r_{i,t} - r_{mkt,t} = \alpha_{i,t}^{capm} + (r_{i,t}^{capm} - r_{mkt,t}).$$

Therefore, $r_{i,t}^{capm} - r_{mkt,t}$ is the amount by which the manager *should* have beaten the market, given his *beta* and the realization of the market (call this market-timing performance), and $\alpha_{i,t}^{capm}$ is the amount in excess of this by which he *actually* beat the market (call this stock-picking performance). Note, the *alpha* obtained in this way should be nearly the same as the annualized *alpha* from the monthly CAPM regression, and it would be exactly the same if $r_{i,t}^{capm}$ were computed without compounding.

To make this more general, I also include additional factors. With these extra factors, it is then possible to isolate relative returns that are due to broader factor-timing. Specifically,

I create a four factor monthly benchmark return,

$$\widehat{r}^{ff}_{i,m,t} = r_{f,m,t} + \widehat{\beta}^{post}_{mktrf,i,t} MKTRF_{m,t} + \widehat{\beta}^{post}_{smb,i,t} SMB_{m,t} + \widehat{\beta}^{post}_{hml,i,t} HML_{m,t} + \widehat{\beta}^{post}_{umd,i,t} UMD_{m,t}$$

where $MKTRF$ is the market factor, SMB is the size factor, HML is the book-to-market factor, and UMD is the momentum factor[3]. Using this monthly benchmark, I then calculate $\alpha^{ff}_{i,t}$ analogously to $\alpha^{capm}_{i,t}$.

With these decompositions of relative returns, I can then investigate whether a manager's confidence in his stock-picking ability, as expressed by his choice of idiosyncratic risk, is sensitive to the portion of relative returns attributable to factor-timing. This is done in Table 7. In the first two columns I use the benchmark based on the single factor market model, and in the second two column I use the benchmark based on the four-factor model. Regardless of whether boldness is measured ex-post or ex-ante, the factor-timing component of relative returns, $\widehat{r}^{bench}_{i,t-1} - r_{mkt,t-1}$, is estimated to have a positive coefficient. Moreover, the point estimates suggest that idiosyncratic risk is actually more sensitive to the factor-timing component than the stock-picking component. This is confirmed by Wald tests, which strongly reject the null that the coefficients are equivalent in favor of the alternative that the coefficient on factor-timing performance is larger than that on the stock-picking performance in columns 2-4. In the first column the p-value of the alternative is 0.0628; thus the null is nearly rejected at the 5% significance level there as well.

[Table 7 about here.]

Taken at face value, these result would seem to suggest that managers are not strict Bayesians who learn rationally about their ability over time. Rather, it appears that success of any kind, tends to make managers more confident in themselves and more bold in their investments. Of course, one could argue that stock-picking ability and market-timing ability

[3]Factors are obtained from the Fama-French Data Library

may be correlated in the population. In this case, it would be rational for a manager to update his belief about his stock-picking ability based on his market-timing performance. Still, it is implausible that managers would update *more* based on factor-timing performance than they would based on stock-picking performance. This is especially true because factor-timing performance in a given year is likely a very noisy indicator of factor-timing ability (and therefore an even more noisy indicator of stock-picking ability). Indeed, market-timing performance reflects only a single observation of the realization of the market. In contrast, stock-picking performance, as measured by *alpha,* reflects the realizations of all of the stocks in a portfolio. Thus, stock-picking performance is not only a more direct measure of stock picking ability, it is likely also a less noisy measure in general.[4]

4.2 September 11th Performance

Another approach to isolating lucky performance is to examine totally unforeseeable shocks to the stock market that had a differential impact across mutual funds. Perhaps the best example of such a shock was the market downturn that followed the terrorist attacks of September 11, 2001. When US exchanges reopened on September 17 (They never opened on September 11th and then were kept closed for the rest of the week), there was a large decline in the market, which was no doubt attributable to the attacks. The Dow Jones Industrial Average was down 7.1% for the day and 14.3% for the week. A 10% one-day drop would have triggered a halt in trading under circuit breaker rules adopted by the New York Stock Exchange after the 1987 market crash. While most sectors declined, some did so more than others. For example, airline stocks declined quite strongly. Defense stocks, on the other hand, actually rose in anticipation of retaliatory actions. As the density plot in Figure 2 shows, mutual funds also experienced a wide distribution of returns on September 17, with a small number even earning positive absolute returns. If one takes the point of view

[4]In principal, one could investigate this further by examining whether factor-timing performance or stock-picking performance in year t, is a better predictor of stock-picking performance in year $t+1$. This would have to be true if factor-timing were truly a better indicator of stock-picking ability.

that the terrorist attacks were completely unforeseen by fund managers, however, managers should not have learned anything about their stock-picking ability from their performance during the shock. For example, if a manager was highly invested in defense stocks prior to September 17, his (relatively) high performance that day could be considered the product of luck rather than skill.

[Figure 2 about here.]

To investigate the effect of the shock on manager confidence, I regress $\Delta Boldness_{i,2002}$ on $r_{i,9/17}$, the September 17th fund return, obtained from the CRSP daily fund return file. Results are shown in Table 8. In the first column, I run the univariate regression of change in ex-post risk on September 17th return. The coefficient on September 17th return is estimated to be positive and statistically significant. In column 2, lagged risk is included. This decreases the magnitude the estimated effect by slightly more than half. According to this point estimate, an additional percentage point of return on September 17th is associated with an increase of approximately 19 basis points of annualized σ the following year. For the median manager, this is a percentage increase of 2.7. In column 3, I repeat the univariate regression using ex-ante idiosyncratic risk rather than ex-post. Again the estimated coefficient is positive and statistically significant, although smaller in magnitude than of column 1. When lagged ex-ante risk is controlled for in column 4, however, I am unable to reject the null that the coefficient is zero–although the point estimate is similar to that of column 2. On the whole, these results would seem to suggest that manager who performed better on September 17th did attribute some of their success to themselves, and therefore took bolder positions the following year.

[Table 8 about here.]

5 Alternative Explanations

One could argue that the results presented thus far are all consistent with a form of career concerns. In particular, after a good year, a manager's confidence in himself might not increase at all, but his superiors' confidence in him may. The resulting increase in the manager's reputational capital could then lead him to become bolder. Indeed, it would seem difficult to differentiate this theory from that which motivated the preceding analysis. For example, the fact that experience appears to diminish sensitivity to lagged performance could also be consistent with career concerns, because the longer a manager's track record, the less others will update their assessment of him from an additional year of data. Still, it can be argued that a manager is more likely to make the mistake of giving himself credit for luck, than others would be. The results of section 4 would then seem to suggest that it is indeed changes in the *managers*' confidence that are driving the observed changes in boldness. Moreover, even if this cannot be established definitively, the results of section 4 are still of great interest, as they suggest that *someone* is learning from luck. Finally, it should also be pointed out that it is not theoretically clear that an increase in reputational capital should lead to an increase in boldness. In fact, the opposite could well be true; once a manager has established a good reputation, it may be in his interest to preserve that reputation by taking more conservative positions. Setting this theoretical argument aside, I will attempt to provide some additional evidence to shed light on these issues.

As mentioned earlier, Chevalier and Ellison (1997)find that the capital flows are positively related to fund lagged relative returns. Mutual fund companies usually receive a fixed percentage of assets under management as compensation. Therefore the flow-performance relationship is primarily what provides them with an incentive to perform well. Interestingly, Chevalier and Ellison, find that the flows of older mutual funds are much less performance sensitive than those younger funds. To the extent that this is true, it means that older funds have lower powered performance incentives. *A priori*, one would then expect career concerns to operate to a lesser degree at these funds. That is, a manager at an older fund should be

less concerned about his stock of reputational capital, because his superiors are less likely to act (positively or negatively) on their beliefs about his talent. Thus, a testable prediction of the career concerns theory is that the boldness of managers at older funds should be less sensitive to lagged relative returns, all else equal. To compute fund age, I obtain the year of the first offer date of each fund from the CRSP fund header file. Different classes of multi-class funds, however, were often first offered at different dates. In these cases it is not clear which year to use. To resolve this, I use two different methods. First, I try dropping multi-class funds with classes that were first offered in different years. Second I form a variable called $MinFundAge_{i,t}$ using the minimum year of first offer associated with any class in a multi-class fund. In the cases where the first offer date is clearly erroneous, as it implies a negative fund age, these observations are dropped. I then repeat the experience regressions from section 3.3, but now allowing for an interaction between fund age and lagged performance. Results are shown in table 9. Columns 1-2 restrict the sample to single-class funds and multi-class funds in which all classes were first offered in the same year, while columns 3-4 use the $MinFundAge_{i,t}$ measure of fund age. As usual, both ex-post and ex-ante measures of risk are used. Only the regression shown in the first column, where the restricted sample is used with ex-post risk, produces a negative point estimate of the interaction effect. This estimate, however, does not reach conventional levels of significance, with a p-value of .2487. In fact, only the estimated coefficient in the fourth column, where the $MinFundAge_{i,t}$ is used with ex-ante risk, is statistically significance at the 5% level, but the sign of the coefficient is positive. Thus, there is little evidence to suggest that managers at older funds are less sensitive to performance than those at younger funds. If anything, there is weak evidence that the opposite is true.

[Table 9 about here.]

It is also interesting to investigate the shape of the relationship between $\Delta Boldness_{i,t}$ and $r_{i,t-1} - r_{mkt,t-1}$ in more detail. A large psychology literature suggests that people suffer from self-serving attributional biases that cause them to credit themselves for success but not

blame themselves for failure. This potentially introduces a wedge between how managers view their performance and how others view it. Evidence of an asymmetry in the shape of the boldness-to-performance relationship would therefore provide further evidence that it is indeed changes in the *managers*' confidence that are driving changes in boldness. As to not impose artificial restrictions on the shape of the relationship, I estimate it semi-parametrically. Specifically, I estimate the equation,

$$\Delta\sigma_{i,t}^{ante} = f(r_{i,t-1} - r_{mkt,t-1}) + \delta\sigma_{i,t-1}^{ante} + \varepsilon_{i,t}.$$

Following Robinson (1988) I perform kernel regressions of $\Delta\sigma_{i,t}^{ante}$ and $\sigma_{i,t-1}^{ante}$ on $r - r_{mkt,t-1}$ and then regress the residuals from the former on those from the from the latter, using ordinary least squares. This provides a consistent estimate of δ. I then perform a kernel regression of $\Delta\sigma_{i,t}^{ante} - \widehat{\delta}\sigma_{i,t-1}^{ante}$ on $r_{i,t-1} - r_{mkt,t-1}$ to obtain an estimate of the function f. All kernel regressions are done with an Epanechnikov kernel and a rule of thumb bandwidth. In Figure 3, I graph $E(\Delta\sigma_{i,t}^{ante}|r_{i,t-1} - r_{mkt,t-1}) = \widehat{f}(r_{i,t-1} - r_{mkt,t-1}) + \widehat{\delta}\sigma_{i,t-1}^{ante}$, evaluated at the median level of $\sigma_{i,t-1}^{ante}$, along with 95% confidence bands. From this figure it is difficult to tell whether an asymmetry exists. While there does appear to be a kink in the graph, it does not occur around the zero relative return point, as one would have expected. In reality different managers likely judge themselves relative to many different benchmark indices. It is possible that if relative returns were measure relative to funds' actual benchmarks an asymmetry around zero would emerge more clearly. [5]

[Figure 3 about here.]

[5]Funds have been required to report their benchmark indices since 1999, but these data have not yet been compiled in any public database

6 Conclusion

Confident managers may have been born this way to some extent, but they may also have enjoyed a lot of success, which led to them to become confident. This is especially interesting to consider when success is due to something beyond a manager's control, as is so often the case. In this paper, I use data on mutual fund managers to examine whether success breeds confidence. I find that the better a manager performs in a given year, the bolder the investments he tends to make in the following year. This is true whether boldness is measured based on the historical returns of a managers' holdings, or based on realized returns. In addition, I find that the more experience a manager possess, the less his investment decisions tend to react to his recent performance. These results are plausibly consistent with a Bayesian framework in which managers learn about their own ability over time. Next, I investigate whether observably lucky success breeds confidence as well, which would be a clear departure from the Bayesian framework. I isolate lucky success in two ways. First, I estimate success that is due to market-timing and not stock-picking. Second, I estimate success that is due to the shock to the market that followed September 11th. In both cases, I find evidence that lucky managers indeed become more confident in themselves, apparently attributing some of their good fortune to themselves.

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Figure 1
Timeline for Calculation of ex-ante Risk at t=2000

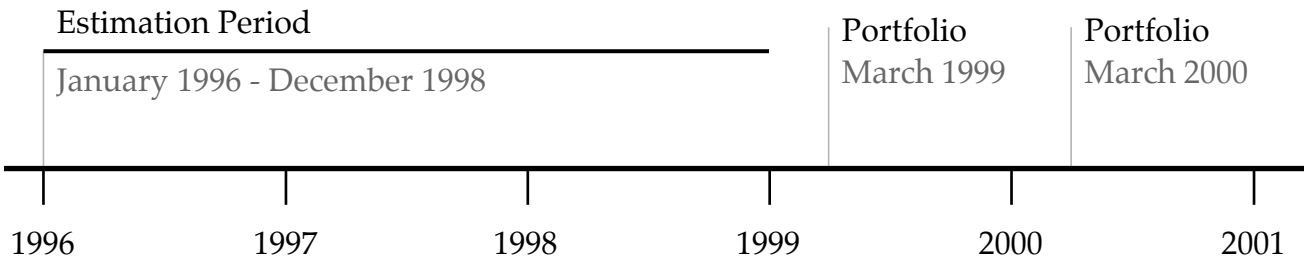

Figure 2
September 17th Fund Return Distribution

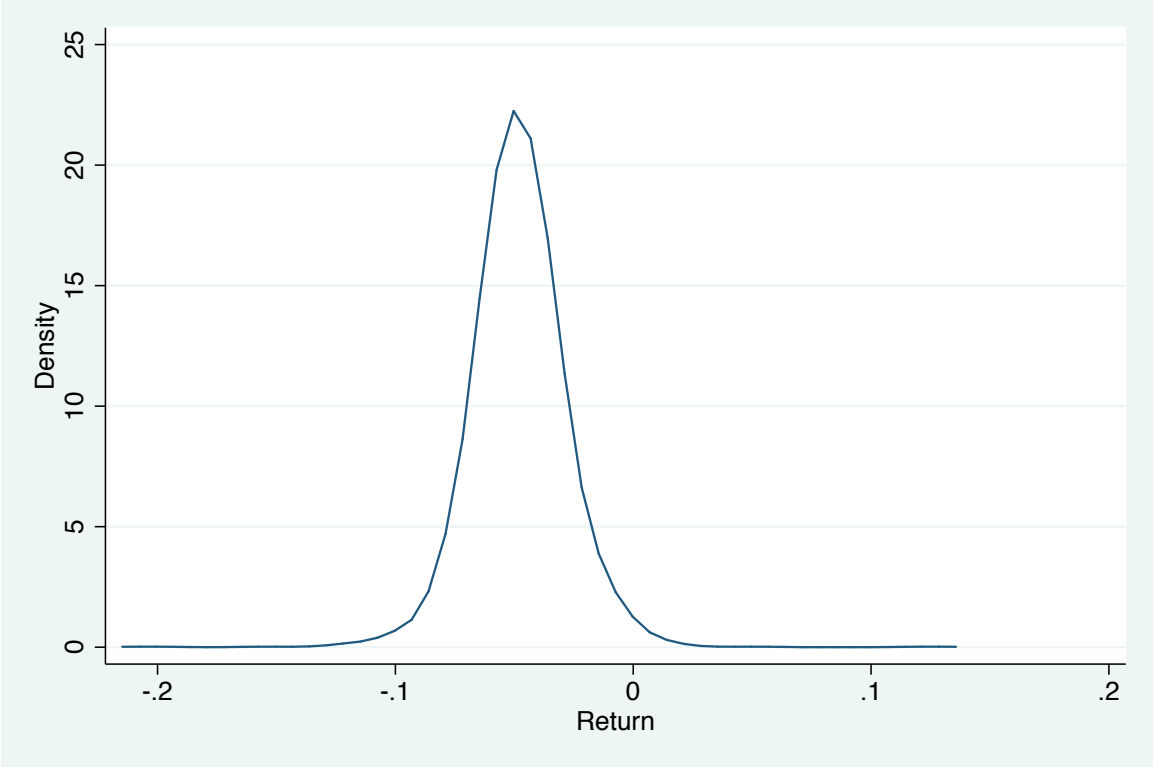

Figure 3
Shape of Boldness-to-Performance Relationship

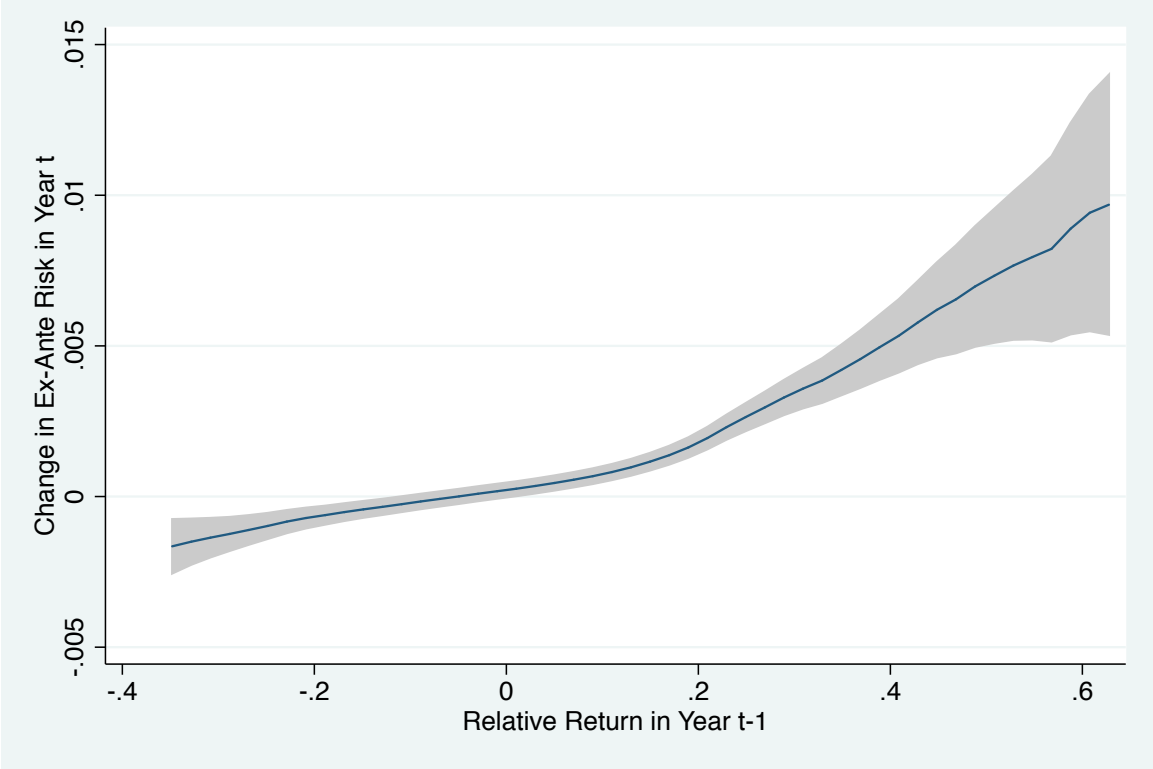

Table 1
Number of Funds by Year and Number of Managers

Year	Single Manager	Multiple Manager	Missing	Total
1980	100	36	97	233
1981	111	35	94	240
1982	131	35	96	262
1983	143	51	91	285
1984	176	56	87	319
1985	200	69	93	362
1986	225	96	95	416
1987	284	114	97	495
1988	322	149	95	566
1989	351	179	78	608
1990	384	209	55	648
1991	408	243	46	697
1992	411	307	49	767
1993	472	389	54	915
1994	538	488	55	1081
1995	615	619	64	1298
1996	638	752	58	1448
1997	682	872	99	1653
1998	726	977	56	1759
1999	690	1011	43	1744
2000	629	1016	30	1675
2001	620	954	27	1601
2002	573	937	18	1528
2003	539	895	18	1452
2004	520	848	17	1385

Table 2
Summary Statistics

This table shows summary statistics for the key variables used in the analysis. Each variable is shown at the level of observation at which it varies.

	Mean	s.d.	N
$r_{i,t-1} - r_{mkt,t-1}$	0.0121	0.159	7534
$\sigma_{i,t}^{post}$	0.0258	0.0219	7534
$\Delta\sigma_{i,t}^{post}$	-0.000488	0.0187	7534
$\sigma_{i,t}^{ante}$	0.0287	0.0198	6159
$\Delta\sigma_{i,t}^{ante}$	-0.0000764	0.0103	6159
$\bar{\sigma}_{i,t}$	0.0963	0.0353	6159
$\Delta\bar{\sigma}_{i,t}$	0.000398	0.0117	6159
$C_{i,t}$	0.0303	0.0398	6159
$\Delta C_{i,t}$	0.0000656	0.0270	6159
$\tilde{C}_{i,t}$	0.0304	0.0399	6159
$\Delta\tilde{C}_{i,t}$	0.000204	0.0269	6159
$\bar{\rho}_{i,t}$	0.0531	0.0653	6159
$\Delta\bar{\rho}_{i,t}$	-0.00199	0.0270	6159
$te_{i,t}^{post}$	0.0266	0.0199	7534
$\Delta te_{i,t}^{post}$	-0.000515	0.0220	7534
$te_{i,t}^{ante}$	0.0294	0.0186	6159
$\Delta te_{i,t}^{ante}$	-0.0000231	0.00960	6159
$Experience_{i,t}$	8.361	6.432	7534
$FundAge_{i,t}$	11.43	10.57	2778
$MaxFundAge_{i,t}$	13.32	12.93	7314

Table 3
The Effect of Past Performance on Risk-Taking, Realized Returns

This table shows the relationship between relative returns for a manager i in year $t-1$ and the change in idiosyncratic risk realized in year t. The variable $r_{i,t-1} - r_{mkt,t-1}$ represents the return of manager i in year $t-1$ net of the value weighted market return. The variable $\sigma^{post}_{i,t}$ represents the idiosyncratic risk of manager i in year t based on realized monthly fund returns. Similarly $te^{post}_{i,t}$ represents tracking error based on realized fund returns.

	(1) $\Delta\sigma^{post}_{i,t}$	(2) $\Delta\sigma^{post}_{i,t}$	(3) $\Delta\sigma^{post}_{i,t}$	(4) $\Delta\sigma^{post}_{i,t}$	(5) $\Delta te^{post}_{i,t}$	(6) $\Delta te^{post}_{i,t}$	(7) $\Delta te^{post}_{i,t}$	(8) $\Delta te^{post}_{i,t}$
$r_{i,t-1} - r_{mkt,t-1}$	0.0319**	0.0347**	0.0268**	0.0273**	0.0133**	0.0169**	0.0100**	0.00960**
	[24.50]	[30.48]	[25.60]	[26.13]	[8.41]	[14.36]	[8.69]	[9.67]
$\sigma^{post}_{i,t-1}$		-0.388**	-0.333**	-0.743**				
		[-48.76]	[-42.51]	[-64.04]				
$te^{post}_{i,t-1}$						-0.573**	-0.616**	-0.899**
						[-77.96]	[-85.59]	[-122.44]
Year FE	No	No	Yes	Yes	No	No	Yes	Yes
Manager FE	No	No	No	Yes	No	No	No	Yes
Observations	7534	7534	7534	7534	7534	7534	7534	7534
Adjusted R^2	0.074	0.296	0.493	0.599	0.009	0.452	0.554	0.738

Table 4

The Effect of Past Performance on Risk-Taking, Historical Holding Returns

This table shows the relationship between relative returns for a manager i in year $t-1$ and the change in idiosyncratic risk held in year t. The variable $r_{i,t-1} - r_{mkt,t-1}$ represents the return of manager i in year $t-1$ net of the value weighted market return. The variable $\sigma^{ante}_{i,t}$ represents the idiosyncratic risk of manager i in year t based on the historical returns of the manager's holding in the first quarter. Similarly $te^{ante}_{i,t}$ represents tracking error based on historical holding returns.

	(1) $\Delta\sigma^{ante}_{i,t}$	(2) $\Delta\sigma^{ante}_{i,t}$	(3) $\Delta\sigma^{ante}_{i,t}$	(4) $\Delta\sigma^{ante}_{i,t}$	(5) $\Delta te^{ante}_{i,t}$	(6) $\Delta te^{ante}_{i,t}$	(7) $\Delta te^{ante}_{i,t}$	(8) $\Delta te^{ante}_{i,t}$
$r_{i,t-1} - r_{mkt,t-1}$	0.00911**	0.00985**	0.00800**	0.00717**	0.00857**	0.00991**	0.00826**	0.00939**
	[10.87]	[12.18]	[9.44]	[8.59]	[10.91]	[13.00]	[10.24]	[11.89]
$\sigma^{ante}_{i,t-1}$		-0.136**	-0.123**	-0.407**				
		[-21.57]	[-18.59]	[-33.59]				
$te^{ante}_{i,t-1}$						-0.132**	-0.135**	-0.409**
						[-20.60]	[-19.27]	[-33.41]
Year FE	No	No	Yes	Yes	No	No	Yes	Yes
Manager FE	No	No	No	Yes	No	No	No	Yes
Observations	6159	6159	6159	6159	6159	6159	6159	6159
Adjusted R^2	0.019	0.087	0.157	0.356	0.019	0.082	0.133	0.341

Table 5
Decomposition of Risk

This table shows how the components of idiosyncratic risk respond to lagged performance. The variable $r_{i,t-1} - r_{mkt,t-1}$ represents the return of manager i in year $t-1$ net of the value weighted market return. The variable $\sigma_{i,t}^{ante}$ represents the idiosyncratic risk of manager i in year t based on the historical returns of the manager's holding in the first quarter. The variable $\Delta C_{i,t}$ represents the change in portfolio concentration realized in year t. The variable $\Delta \tilde{C}_{i,t}$ represents the change in portfolio concentration realized in year t at year $t-1$ prices. The variable $\Delta \bar{\sigma}_{i,t}$ represents the change in mean portfolio volatility. The variable $\Delta \bar{\sigma}_{i,t}$ represents the change in mean pairwise portfolio correlation.

	(1) $\Delta C_{i,t}$	(2) $\Delta C_{i,t}$	(3) $\Delta \tilde{C}_{i,t}$	(4) $\Delta \tilde{C}_{i,t}$	(5) $\Delta \bar{\sigma}_{i,t}$	(6) $\Delta \bar{\sigma}_{i,t}$	(7) $\Delta \bar{\rho}_{i,t}$	(8) $\Delta \bar{\rho}_{i,t}$
$r_{i,t-1} - r_{mkt,t-1}$	-0.0161**	-0.0157**	-0.0167**	-0.0166**	0.0121**	0.00937**	0.0114**	0.00985**
	[-7.26]	[-6.49]	[-7.57]	[-6.90]	[12.69]	[9.36]	[5.13]	[4.14]
$\sigma_{i,t-1}^{ante}$		-0.0289		-0.0254		-0.0818**		-0.229**
		[-1.52]		[-1.35]		[-10.42]		[-12.29]
Year FE	No	Yes	No	Yes	No	Yes	No	Yes
Observations	6159	6159	6159	6159	6159	6159	6159	6159
Adjusted R^2	0.008	0.012	0.009	0.012	0.025	0.092	0.004	0.044

Table 6
Experience As A Mitigating Factor

This table show how managers' reaction to lagged performance changes with experience. The variable $r_{i,t-1} - r_{mkt,t-1}$ represents the return of manager i in year $t-1$ net of the value weighted market return. The variable $Experience_{i,t}$ represents the number of years of experience of manager i in year t. The variable $\sigma^{post}_{i,t}$ represents the idiosyncratic risk of manager i in year t based on realized monthly fund returns. The variable $\sigma^{ante}_{i,t}$ represents the idiosyncratic risk of manager i in year t based on the historical returns of the manager's holdings in the first quarter. The variable $\Delta\bar{\sigma}_{i,t}$ represents the change in mean portfolio volatility. The variable $\Delta\bar{\sigma}_{i,t}$ represents the change in mean pairwise portfolio correlation.

	(1) $\Delta\sigma^{post}_{i,t}$	(2) $\Delta\sigma^{ante}_{i,t}$	(3) $\Delta\bar{\sigma}_{i,t}$	(4) $\Delta\bar{\rho}_{i,t}$
$r_{i,t-1} - r_{mkt,t-1}$	0.0347**	0.0101**	0.0157**	0.0241**
	[21.38]	[7.44]	[9.81]	[6.35]
$Experience_{i,t} \times (r_{i,t-1} - r_{mkt,t-1})$	-0.000955**	-0.000252**	-0.000771**	-0.00173**
	[-6.31]	[-1.97]	[-5.10]	[-4.82]
$Experience_{i,t}$	0.0000160	0.0000121	-0.0000359	-0.0000121
	[0.66]	[0.62]	[-1.57]	[-0.22]
$\sigma^{post}_{i,t-1}$	-0.335**			
	[-42.76]			
$\sigma^{ante}_{i,t-1}$		-0.123**	-0.0830**	-0.231**
		[-18.56]	[-10.58]	[-12.37]
Year FE	Yes	Yes	Yes	Yes
Observations	7534	6159	6159	6159
Adjusted R^2	0.496	0.157	0.096	0.048

Table 7
Stock-Picking vs. Market-Timing Performance

This table shows how a manager's risk-taking responds to market-timing and stock-picking performance. The variables $r^{capm}_{i,t-1} - r_{mkt,t-1}$ and $r^{ff}_{i,t-1} - r_{mkt,t-1}$ represent the excess return that would be predicted by the CAPM and four factor (Fama-French) models, repsectively, based on year t factor loadings. The variables $\alpha^{capm}_{i,t-1}$ and $\alpha^{ff}_{i,t-1}$ represent residual stock picking performance.The variable $\sigma^{post}_{i,t}$ represents the idiosyncratic risk of manager i in year t based on realized monthly fund returns. The variable $\sigma^{ante}_{i,t}$ represents the idiosyncratic risk of manager i in year t based on the historical returns of the manager's holdings in the first quarter.

	(1) $\Delta\sigma^{post}_{i,t}$	(2) $\Delta\sigma^{ante}_{i,t}$	(3) $\Delta\sigma^{post}_{i,t}$	(4) $\Delta\sigma^{ante}_{i,t}$
$r^{capm}_{i,t-1} - r_{mkt,t-1}$	0.0305**	0.0149**		
	[11.62]	[7.10]		
$\alpha^{capm}_{i,t-1}$	0.0264**	0.00732**		
	[24.59]	[8.44]		
$r^{ff}_{i,t-1} - r_{mkt,t-1}$			0.0349**	0.0104**
			[27.83]	[10.33]
$\alpha^{ff}_{i,t-1}$			0.0184**	0.00527**
			[14.42]	[5.03]
$\sigma^{post}_{i,t-1}$	-0.333**		-0.322**	
	[-42.52]		[-41.12]	
$\sigma^{ante}_{i,t-1}$		-0.123**		-0.121**
		[-18.47]		[-18.22]
Year FE	Yes	Yes	Yes	Yes
Observations	7534	6159	7534	6159
Adjusted R^2	0.494	0.159	0.502	0.160

Table 8
September 11th Performance

This table shows how managers' risk-taking responded to their returns on the first day after the market opened following the September 11th terrorist attacks. The variable $r_{i,9/17}$ represents manager i's one day return on September 17th. The variable $\sigma_{i,t}^{post}$ represents the idiosyncratic risk of manager i in year t based on realized monthly fund returns. The variable $\sigma_{i,t}^{ante}$ represents the idiosyncratic risk of manager i in year t based on the historical returns of the manager's holdings in the first quarter.

	(1) $\Delta\sigma_{i,2002}^{post}$	(2) $\Delta\sigma_{i,2002}^{post}$	(3) $\Delta\sigma_{i,2002}^{ante}$	(4) $\Delta\sigma_{i,2002}^{ante}$
$r_{i,9/17}$	0.123**	0.0544**	0.0799**	0.0408
	[4.30]	[2.07]	[2.26]	[1.23]
$\sigma_{i,2001}^{post}$		-0.244**		
		[-10.90]		
$\sigma_{i,2001}^{ante}$				-0.184**
				[-7.97]
Observations	466	466	394	394
Adjusted R^2	0.036	0.231	0.010	0.146

Table 9
The Effect of Fund Age

This table show how managers' reaction to lagged performance changes with fund age and experience. The variable $r_{i,t-1} - r_{mkt,t-1}$ represents the return of manager i in year $t-1$ net of the value weighted market return. The variable $FundAge_{i,t}$ repesents the age of manager i's fund (for single class funds). The varible $MinFundAge_{i,t}$ represents the age of the oldest class of manager i's fund (for multi-class funds). The variable $Experience_{i,t}$ represents the number of years of experience of manager i in year t. The variable $\sigma^{post}_{i,t}$ represents the idiosyncratic risk of manager i in year t based on realized monthly fund returns. The variable $\sigma^{ante}_{i,t}$ represents the idiosyncratic risk of manager i in year t based on the historical returns of the manager's holdings in the first quarter.

	(1) $\Delta\sigma^{post}_{i,t}$	(2) $\Delta\sigma^{ante}_{i,t}$	(3) $\Delta\sigma^{post}_{i,t}$	(4) $\Delta\sigma^{ante}_{i,t}$
$r_{i,t-1} - r_{mkt,t-1}$	0.0343**	0.0109**	0.0355**	0.00871**
	[12.68]	[4.68]	[20.62]	[5.87]
$FundAge_{i,t} \times (r_{i,t-1} - r_{mkt,t-1})$	-0.000243	0.000249		
	[-1.15]	[1.51]		
$MinFundAge_{i,t} \times (r_{i,t-1} - r_{mkt,t-1})$			0.000137	0.000271**
			[1.31]	[3.29]
$Experience_{i,t} \times (r_{i,t-1} - r_{mkt,t-1})$	-0.000598**	-0.000693**	-0.00105**	-0.000393**
	[-2.34]	[-3.39]	[-6.46]	[-2.88]
$FundAge_{i,t}$	-0.0000809**	-0.0000222		
	[-2.67]	[-0.98]		
$MinFundAge_{i,t}$			-0.0000537**	-0.0000162
			[-4.24]	[-1.64]
$Experience_{i,t}$	0.000106**	0.0000982**	0.0000317	0.0000215
	[2.18]	[2.48]	[1.24]	[1.05]
$\sigma^{post}_{i,t-1}$	-0.332**		-0.360**	
	[-24.96]		[-44.47]	
$\sigma^{ante}_{i,t-1}$		-0.146**		-0.128**
		[-14.02]		[-18.85]
Year FE	Yes	Yes	Yes	Yes
Observations	2778	2222	7314	5999
Adjusted R^2	0.483	0.174	0.515	0.163