Labor Mobility and Capital Misallocation in the Mutual Fund Industry

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Abstract

If capital won't come to fund managers, fund managers will go to capital. I document that fund managers move across mutual fund firms to manage amounts of capital that better match their skill, which improves the allocative efficiency of capital across fund managers. For causal identification, I exploit exogenous shocks to fund managers' ability to switch firms due to state-level changes to non-compete laws. In states that strengthen the enforceability of non-compete agreements, the propensity of fund managers to switch mutual fund firms is halved, capital misallocation across managers increases by about 10%, and the sum of monthly value added of managers declines by over \$25 million. These results indicate that fund managers' mobility across firms plays an important role in the efficient allocation of capital within the mutual fund industry.

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1 Introduction

Assessing capital misallocation and identifying its root causes are first-order issues in economics and finance, given the role of inputs allocation in aggregate productivity. The literature has mainly focused on the allocation of capital across firms or across establishments.[1] Studying capital misallocation across workers has proved more challenging. Indeed, it requires rich worker-level data and specific settings in which a clear match between workers and capital can be identified. In this paper, I study the allocation of capital in a particular group of workers: mutual fund managers. Mutual funds play a major role in the economy. They manage tens of trillions of dollars and make up about one fourth of all financial assets held by U.S. households.[2] Unique features of the mutual fund industry allow me to study capital misallocation across workers: the observability of the productivity of fund managers and of the capital they manage. Because mutual fund managers vary in skills, the value added of the mutual fund industry depends on the allocation of capital across managers.[3]

A large finance literature studies mutual funds and, in particular, the allocation of capital across funds and across fund managers. It mostly emphasizes the role of capital flows from and toward funds for reallocating capital across fund managers, i.e., how *capital goes to managers.* However, by moving from one mutual fund firm to another, managers can run larger or smaller funds, and thus manage more or less capital. Therefore, the match between managers and capital can in principle also occur by managers moving across mutual fund firms, i.e., by *managers going to capital.* The contribution of this paper is to show that fund managers' mobility across mutual fund firms is a key factor in the efficient allocation of capital across mutual fund managers.

In frictionless capital markets, fund managers' mobility across mutual fund firms would be irrelevant. Indeed, capital flows across funds and thus across managers, would ensure that more (less) skilled managers manage more (less) capital (Berk and Green, 2004). However, an extent literature suggests that capital might not flow efficiently across funds and fund managers.[4] Given

[1] Restuccia and Rogerson (2017) review the macroeconomics literature on capital misallocation.

[2] The ICI's Investment Company Fact Book reports 18.75 trillions of total net assets for mutual funds in the United States in 2017.

[3] An extensive body of papers documents a large dispersion in skills in the mutual fund industry. See for instance Kosowski et al. (2006); Fama and French (2010); Kacperczyk et al. (2014); Berk and Van Binsbergen (2015).

[4] One reason might be that investors learn imperfectly about fund manager skills (Choi et al., 2016), due to behavioral biases (Bailey et al., 2011), media coverage and recommendations (Solomon et al., 2014; Kaniel and Parham, 2017), and mutual funds' marketing (Roussanov et al., 2018). Another possible explanation is an asymmetry of information between investors, managers, and firms. Investors might know less about fund managers'

this, managers' mobility across mutual fund firms can possibly affect capital allocation and the match between capital and managers' skills.

I develop a model to study the link between fund managers' mobility across mutual fund firms and the allocative efficiency of capital across fund managers. I consider a set of fund managers differing in their skills and subject to decreasing returns to scale in the managing of capital. Each fund manager is employed by a firm. Absent capital market frictions, investors allocate capital efficiently across fund managers so that the marginal products of capital are equalized across managers (Berk and Green, 2004). Suppose now that capital markets are not frictionless so that the allocation of capital across mutual fund managers is imperfect. Through its internal labor market, a mutual fund family firm can reallocate managers across its own funds until their marginal products of capital are equalized (Berk et al., 2017). However, without fund managers' mobility across firms, a given firm only reallocates capital across its current employees and a wedge may persist between the marginal products of managers employed by different firms. These discrepancies can be reduced by the mobility of managers across firms. Frictionless mobility of fund managers across mutual fund firms leads to the equalization of marginal products across all managers, and therefore to an efficient allocation of capital. Conversely, frictions in the external labor market prevent such equalization.

Investigating empirically mutual fund managers' external mobility and capital allocation requires to track fund managers across time and across firms. For this purpose, I build a novel manager-level dataset by matching fund managers' information from the S&P Capital IQ-People Intelligence database to the CRSP and Morningstar mutual fund databases. S&P Capital IQ documents the profiles and careers of professionals and assigns a unique identifier to each individual, allowing me to track fund managers across time, across firms, and across geographical locations, while monitoring their performance and assets under management (AUM). My dataset features over 5,500 different active equity fund managers between 2000 and 2018. About 20% of fund managers in my sample switch fund family firm at least once. Importantly, these moves tend to involve large changes in AUM: almost $500 million on average ($107 million at the median).

Assessing capital misallocation across fund managers requires estimating the relation between each manager's value added and AUM. Following Berk and Van Binsbergen (2015), I define a manager's value added as the product of gross alpha and AUM. For each manager, I estimate

ability than mutual fund firms (Berk et al., 2017; Kaniel and Orlov, 2019) and than managers themselves (Ibert, 2018).

the slope and intercept coefficients of gross alpha regressed on AUM using the econometric procedures of Pástor et al. (2015) and Zhu (2018). These estimates allow me to assess how AUM affects gross alpha and thus value added. I then calculate each manager's optimal AUM (which maximizes value added), its distance with respect to the manager's actual AUM (capital misallocation), and the manager's marginal product of capital given the actual AUM.

I use these measures to study the factors driving fund managers' mobility across firms, and how capital misallocation and value added vary after a manager switches firm. I find that the capital misallocation incurred by a fund manager strongly predicts her switch to another mutual fund firm. After controlling for various determinants of departures, a twofold increase in the capital misallocation incurred by a manager raises the likelihood of the manager switching firms by about 15% relative to the sample mean. I also find that for managers switching firms, misallocation is reduced by about 30% relative to that of managers who do not switch firms. This leads to an increase in the value added of switchers of over $0.8 million per month.

To address the concern that the mobility of fund managers across firms might be correlated with unobserved factors, I rely on plausibly exogenous and well-defined variations in the intensity of managers' mobility. Specifically, I exploit changes in the legal enforceability of non-compete clauses (NCCs), which are staggered across US states. In practice, NCCs are governed at the state level and preclude employees from moving to a competing firm for a period of time after leaving their employer. They are especially frequent in high-skill, high-paying jobs and industries, such as finance.[5] State-level NCCs enforceability changes corresponding to state Supreme Court rulings and state law changes have been shown to affect the mobility of workers in different industries.[6]

I build a state-level dataset using the office addresses of professionals in S&P Capital IQ-People Intelligence to identify each fund manager's work location. I confirm in my dataset that state-level changes in NCCs enforceability affect the mobility of mutual fund managers. Using a difference-in-difference setting, I find that stronger NCCs enforceability decreases the percentage of fund managers changing firms by more than 40% of the sample mean, relative to control states.

I construct two measures of state-level capital misallocation based, as per the theory, on the

[5] Starr et al. (2018) indicate that NCCs are very likely to be found in high-skill, high-paying jobs, with an incidence rate of 50% for management occupations in finance and insurance. In addition, anecdotal evidence of legal disputes (mentioned in Section 4.4) suggests that investment managers are affected by NCCs.

[6] See for instance Marx et al. (2009); Bishara (2010); Garmaise (2011); Starr (2018); Ewens and Marx (2017); Jeffers (2018).

dispersion in the marginal products of capital across fund managers. Specifically, for each state and month, I compute the standard deviation and the difference between the 75th and the 25th percentiles of the marginal products of capital of managers employed in that state. To obtain a measure of value added by managers at the state level, I compute for each state and month the sum of the value added of managers employed in that state. I then test whether NCCs enforceability changes affect state-level capital misallocation and the value added by mutual fund managers. I show in a difference-in-difference setting that, following an increase in NCCs enforceability, capital misallocation rises by 9% to 12% in treated states relative to control states. Consistent with this result, I find that state-level value added of fund managers decreases by more than $25 million per month in treated states after the increase in NCCs enforceability. This effect is both statistically and economically significant.

Overall, my empirical findings provide direct evidence that inter-firm mobility frictions have real consequences as they lead to a larger mismatch between capital and skill among mutual fund managers and, thereby, to lower labor productivity in the mutual fund industry. In conclusion, these results indicate that managers' mobility across firms plays an important role in the efficient allocation of capital in the mutual fund industry.

This paper contributes to the literature on mutual funds studying the match between capital and skills. Berk and Green (2004) predict that capital flows across funds ensure an efficient match. However, Song (2020) shows that skill and capital are mismatched among actively managed equity mutual funds because investors evaluate skill incorrectly when allocating capital across funds. Fang et al. (2014) and Berk et al. (2017) show that mutual fund firms improve the match between skills and capital by reallocating managers across funds *within* the firm. This paper highlights that managers' mobility *across* firms plays an important role too, and provides direct causal implications for the value added by the mutual fund industry.[7]

This paper also contributes to the literature studying the labor market for fund managers. Previous works have shown that the labor market plays a role in disciplining asset managers. Khorana (1996) documents that fund performance is inversely related to the probability of managerial replacement, Chevalier and Ellison (1999) study the incentives created by the termination-performance relationship and Ellul et al. (2020) further investigate the impact of fund liquidations on fund managers' careers. Instead, I show that the labor market for fund managers plays a role in the efficient allocation of capital across managers, and thus improves

[7]The paper is also close to Gabaix and Landier (2008) and Tervio (2008), which study how CEOs are matched to firms according to skills and firm size.

productivity.[8]

Finally the results in this paper also contribute to our understanding of how labor market frictions affect aggregate productivity and the allocation of resources in the economy. Hopenhayn and Rogerson (1993) and Lagos (2006) show that labor market policies that interfere with job reallocation across firms can have a negative effect on average productivity. Bryan and Morten (2019) show that reducing barriers to labor migration can lead to aggregate productivity gains. Regarding the asset management industry, Acharya et al. (2016)'s model suggests that limiting fund managers' mobility can allow firms to learn about managers' talent and improve capital allocation across managers. This paper provides evidence that restricting fund managers' mobility may lead to lower productivity in the mutual fund industry.[9]

The paper proceeds as follows. Section 2 presents a model to study the role of fund managers' mobility across firms in the capital allocation process. Section 3 presents the data and descriptive statistics. Section 4 discusses the empirical strategy. Section 5 presents the empirical results. Section 6 concludes.

2 Theoretical framework

In this section, I analyze a stylized model featuring investors, asset managers and mutual fund family firms. The model illustrates the equivalent role of capital mobility and managers' mobility in the process of efficiently matching capital and managers. I enrich the framework developed in Berk et al. (2017) by allowing managers to move across firms and provide a set of testable predictions on the relation between managers' mobility frictions and capital misallocation across managers.

2.1 The model

Investors are endowed with a total amount of capital $\mathbf{K}$. There exists a continuum of managers $m \in [0, M]$ with density $\mu(m)$ representing the measure of managers of type m in the economy. Managers differ in their skill, i.e., their ability to extract money from financial markets. Specif-

[8] Labor mobility in other subsets of the finance industries have also been the subject of studies. Kisin and Hamilton (2017) investigate labor mobility between mutual funds and hedge funds and Kempf (2019) studies financial analysts' mobility from rating agencies to investment banks.

[9] Cici et al. (2018) find that stronger NCCs have a positive effect on fund managers' performance. Clifford and Gerken (2017) and Gurun et al. (2019) study the market for financial advice and the effect of relaxing a specific type of non-compete agreements that transfer ownership of client relationships from the firm to the advisor.

ically, I use the framework introduced by Berk and Van Binsbergen (2015) and assume that if manager $m \in [0, M]$ manages an amount of capital k, she creates value added $v_m(k)$ given by:

$$v_m(k) = \underbrace{k}_{\text{capital under management}} \times \underbrace{\alpha_m(k)}_{\text{\% gross alpha created with capital } k} \tag{1}$$

where $\alpha_m{}'(k) < 0$. In words, the alpha (before fees and expenses) generated by a manager is a decreasing function of the capital she manages. This is motivated by the assumption that positive net present value investment opportunities are in finite supply, so that managers face decreasing returns to scale.[10] One critical assumption I make is that the production technology in equation (1) is attached to the manager and not to the specific fund entity she manages, nor to the firm employing the manager.[11] A situation in which this modeling choice is justified is one where managers are the repository of investing expertise. In other words, a manager's performance is primarily driven by her trading ideas and "style" implementable in different corporations, as suggested for instance by Bertrand and Schoar (2003) for CEO and Ewens and Rhodes-Kropf (2015) for venture capitalists, while firm's infrastructure and organizational capital have a minor impact on the manager's investment performance.

Assuming that the function α_m is known, the optimal amount of capital k^*_m manager m should be managing to maximize $v_m(k)$ is given by the condition

$$v_m{}'(k^*_m) = \alpha_m(k^*_m) + k^*_m \alpha_m{}'(k^*_m) = 0. \tag{2}$$

Figure 1 shows the gross alpha and value added functions of the manager when the function α_m is linear, i.e., $\alpha_m(k) = a_m - b_m k$, where a_m and b_m are positive constant parameters. Note that the value added decreases as the amount of capital under management departs from the optimum k^*_m, i.e., as misallocation at the manager level increases.

There is a continuum of firms $f \in [0, F]$ employing managers. Each manager runs one fund in a given firm. I assume that each manager is initially assigned to an employer independently of her skill, i.e., before economic agents start making decisions an initial random matching between firms and managers took place. Let W_m refers to the compensation of manager m. For a given

[10] Decreasing return to scale can be due, for instance, to the fact that strategies only apply to few stocks or that prices move if large trades are executed. Cf. Chen et al. (2004); Pástor et al. (2015); Zhu (2018); Barras et al. (2018); Pastor et al. (2019) for empirical evidence regarding diseconomies of scale in the US mutual fund industry. The findings of Rossi et al. (2018) also suggest diseconomies of scale at the pension fund management company level in the UK.

[11] The labor literature (cf., in particular Abowd et al., 1999; Graham et al., 2011) suggests that firm effects are not as important as person effects in worker compensation.

firm f, I denote $L_m(f)$ and $k_m(f)$ respectively the mass of manager m employed by firm f and the amount of capital that is managed by each manager of this type in the firm, where $m \in [0, M]$. Firm f profit are expressed as follows:

$$\int_0^M L_m(f)\left[v_m(k_m(f)) - W_m\right] dm. \tag{3}$$

2.2 Capital mobility

First, I assume that capital is mobile and all agents know the function α_m for all $m \in [0, M]$. In this case, managers' mobility across firms is irrelevant. Indeed, investors maximize the NPV of investment by allocating capital to the different managers in the economy. For all $m \in [0, M]$, investors provide the amount of capital $\tilde{k}_m$ solving

$$\tilde{k}_m = \arg\max_{k_m} \int_0^M \mu(i)\left[v_i(k_i) - W_i\right] di, \tag{4}$$

subject to

$$\int_0^M \mu(i) k_i di \leq \mathbf{K}. \tag{5}$$

The first order conditions with respect to k_m, for all $m \in [0, M]$, are:

$$v_m{}'(\tilde{k}_m) = \lambda, \tag{6}$$

where λ is the Lagrange multiplier associated with (5). Thus, the marginal products of capital (MPK) are equalized across the different managers.

Given that the optimal allocation of capital across managers is directly obtained by investors' allocation, there is no role for firms nor managers' mobility in this economy. Appendix A describes firms' and managers' optimization procedure and explicitly shows they lead to the same first order conditions.

2.3 Managers' mobility

Assume now that investors do not directly provide the optimal amount of capital to each manager, i.e., the condition (6) is not verified.[12] As in Berk et al. (2017), I show that through internal reallocation by firms, marginal returns on capital are equalized across managers within

[12] One way to motivate this is to assume that investors do not know the functions α_m and cannot perfectly differentiate between managers (Berk et al., 2017). Another possibility is to assume investor capital is "slow moving". Suppose for instance that investors optimized in the first place but there is a negative capital supply shock due to some liquidity constraints. If remaining investors' capital is not rebalanced across the different managers, we can end up in a situation where marginal products of capital are not equated across all managers.

each firm. Furthermore, because managers can switch freely between firms, I show that the marginal returns on capital are also equalized across managers working in different firms and the resulting capital allocation is the same as in the previous section.

For simplicity of exposition, I assume that investors provide an exogenous amount of capital to each manager. This implies that each firm has an exogenous amount of capital under management, denoted $K(f)$ for firm f, corresponding to the capital provided by investors to managers initially in the firm, and such that

$$\int_0^F K(f)df = \mathbf{K}.$$

2.3.1 Firms' problem: internal capital allocation and labor demand

Firms maximize profits given in equation (3) by optimizing over two dimensions. The first one is the amount of capital managed by each employee (i.e., internal reallocation), the second one is labor demand, i.e., the mass of each type of manager the firm is willing to employ. This optimization can be separated into two stages. First, for a given set of masses of employed managers $(L_m(f))_{m\in[0,M]}$, a firm can determine the optimal internal capital allocation between its different managers in order to maximize profits.[13] Second, the firm can adjust its labor demand for each type of manager, knowing the result of the first optimization procedure.

Specifically, firm f first chooses the amount of capital $k_m(f)$ to be managed by managers of type m, taking W_m and $L_m(f)$ as given. This leads to the optimization over $k_m(f)$, for all $m \in [0, M]$:

$$\max_{k_m(f)} \int_0^M L_i(f) \left[v_i(k_i(f)) - W_i\right] di, \tag{7}$$

subject to

$$\int_0^M L_i(f)k_i(f)di \leq K(f), \tag{8}$$

where $K(f)$ is the total AUM of firm f provided by outside investors.[14] The first order conditions with respect to $k_m(f)$, for all $m \in [0, M]$, are:

$$v_m{}'(k_m(f)) = \lambda_f, \tag{9}$$

[13] In practice, a firm cannot arbitrarily move capital from one of its funds to another but it can promote (or demote) a manager by assigning her more or less funds, i.e., it decides which manager gets to manage which fund, as documented by Berk et al. (2017).

[14] Note that, through the inequality in the constraint (8), I implicitly assume the firm can, if needed, allocate assets in a zero alpha project, i.e., indexing, such that there is no value destroyed by allocating too much capital to active managers. Assuming that managers fully "optimize" and do not actively manage capital in excess of k_m^* (as in Berk and Van Binsbergen, 2015) and thus produce zero alpha on the remaining capital is equivalent.

where λ_f is the Lagrange multiplier associated with (8) for firm f. Thus, the marginal returns on capital are equalized across the different managers working in the firm.

Let denote $V(L(f))$ the solution to problem (7), where $L(f)$ refers to given masses of employed managers: $L(f) = (L_m(f))_{m\in[0,M]}$. Once we know the condition characterizing $k_m(f)$, we can write down the firm's optimization problem regarding labor demand:

$$\max_{L(f)} V(L(f)) = \max_{(L_m(f))m\in[0,M]} \int_0^M L_i(f)\left[v_i(k_i(f)) - W_i\right] di, \tag{10}$$

which leads to the following first order condition with respect to $L_m(f)$ for all $m \in [0, M]$:

$$v_m(k_m(f)) - W_m + \int_0^M L_i(f)\left[\frac{\partial k_i(f)}{\partial L_m(f)} v_i{}'(k_i(f))\right] di = 0. \tag{11}$$

Using the result in equation (9) and the expression of the derivative with respect to $L_m(f)$ of the (binding) constraint (8), equation (11) gives

$$W_m = v_m(k_m(f)) - \lambda_f k_m(f), \tag{12}$$

i.e., manager m compensation is set such that marginal labor cost equalizes marginal labor productivity.[15]

Finally, the firm's equilibrium profit can be expressed as

$$\int_0^M L_i(f)\lambda_f k_i(f)di = \lambda_f K(f). \tag{13}$$

Therefore, the firm's profit is non zero and is proportional to its total assets under management and internal marginal return on capital. The more severe the binding constraint (8), the higher its "shadow value", the greater is the value created by the firm through internal reallocation and so its profit.

2.3.2 Managers' problem: compensation maximization and mobility across firms

Firms cannot move capital from one to another, i.e., capital is perfectly segmented between firms. However, managers can move across firms. In equilibrium, each manager maximizes her compensation by choosing the firm she works for, such that the manager market clears, i.e.,

$$\int_0^F L_m(f)df = \mu(m).$$

[15] Note that labor income of the manager is concave in the size of the funds under management, as documented empirically by Ibert et al. (2017). For additional empirical evidence on portfolio manager compensations in the mutual fund industry, see Ma et al. (2019).

for all $m \in [0, M]$. Consider a manager $m \in [0, M]$. She chooses her employer f_m to maximize her compensation given in (12):

$$f_m = \arg\max_f \; v_m(k_m(f)) - \lambda_f k_m(f), \tag{14}$$

where $k_m(f)$ is the optimal amount allocated to manager m, obtained from firm f's optimization. If $\lambda_f > 0$, the first order condition of (14) combined with (9) gives:

$$\frac{\partial \lambda_f}{\partial f} = 0. \tag{15}$$

This result implies that the Lagrange multipliers λ_f, i.e., the marginal returns on capital, are equalized across all firms.

Note that condition (15) makes potentially possible a range of equilibria in terms of assignment of managers to firms, i.e., values of $(L_m(f))_{m\in[0,M],f\in[0,F]}$. Determining which equilibrium prevails requires further assumptions (c.f. for instance Crawford and Knoer, 1981).[16] But crucially, condition (15) implies that, regardless of the equilibrium assignment, marginal products of capital are equalized across firms and therefore across all managers in the economy, mimicking the result in equation (6) obtained with perfect capital allocation by investors.

2.4 The effect of introducing inter-firm moving costs

I study now the implications of introducing switching costs faced by managers when moving across firms. Clearly, in the configuration described in section 2.2, frictions preventing managers to move freely across employers have no effect on the efficiency of capital allocation. Indeed, investors allocate the optimal amount of capital to each manager, independently of employers. On the other hand, in the framework of section 2.3, managers' mobility across firms is crucial in order to obtain the optimal capital allocation. Hence, as I show below, frictional labor mobility can lead to capital misallocation across managers.

Keeping the same configuration as in section 2.3, I assume that a given manager of type m faces a cost $c_m(f)$ when moving to firm f. I remain agnostic on the form of $c_m(f)$, the only assumption being that it is not constant across firms. One example is a situation in which, after the initial matching between firms and managers took place, managers face a positive cost to move to any firm that is not the initial employer.

[16] It can be easily shown that one obvious equilibrium outcome is $L_m(f) = \mu(m)\frac{K(f)}{\mathbf{K}}$, i.e., each firm employs a fraction of each type of managers, proportionally to its relative size.

The introduction of moving costs does not change the optimization problem of the firm. However it affects the choice of employer f_m by manager $m \in [0, M]$ in (14), now given by

$$f_m = \arg\max_f \ v_m(k_m(f)) - \lambda_f k_m(f) - c_m(f). \tag{16}$$

If $\lambda_f > 0$, (9) and (16) give the following first order condition:

$$\frac{\partial \lambda_f}{\partial f} k_m(f_m) = -\frac{\partial c_m(f_m)}{\partial f}. \tag{17}$$

That is, in equilibrium, the marginal gain to switch firm (assets under management times the variation in marginal return on capital) equates its marginal cost.

By multiplying both sides of equation (17) by $L_m(f_m)$ and integrating over m, one obtains, using equation (8)

$$\frac{\partial \lambda_f}{\partial f} = -\frac{\mathcal{C}(f_m)}{K(f_m)}, \tag{18}$$

where

$$\mathcal{C}(f) = \int_0^M L_i(f) \frac{\partial c_i(f)}{\partial f} di.$$

$\mathcal{C}(f)$ can be seen as an aggregate measure of the marginal cost to move to firm f.

The key implication of (18) is that, in equilibrium, a firm to which it is more (less) costly to move, i.e., larger (lower) $\mathcal{C}(f)$, has a lower (higher) internal marginal return on capital λ_f. The intuition is that, because of the managers' moving costs, the firm suboptimally employs too few (many) managers and thus allocates too much (little) capital to its employees compared to the frictionless case, lowering (increasing) marginal returns on capital. Furthermore, this effect is exacerbated (attenuated) when the firm has more capital, i.e., larger $K(f)$, to allocate across its managers.

This result implies that as soon as manager's employer choice is distorted by costs, the Lagrange multiplier λ_f is no longer equalized across firms. Therefore there is a case of capital misallocation as there exists a non-zero dispersion of marginal returns on capital across managers.

2.5 Empirical implications

The main conclusion from the stylized model developed above is that investors' capital mobility across managers and managers' mobility across firms are two equivalent channels that can operate to obtain the optimal allocation of capital across managers. That is, both channels can lead to equalization of marginal returns on capital across all managers in the economy. The role of managers' mobility depends on investors' capital allocation. If the latter is efficient, managers' mobility across firms is irrelevant to the efficiency of the allocation of capital across managers. However, if investors' capital allocation is imperfect, managers' mobility is crucial to improve capital allocation. Therefore, in that case, introducing (heterogeneous) switching costs, preventing managers to move freely across firms, would worsen the allocative efficiency of capital.

The goal of the rest of the paper is to determine empirically whether the labor market channel operates in the capital allocation process. In an ideal experiment, the researcher would face several markets featuring similar managers, firms and investors and would randomly introduce, in certain economies, costs for managers changing employer. One could then compare the degree of capital misallocation across frictional and frictionless labor markets. Doing so would isolate the role of labor mobility. If investors' capital allocation is imperfect and managers and firms are rational and informed about managers' skill, distorting managers' mobility should have a negative impact on both the efficiency of capital allocation and the total value added of managers (as the value added of a manager decreases when capital deviates from her optimal amount of assets under management). This can be summarized by the following two predictions:

Prediction 1: If investors' capital allocation is imperfect then when a manager switches firm, her capital misallocation decreases and her value added increases.

Prediction 2: If investors' capital allocation is imperfect then when managers' mobility costs are introduced, capital misallocation across managers increases and the total value added of managers decreases.

3 Data and descriptive statistics

This section describes the dataset used in the empirical analysis. The mutual fund industry reporting requirements allow to observe key quantities appearing in the model. Indeed, one can collect funds' performance and fees, assets under management and identity of the managers and firms. For my empirical analysis, I build a manager-level dataset combining three databases that are the CRSP Survivorship Bias Free Mutual Fund database, the Morningstar mutual funds database and the S&P Capital IQ - People Intelligence database.

3.1 Fund data

My first data source is the CRSP Survivorship Bias Free Mutual Fund database, reporting fund-level information. I start by collecting all funds' data up to December 2018. Then, I remove all passive funds. I identify the latter using CRSP's flag indicating whether a fund is an index fund or an ETF. I also rely on fund names to identify additional passive funds not flagged by CRSP.[17] I also discard money market funds. I identify the latter using either fund name (if the latter contains the case insensitive character "money market' or "money mkt"') or fund holdings (if on average the fund holds more than 20% of assets in cash, following Berk et al., 2017). Finally I remove bond funds according to fund classification (fund style provided by CRSP) and bond holdings (if on average, over 50% of fund's assets are in either bonds or cash, following Berk et al., 2017). I also drop all funds classified as alternative (non equity) by CRSP and funds without information on holding composition that are not classified as equity by CRSP. To address the possibility of incubation bias, I follow Kacperczyk et al. (2014) and exclude observations for which the date of the observation is prior to the reported fund's starting date as well as observations for which the names of the funds are missing in the CRSP database.

For each fund in my sample, I collect monthly TNA (Total Net Assets) and net return provided by CRSP. To adjust for the effect of inflation, I restate all TNA observations in January 2000 dollars. I replace any missing fund's TNA by the most recent observation in the past. Then I drop all observations with missing TNA or return. I also collect expense ratios available from CRSP. As for TNA, I replace any missing expense ratio by the most recent observation in the past. Then I drop all observations with missing expense ratio.

Beginning in December 1999, CRSP provides for each fund a management company code, i.e., a unique identifier for the management company. For each fund observation, I gather the management company's identifier as well as the company name provided by CRSP. Thanks to the identifier and each observation's date, I also keep track of the management company address provided by CRSP (beginning in January 2000). I replace any missing management company code by the previous non missing observation if and only if the next available non missing observation is the same. Then, I drop observations with missing company identifier.

I collect portfolio manager names available from CRSP.[18] Because the manager names pro-

[17] I remove the fund if its name contains one of the following case insensitive character: "index", "idx", "indx", "mkt", 'market", "composite", "s&p", "russell","nasdaq", "dow jones", "wilshire", "nyse", "ishares", "spdr", "holdrs", "ETF", "Exchange-Traded Fund","Exchange Traded Fund", "PowerShares", "StreetTRACKS", "100", "400", "500", "600", "1000", "1500", "2000", "3000", "5000".

[18] I set to missing the portfolio manager names that contain one of the following character: "inv assoc", "invst", "assoc.", "manage", "mgmt", "asset mgt", "asset m", "asset allocation", "international", "inc.", "mgt", "capital", "capitl", "quantitative", "trust co", "trust bank", "wells fargo", "national bank", "natl bank", "duff & phelps", "payden & rygel", "& assoc", "& co", "& sime", "& field", "sullivan & smith", "& wiley", "SCUDDER, STEVENS & CLARK", "SCUDDER STEVENS & CLARK", "scudder stvns & clrk", "invest corp", "Jennison Assoc Cap Corp",

vided by CRSP might not be recorded consistently over time and across funds, I augment CRSP data with the manager information provided by the Morningstar mutual fund database. The latter offers a clean and complete list of managers for each fund which is part of the Morningstar database. This information is publicly available in the "Management" section of the Morningstar's webpage of each fund.[19] Using each fund's ticker and observation date provided by CRSP, I scrape the corresponding Morningstar's webpage and extract the history of portfolio managers' complete names as well as the managers' start and end dates with the fund. However, there are examples of funds in CRSP that are not covered by Morningstar. To ensure that I do not introduce survivorship bias into my dataset, I only use Morningstar's data to update the manager names in CRSP when possible, but, importantly, I still use the data in CRSP database that I could not update. For those funds for which I cannot update manager names, I use the information provided by CRSP. I replace any missing portfolio manager name by the previous non missing observation if and only if the next available non missing observation is the same.

Finally, I merge the different share classes of a fund using the CRSP Class Group code, which is a unique identifier for the different classes of a fund provided by CRSP (beginning in December 1999). For the quantitative attributes of funds (e.g., returns), I take the weighted average, where the weights are the lagged TNAs of each share class. I drop any fund observations before the fund's (inflation adjusted) AUM combined across all share classes reached \$5 million. I also drop funds with fewer than two years (24 months) of data.

3.2 Computing alpha and value added

I follow Berk and Van Binsbergen (2015) and Berk et al. (2017) and define a fund's alpha as excess-return from investing in the next best alternative opportunity defined as a set of index funds. Let $R_{i,t}$ be the monthly gross return of mutual fund i between time $t-1$ and t. The

"AMERICA CORP", "LLC", "CIMCO Inc", "Batterymarch Financial Inc", "CLAY FINLAY INC", "Martin Currie Inc", "Advisor", "Ltd", "Investment", "Limited", "Mgrs", "Partner", "Invstmnt", "Associate", "Investment", "Committee", "Research", "DIRECTOR", "Blackrock", "Acadian", "State Street", "JP Morgan", "JPMorgan", "Vanguard", "counselor", "portfolio", "Fid Intl Inc", "Fid Tr Intl", "FIRST OF AMERICA INV. CORP.", "Bank of Ireland", "Bankers Trust", "SBC Financial Services", "John Mcstay Invmt Counsel", "Caterpillar Inv", "Credit Suisse", "DSI-International", "LSV", "Ft Washington Inv Adv", "ADV", "INTL", "equity", "Brinson Global Eqty Comm", "ICCC", "PBHG", "LOUT", "CIMCO", "VNSM", "ICAP", "GÃ", "National City", "HIBERNIA BANK", "Compass Bank", "SCM", "CÃ", "Invesco", "TCW", "Adv", "ADV", "Financial", "AXA",

[19]See for instance financials.morningstar.com/fund/management.html?t=AASSX.

gross alpha of the fund is defined as

$$\alpha_{i,t} = R_{i,t} - R^B_{i,t},$$

where $R^B_{i,t}$ is the projection of fund i gross return on a set of Vanguard index funds available at time t. The whole set is composed of the following funds (tickers are given in parentheses): S&P 500 Index (VFINX), Extended Market Index (VEXMX), Small-Cap Index (NAESX), European Stock Index (VEURX), Pacific Stock Index (VPACX), Value Index (VIVAX), Balanced Index (VBINX), Emerging Markets Stock Index (VEIEX), Mid-Cap Index (VIMSX), Small-Cap Growth Index (VISCX), Small-Cap Value Index (VISVX). The rationale behind using Vanguard index funds as benchmarks, instead of long-short factor portfolios, is that these funds include transaction costs and reflect the dynamic evolution of alternative investment opportunities for investors through time.[20] This approach also allows to not restrict attention to funds that hold only US equity as the "benchmark" alternative investment includes funds that hold non-US stocks. Formally, the projection of fund i return $R^B_{i,t}$ is computed as:

$$R^B_{i,t} = \sum_{k=1}^{n(t)} \beta_i^k R^I_{k,t},$$

where $n(t)$ is the total number of index funds offered by Vanguard at time t, $R^I_{k,t}$ is the return of the index fund k at time t and the coefficients β_i^k are obtained from the projection of i^{th} active mutual fund onto the set of orthogonalized Vanguard index funds. I refer to Berk and Van Binsbergen (2015) for further details. The realized value added of fund i is then defined as

$$v_{i,t} = k_{i,t-1} \times \alpha_{i,t} = k_{i,t-1} \times (R_{i,t} - R^B_{i,t}),$$

where $k_{i,t-1}$ is the TNA of fund i at the end of time $t-1$.

3.3 Manager data

Following managers over time using manager names provided by both CRSP and Morningstar is difficult due to names spelling differences and format changes.[21] To overcome this issue, I combine manager information from CRSP and Morningstar with data from the S&P Capital IQ - People Intelligence database. The latter documents the careers of professionals in public companies and public investment firms as well as in private companies, private investment

[20] Vanguard was the first company to offer self-proclaimed index fund of each type.

[21] E.g., because first and middle names are differently abbreviated or even excluded in CRSP, identical last names appearing in different funds or different periods can refer to different managers.

firms, corporate investment arms, and financial services investment arms. Each professional has a unique identifier called "person id", each company has a unique identifier called "company id" (that can be mapped to other standard firm identifiers) and each job (i.e., match between a professional and a company) has a corresponding standardized function identifier as well as an office address.

First, I download all the data in the S&P Capital IQ - People Intelligence database on professionals that have ever had a "finance" occupation.[22] Then, I map each management company and fund in CRSP with a company identifier in Capital IQ using by order of priority: ticker, CIK, CUSIP and name.[23] Finally, for each manager-fund observation in CRSP, I look for the (potentially incomplete) manager name reported by CRSP or Morningstar into the list of full names of the sub-group of professionals linked to this fund or management company in Capital IQ. When I find a unique match, I assign the unique "person id" identifier from Capital IQ to this manager-fund observation in CRSP and I keep track of the office address of the fund manager. This allows me to track carefully each manager across time, firms and geographical locations thanks to a unique "person id". I am able to identify 82% of manager-fund observations from CRSP in Capital IQ using this procedure.

To obtain a panel at the manager level, I merge all observations with the same person id and date. Following Berk et al. (2017), I consider a fund's AUM is divided equally among its managers. Therefore the AUM of manager m at time t is defined as the sum:

$$k_{m,t} = \sum_{i \in \Omega_{m,t}} \frac{k_{i,t}}{n_{i,t}}, \tag{19}$$

where $\Omega_{m,t}$ is the set of funds managed by manager m at time t and $n_{i,t}$ is the number of managers managing fund i at time t. I use the same procedure to define a manager's flow, where a fund's flow is defined as the difference between the fund's current TNA and the fund's lagged

[22]To achieve this, I select professionals that have ever had a standardized function identifier in the following list: Chief Investment Officer, Head of Investment Banking, Finance and Accounting Professional, Investment Banking Professional, Investment Professional, Member of Pension/Benefit Fund Investments Committee, Member of Investment Committee, Chairman of Investment Committee, Chairman of Pension/Benefit Fund Investments Committee, Co-Chairman of Investment Committee, Co-Chairman of Pension/Benefit Fund Investments Committee, Vice Chairman of Investment Committee, Vice Chairman of Pension/Benefit Fund Investments Committee, Equity Analyst, Fixed Income Analyst, Other Analyst, Co-Chief Investment Officer.

[23]For the funds and companies unmatched in Capital IQ using the tickers, CIK or CUSIP, I first clean the name by removing connectors and generic words such as "the", "mgr", "associates", "advisors", etc. I do the same for company names in Capital IQ. Finally I try to match the lower case cleaned name from CRSP with lower case cleaned company names from Capital IQ.

TNA multiplied by the fund's return.

Similarly, manager's m value added is the sum:

$$v_{m,t} = \sum_{i \in \Omega_{m,t}} \frac{v_{i,t}}{n_{i,t-1}}, \tag{20}$$

where $v_{i,t}$ is the value added of fund i at time t. Finally, I define the gross alpha of a manager as the weighted average of her funds' gross alpha, where the weights are the lagged TNAs of each fund.

I also record the following additional variables at the manager level through time: manager's style (main fund style according to TNA), number of funds, number of comanagers, experience and tenure. To compute the number of managed funds, I count the number of different CRSP Class Group codes the manager is associated with in a given month. Experience is the elapsed time since the first observation of a manager in the sample. Tenure is the time with the current management company, i.e., the length of the current job spell in the sample.

I rely on the management company identifiers provided by CRSP to track managers' employer changes as it uniquely identifies the management company over time.[24] To identify managers switching firm, I require a change in the management company of the manager with respect to the previous period, as well as a full change in the identifiers of funds managed by the manager with respect to the previous period. This allows me to avoid flagging management company mergers or acquisitions as managers' decision to change firm. For each manager observation, the state of location is defined using the state identifier of the primary office address provided by Capital IQ.[25] If the latter is missing, I use the management company state provided by CRSP. I replace any missing manager's state of location by the most recent observation in the past if I do not observe a firm change. Then, I drop observations with missing state of location.

I keep in my sample only managers with at least two years (24 month) of data. Furthermore, because several CRSP identifiers are only available from 2000 and because Capital IQ coverage is substantially weaker before 2000, I focus on the sample period from January 2000 to December 2018.[26] I end up with a sample of 5,586 distinct fund managers. The number of managers simultaneously in the sample goes from 1,170 in January 2000 to 3,256 in December 2015.

[24] I do not use the company id provided by Capital IQ as the latter sometimes differs across funds in the same family firm.

[25] Pool et al. (2012), Pool et al. (2015) and Pool et al. (2019) rely on the LexisNexis Public Records database to identify the home address of fund managers'. In my case, I use Capital IQ because the provided addresses correspond to office addresses.

[26] Capital IQ coverage starts in 1998 but it is only after 2000 that a significant number of managers appears to be identified.

3.4 Summary statistics and stylized facts

Table 1 presents summary statistics for the managers in my sample. The average TNA is about \$1 billion. The distribution is highly skewed as evidenced by the median (\$197 million) and the top 5% of TNA (above \$4.7 billion). Managers run on average two funds and collaborate with four other managers. They produce on average a monthly gross alpha of zero. The average monthly value added is slightly negative (-\$0.8 million) and the median is virtually equal to zero. Monthly flows are on average about half a million. Managers have on average 8 years of experience in the mutual fund industry and 5 years of tenure with employer.

I am able to identify 964 cases of fund manager changing mutual fund firm in my sample. Figure 2 displays the time series evolution of the fraction of mutual fund managers I identify as having switched firm in a given year from 2000 to 2018. There is on average 2.2% of managers changing firm each year, with clear spikes in 2003, 2008 and 2012. Figure 3 shows the distribution of the number of firm changes each manager experiences during her career. About 20% of managers switch firm at least once and I record at most three firm switches throughout a career.

Table 2 reports the distribution of key characteristics for switching managers just before the firm change. For the 964 cases of manager changing firm, I report data on experience and tenure, flows, performance, AUM and number of funds. I also present the variation of TNA over the next month, i.e., the difference between the manager's TNA just after and just before the firm change. Switching managers have on average 6 years of experience in the mutual fund industry and have spent 3 years within the firm they leave. Asset flows over the past month (year) have an average slightly negative value of -\$3.7 million (-\$29 million) but the median value of -\$0.4 million (-\$4.8 million) is much closer to zero. The median values of gross alpha and value added over the past month and year are close to zero. Table 2 also reports the distribution of "Liquidated fund" that is a dummy variable taking the value of one if the manager experiences the liquidation of one of her funds the period before she moves. This never appears to be the case.

Switching managers manage on average \$388 million of assets before they move, but the distribution is highly skewed with a median of \$81 million. These statistics are lower compared to their counterparts in the whole sample of managers reported in Table 1. A key observation is that manager moves across firms involve large changes in AUM. On average, the absolute variation of manager TNA is \$497 million, which corresponds to 31 times the average of the absolute value of monthly flows (\$16 million). The median absolute variation in AUM when a manager switches firm is \$107 million, which is more than 40 times the median value of absolute fund flows (\$2.5 million). These observations suggest that the magnitude of capital reallocation following a firm change can be severe. Note that the variations in AUM following firm change are both positive and negative with a slightly negative median value of -\$10 million.

4 Empirical strategy

The main objective of the paper is to understand how managers' mobility across firms affects the misallocation of capital across managers. In this section, I provide details about how I proxy for capital misallocation at the manager level as well as the specifications used in the paper to provide micro evidence that managers' mobility is a channel through which capital is efficiently reallocated across managers. Then, I describe how I use changes in US states' enforceability of non-compete agreements to examine the causal impact of manager mobility frictions on capital misallocation and value added of fund managers at a more macro level. I give details about the empirical methodology I employ to tease out the role of mobility frictions.

4.1 Measuring manager skills and returns to scale

Examining capital misallocation across fund managers requires knowing the form of the value added function of managers, given in equation (1). In particular, one needs to specify the form of the gross alpha function in order to capture the effect of the amount of capital under management on managers' productivity. In my empirical analysis, I follow the literature studying the relationship between fund size and performance and I use a reduced form specification assuming that gross alpha decreases linearly with AUM. Namely, I assume

$$\alpha_m(k) = a_m - b_m k. \tag{21}$$

where a_m and b_m are positive constant parameters. The intercept a_m corresponds to the excess return generated on the first dollar of capital actively invested by the manager, while b_m controls the slope of the relation between the gross alpha and the amount of AUM.

Assuming this linear form is convenient for at least two reasons. First, one can derive the closed form expression for the optimal amount k_m^* manager m should be managing to maximize value added $v_m(k) = k \times \alpha_m(k)$:

$$k_m^* = \frac{a_m}{2b_m}, \tag{22}$$

as well as the expression for manager's marginal return on capital ${v_m}'(k)$ when running a fund of size k:

$$ {v_m}'(k) = a_m - 2b_m k. \tag{23} $$

Second, I can rely on the econometric procedures developed in the literature to study returns to scale in active management in a linear regression framework.

Several papers have focused on the estimation of the effect of fund size on fund alpha.[27] Pástor et al. (2015) emphasize that direct OLS estimators can be biased and propose a procedure using a panel regression with fund fixed effects and an instrumental variable for fund size based on a recursive demeaning procedure.[28] Their method indicates decreasing returns, though estimates are insignificant. Zhu (2018) modifies Pástor et al. (2015)'s panel estimator to make it more suitable for the fund size process and establishes diseconomies of scale at the fund level.[29] These methodologies are mainly developed to estimate a common slope across all funds. However, as made explicit in the model of section 2 and aknowledged by Zhu (2018), because a manager's level of AUM is determined endogenously, managers heading small funds are likely to differ from their peers heading large funds in their returns to scale technology as investment ideas of some managers are less scalable than others.

Estimating directly the parameter b_m manager by manager using time series regressions leads to imprecise estimates especially for managers with short track record.[30] Zhu (2018) proposes a procedure to reduce the estimation error, which consists in sorting funds into portfolios and estimate the slope in each portfolio. I follow this approach by applying Zhu (2018)'s procedure at the manager level. In doing so, I estimate manager-specific parameters a_m and b_m.

First, I sort the mutual fund managers into ten groups based on the ranking of their average AUM calculated over the sample period. Then, I estimate b_m using the panel estimator of Zhu (2018) in each group of managers. This implementation choice assumes that all the managers in a group share the same b_m value, but this method actually increases the accuracy of the estimate

[27] See Chen et al. (2004) for an early reference.

[28] Reuter and Zitzewitz (2015) propose an empirical strategy exploiting a discontinuity in fund flows across Morningstar star ratings to generate exogenous variation in size.

[29] Pástor et al. (2020) focuses on trading costs as one important causes of diminishing returns to scale for actively managed equity mutual funds. They propose a method to derive a mutual fund's proportional trading costs using the fund's holdings and turnover. Zhu (2018)'s approach allows to focus on funds' AUM and performance.

[30] Despite the overall trend of decreasing returns to scale, Zhu (2018) finds that 29% of funds in her sample end up with an estimate indicating increasing return to scale, using the fund-by-fund OLS regression, but the estimation error is severe. In addition, Barras et al. (2018), who propose a non-parametric approach based on individual fund time series regressions, find that there is decreasing return to scale for only 85.9% of the funds.

because of the sharp reduction in estimation errors. Once the group-specific $\hat{b}_m$ estimates are obtained, manager-specific $\hat{a}_m$ estimates can be recovered. I provide a brief description of the procedure below and refer to Zhu (2018) for additional details:

1. I sort managers into 10 groups according to their average AUM defined as $\bar{k}_m = \frac{1}{T_m}\sum_{t=1}^{T_m} k_{m,t}$, where T_m is the number of observations for manager m and $k_{m,t}$ the AUM of manager m at time t.

2. In each group g, I estimate the decreasing return to scale parameter b_g using Zhu (2018)'s methodology.[31] To do so, I define the recursively forward-demeaned variables for each manager m as follows:
$$\bar{\alpha}_{m,t} = \alpha_{m,t} - \frac{1}{T_m - t + 1}\sum_{s=t}^{T_m} \alpha_{m,s},$$
$$\bar{k}_{m,t-1} = k_{m,t-1} - \frac{1}{T_m - t + 1}\sum_{s=t}^{T_m} k_{m,s-1},$$
where $\alpha_{m,t}$ is the gross alpha of manager m at time t. The estimator is implemented via two-stage least squares. The first stage consists in regressing forward-demeaned manager AUM $\bar{k}_{m,t-1}$ on AUM $k_{m,t-1}$
$$\bar{k}_{m,t-1} = \psi + \rho k_{m,t-1} + \nu_{m,t-1}.$$
The second stage involves the regression of forward-demeaned alpha on the fitted value from the first-stage denoted $\bar{k}^*_{m,t-1}$:
$$\bar{\alpha}_{m,t} = b_g \bar{k}^*_{m,t-1} + u_{m,t}.$$
I denote as $\hat{b}_g$ the estimator of b_g above and I assign to each manager m in group g the estimated decreasing return to scale parameter $\hat{b}_m = \hat{b}_g$.

3. Then, I recover manager-specific estimate of a_m as:
$$\hat{a}_m = \frac{1}{T_m}\sum_{t=1}^{T_m}(\alpha_{m,t} + \hat{b}_m k_{m,t-1}).$$

Note that, even if my sample of analysis goes from 2000 to 2018, several managers have track records going back to pre-2000 period. To reduce estimation error as much as possible, for each

[31] Following most papers estimating decreasing return to scale, I exclude manager-month observations with lagged AUM below \$15 million. I also exclude observations for which the set of funds managed by the manager differs with respect to the previous period.

manager identified in my sample, I use the longest possible time series of gross alpha and AUM (even if it involves data before 2000) to estimate the a_m and b_m coefficients.

Table 3 reports summary statistics of the estimated skill parameters. The positive estimates of b_m suggest that the relation between a manager's AUM and her gross alpha is negative in each AUM-sorted group. This coefficient is statistically significant in all groups according to the values of t-stats, ranging from 2.81 to 7.47. There is a clear decreasing pattern in the magnitude of b_m as the average AUM of the manager-group increases. Indeed, for group 1, with the lowest average AUM, b_m has a value of 0.61×10^4. As AUM are reported in \$million, this means that an additional million of assets under management leads to a decrease in monthly gross alpha of more than half a basis point. At the other extreme, in group 10, b_m has a value of 0.003×10^4, i.e., it requires more than \$300 million of assets to make the monthly gross alpha decrease by one basis point. Hence managers heading large funds are characterized by a relatively flat decreasing returns to scale technology, while performance of managers heading small funds suffers much more when fund size increases.

Table 3 also reports summary statistics of the estimates of a_m (monthly gross alpha on the first dollar) for all managers in each group. There is no monotonic pattern in the mean value of a_m across groups. While the average value in group 1 is around 8 bps, it decreases to 2 bps in group 5 and then increases again up to 10 bps in group 10. The variations in a_m are large, with standard deviations between 2 and 10 times the mean value. The main conclusion is that managers with larger AUM are not necessarily running investment strategies with larger alpha on the first dollar but instead more scalable strategies. Panel A of Figure 4 presents the overall distribution of $\hat{a}_m$ across managers. It shows that about a quarter of managers fails to generate a positive alpha on the first dollar they manage.

Once one is armed with estimates of the parameters a_m and b_m for each manager, one can compute the corresponding implied optimal level of AUM k_m^*. The latter corresponds to the amount of assets maximizing the value added of each manager and is defined by (22). I set k_m^* to zero for managers who have a negative estimate $\hat{a}_m$. Indeed, a negative a_m suggests that the manager is not able to have a positive alpha on the first dollar she manages, i.e., she does not create value at any scale. Thus, it is optimal to not allocate any capital to this manager.[32]

Statistics regarding the distribution of k_m^* in each group of managers are presented in the right part of Table 3. It reveals that the average value of k_m^* clearly increases (from \$12 million

[32]Shorting the manager's fund shares would require the manager to run a fund with some capital, which is sub-optimal in the first place.

in group 1 to \$2.2 billion in group 20) and so does the actual average AUM in each group. Panel B of Figure 4 reports the corresponding distribution of k_m^* across managers. Its shape suggests that the density of optimal AUM is geometrically decreasing from 0 to about \$2 billion.

4.2 Measuring capital misallocation at the manager level

I use the estimates of manager skills and returns to scale described above to construct measures of capital misallocation at the manager level, building on the stylized theoretical framework presented in section 2.

The first measure of misallocation relates to managers' marginal product of capital (MPK), defined as the derivative of the manager's value added with respect to the amount of capital under management. Indeed, a manager m managing her optimal level of assets k_m^*, defined in (22), has a marginal return on capital equal to zero:

$$v_m'(k_m^*) = a_m - 2b_m k_m^* = 0.$$

However, if the manager is underfunded (overfunded), i.e., manages an amount of assets below (above) k_m^*, her MPK is positive (negative), i.e., an additional dollar of assets would increase (decrease) the manager's value added. Therefore, I use the absolute value of the marginal product of capital as a measure of capital misallocation for manager m at time t:

$$|MPK|_{m,t} = |a_m - 2b_m k_{m,t}|, \tag{24}$$

where $k_{m,t}$ is the AUM of manager m at time t, calculated in (19).

I consider a second measure of misallocation that can be expressed in dollars. Relying again on the estimates of the parameters a_m and b_m obtained in section 4.1, I use the theoretical amount of assets maximizing the value added of each manager, defined as $k_m^* = \hat{a}_m / 2\hat{b}_m$ (set to zero for managers with a negative estimate $\hat{a}_m$). I compute a dollar misallocation for manager m at time t as follows:

$$\$Misallocation_{m,t} = |k_{m,t} - k_m^*|. \tag{25}$$

This misallocation measure represents the (absolute) dollar spread between the current manager's TNA and her optimal level of capital.

To ensure that my findings are not driven by outliers, the measures of misallocation and value added at the manager level are winsorized at the 1st and 99th percentiles in the regressions described below. The results presented in the paper remain valid when these variables are not winsorized.

4.3 Specifications to study the relation between misallocation and managers' mobility

The main prediction from section 2.3 is that, if managers' mobility plays a role in reaching a more efficient capital allocation, managers that can reduce their level of capital misallocation should move across firms and as a consequence managers should see their marginal product of capital and dollar misallocation getting closer to zero after they switch from one firm to another.

To test whether a manager with a given level of capital misallocation is more likely to switch firm compared to an otherwise similar manager with a lower level of capital misallocation, I consider the following specification:

$$Switch_{m,t} = \beta \log(Misallocation_{m,t}) + \gamma X_{m,t} + \delta_t + \lambda_m + \eta_{style} + \theta_f + \epsilon_{m,t}. \tag{26}$$

$Switch_{m,t}$ is a dummy variable set to one if the manager switches firm next period $t + 1$, i.e., manager m departs from her current employer at the end of period t. $Misallocation$ corresponds to the measures developed above in (24) and (25). X is a vector of control variables including the manager's (log) TNA, (log) number of funds and comanagers, flow, (log) tenure, (log) experience, the share of manager's funds with a retail share class and a dummy indicating whether the manager has incurred an internal capital reallocation in this firm.[33] δ_t, λ_m, η_{style} and θ_f are respectively time, manager, style and firm fixed effects. Standard errors are clustered at the firm level. If capital misallocation induces managers to move across firms, one should observe $\beta > 0$ in (26).

Then, I test whether a manager switching firm sees a decrease in her capital misallocation and as a consequence an increase in her value added, compared to otherwise similar non switching managers. Note that as illustrated in Figure 1, when the distance to the optimal AUM k^*_m rises, value added drops. Therefore, if capital misallocation decreases after a manager switches firm, one should observe and increase in the manager's value added. I implement the following specification:

$$Y_{m,t} = \beta\{Switch \times Post\}_{m,t} + \gamma X_{m,t} + \delta_t + \lambda_m + \eta_{style} + \theta_f + \epsilon_{m,t}. \tag{27}$$

$Y_{m,t}$ corresponds to measures of misallocation and value added. I consider as dependent variables $\log|MPK_{m,t}|$, $\log(\$Misallocation_{m,t})$ and $v_{m,t}$, where the latter is the value added of manager

[33] I follow Berk et al. (2017) and define an internal capital reallocation as a situation in which the manager remains in the same firm but a fund is added to or taken away from the set of the manager's funds with respect to the previous period.

m at time t. $\{Switch \times Post\}_{m,t}$ is an indicator variable that takes the value of one if manager m has switched firm by time t, zero otherwise. X includes the (log) manager's experience. I do not include TNA, number of funds and comanagers, flow and tenure because these variables are likely to be bad controls as they are also affected by the firm change. δ_t, λ_m, η_{style} and θ_f are respectively time, manager, style and firm fixed effects. Standard errors are clustered at the firm level. This specification can be seen as a difference-in-difference comparing the variation in the dependent variable after a manager switches firm with respect to the variation in the same variable for otherwise similar non switching managers. If switching across firms allows managers to reduce capital misallocation, one should observe $\beta < 0$ (resp. $\beta > 0$) in (26) when the dependent variable is misallocation (resp. value added).

To study the timing of the effect and show that the variations in misallocation and value added are really due to the firm change, I also estimate the following specification with the same dependent variables as in (27):

$$Y_{m,t} = \sum_k \beta_k \{year\ k\ to\ firm\ change\}_{m,t} + \delta_t + \lambda_m + \eta_{style} + \theta_f + \epsilon_{m,t}, \tag{28}$$

where $\{year\ k\ to\ firm\ change\}_{m,t}$ is a specific indicator that is equal to 1 if manager m eventually switches firm and the period t is part of year k before or after the firm change.

Finally, to compare the effect of changing firm on fund managers incurring a large misallocation in the initial firm with the effect on fund managers incurring a lower misallocation, I estimate a variation of specification in equation (27). Namely, this alternative specification splits the indicator $\{Switch \times Post\}_{m,t}$ into two separate terms $\{SwitchHighRetail \times Post\}_{m,t}$ and $\{SwitchLowRetail \times Post\}_{m,t}$. The first term is an indicator that takes the value of one if manager m has switched firm by time t but a majority (more than half) of the manager's funds in the initial firm had a retail share class, zero otherwise. $\{SwitchLowRetail \times Post\}$ takes the value of one if manager m has switched firm by time t but a minority of the manager's funds in the initial firm had a retail share class. The intuition is that retail investors are more likely to allocate capital across mutual funds for reasons unrelated to manager skills leading to larger misallocation levels.[34] Therefore, a fund manager moving away from a firm where she managed retail funds should see a larger drop in misallocation than a similar manager moving from a firm where she managed institutional funds.

[34] See for instance Frazzini and Lamont (2008) and Bergstresser et al. (2008).

4.4 Changes in the enforceability of non-compete agreements as shocks to managers' mobility costs

The regressions described in the previous section study capital misallocation at the manager level and can provide micro evidence on the factors driving managers' mobility across firms and the effect of the latter on managers' misallocation and value added. However, because managers' mobility implies effects external to the manager that actually switches firm, its total impact would not appear in manager-level studies. One must move to a more macro level of analysis.

Considering several segmented mutual fund markets and simply running regressions of measures of capital misallocation on managers' mobility, both aggregated at the market level, is however confounded by concerns regarding omitted variables and reverse causality. For example, managers operating in markets where more information regarding fund performance is public might change employer more often, this would likely be associated with lower misallocation. To the extent that such additional factors are unobserved by the econometrician, regressions of aggregated capital misallocation on the intensity of managers' mobility across firms would reflect this relationship and be biased.

To address this issue, I exploit shocks that isolate exogenous changes in managers' mobility costs. I rely on staggered changes in US states' labor policies, affecting the ability of managers to change employer. Specifically, I use state-level variations in the enforceability of non-compete clauses (NCCs), as exogenous shocks to the cost managers face when changing employer. NCCs are special clauses in labor contracts in which the employee covenants neither to join nor to found a competing firm within 1–2 years of leaving. These clauses are governed at the state level.[35] State NCCs policy changes should therefore—given fixed outside options—alter fund managers' ease to switch mutual fund firms, i.e., affect managers' mobility costs. Indeed, stronger (resp. weaker) NCCs enforcement should deter (resp. facilitate) fund managers from switching employers as failures to comply with the clauses are more (resp. less) likely to result in cases brought to court if NCCs are more (resp. less) enforceable. This setting allows me to test whether fund managers' mobility across firms affects the efficiency of capital allocation, eliminating concerns regarding unobserved variables affecting jointly managers' mobility and capital misallocation. Indeed, it allows me to compare variations in capital misallocation caused by exogenous shocks to labor mobility frictions (ceteris paribus), between affected and unaffected US states.

According to a survey on more than 11,000 labor force participants in the US, Starr et al.

[35] For instance California bans the use of NCCs.

(2018) document that nearly one in five labor force participants were bound by NCCs in 2014. Furthermore, their results indicate that NCCs are even more likely to be found in high-skill, high-paying jobs, with an incidence rate of 50% for management occupations in finance and insurance. Although I do not observe manager-level contracts, Starr et al. (2018)'s findings as well as legal disputes in recent years and online anecdotal evidence on job search platforms suggest that investment managers are likely to be affected by NCCs and thus state-level legislation changes.[36,37]. I describe below how I test empirically that managers' mobility is affected by NCCs changes. The results presented in Section 5 validate this claim.

Ewens and Marx (2017) record thirteen state-level changes during my sample period (2000-2018) that correspond to state Supreme Court rulings and state legislature changes. Increase in enforceability concerns Ohio (2004-Q1), Vermont (2005-Q3), Idaho (2008-Q2), Wisconsin (2009-Q3), Georgia (2010-Q4), Colorado (2011-Q2), Illinois (2011-Q4) and Texas (2011-Q4) while decrease in enforceability affects Louisiana (2001-Q2), Oregon (2007-Q4), South Carolina (2010-Q2), New Hampshire (2012-Q2) and Kentucky (2014-Q2). I build on Ewens and Marx (2017)'s work and use this set of NCC law changes in my empirical analysis. The next section discusses the geographical location of the "treated" states and of fund managers.

Ewens and Marx (2017) also provide background on the political economy of the change. None of these policy variations were driven by cases related to or prospects of the asset management industry in those states. Hence, the fact that none of the changes in non-compete enforceability targeted specifically the mutual fund sector supports the exogeneity assumption of NCC law changes in my study. Jeffers (2018) also shows that GDP per capita follows very similar trends in states that are affected by changes and others, suggesting the changes in enforceability are not a response to different economic environment in the treated states, and thus, arguably unlikely to be related to capital allocation in the mutual fund sector.

[36] The typical investment manager NCCs documented online has a period of 12-month and restricts the following activities: "*directly or indirectly performing asset management services, trading services or investment advisory services; or working for or having an interest in a company, partnership or other entity that competes with [the fund and its affiliates]*".

[37] Cf. the following cases of legal disputes: Frank Russell Investment Management Company and Wellington Management Company (1998), Graham Capital, Moore Capital, Tudor Investment Corporation as well as more recently Mikhail Malyshev and Jace Kohlmeier versus Citadel (2009) and Christopher Rokos versus Brevan Howard (2015). For online anecdotes, cf. comments on NCCs for several investment management firms on Glassdoor.com for instance.

4.5 State-level measures

Changes in US states' enforceability of NCCs allow me to study the relationship between managers' mobility across firms and capital misallocation across managers at a more macro level. Carrying out this analysis requires to aggregate the variables of interest at the state level in order to make comparisons across states.

I use each manager's current state of location, as described in Section 3, to build a panel at the US state level. Table 4 presents summary statistics when the counts of managers, firms, TNA, funds and value added are summed the state-month level. I drop observations with strictly less than two managers as I cannot exploit these observations in the specifications using state-level capital misallocation, described below. The average state-month observation features 60 managers in 20 firms and $62 billion of assets under management in 50 funds. The distributions of these variables are highly skewed as evidenced by the median values. To test that changes in NCCs enforceability do affect managers' mobility across firms, I compute the count of managers changing firm at the end of each month in each state ($\#Switches$) and the percentage of switching managers. The latter is defined as:

$$\%Switchers_{s,t} = 100 \times \frac{\#Switches_{s,t}}{\#Managers_{s,t}}, \tag{29}$$

where $\#Managers_{s,t}$ is the count of managers in state t in period t. Table 4 shows that the averages of the number and percentage of switching managers are respectively 0.1 and 0.2. To ensure that my findings regarding managers' mobility are not driven by outliers (e.g., states with few managers incurring several moves), the percentage of switching managers is winsorized at the 1st and 99th percentiles in the regressions described below.

To measure capital misallocation across managers at the state level, I build on the stylized theoretical framework developed in section 2 and construct measures of the dispersion of marginal products on capital (MPK) across managers.[38] The intuition is that the extent of capital misallocation is worse when there is a greater dispersion of marginal products. For each month and state, I compute two measures of dispersion using the variable MPK defined in the Section 4.2. The first one, denoted $\sigma(MPK)_{s,t}$, is the standard deviation of the marginal products of capital of managers employed in state s in period t. The second one, denoted $(MPK\ 75-25)_{s,t}$, is the difference between the 75th and 25th percentiles of the MPK of managers employed in state s in period t. State-level measures of managers' value added are calculated by summing for each

[38] This type of measures is often used in the resource misallocation literature, in particular Hsieh and Klenow (2009).

state and month the value added of managers employed in that state in that month. Note that this measure is independent of the estimates of manager skills and returns to scale.

Obviously, fund managers are not evenly distributed across US states. Panel A of Figure 5 shows the geographic distribution of fund managers. The largest states in terms of the average number of fund managers over my sample period are New-York (495 managers), Massachusetts (360 managers), California (270 managers), Pennsylvania (208 managers), Illinois (168 managers) and Texas (94 managers). As described below, I control for the number of managers, firms and funds as well as TNA in my regressions at the state level. Panel B of Figure 5 shows the geographic location of states that are "treated" by changes in NCCs enforceability. There are both large and small states in terms of average number of fund managers among the treated states. For instance Illinois, Texas, Ohio and Georgia are relatively large states with NCCs law changes over the sample period. Louisiana, South Carolina, Kentucky and New Hampshire are also treated but features much fewer fund managers.

Table 5 compares characteristics of states that are affected by changes in NCCs enforcement ("treated") and states that are not ("control"). The statistics correspond to monthly observations in the year 2000, i.e., before any enforceability shock occurs. The table provides t statistic of differences in means between treated and control states. Table 5 shows that there are fewer managers on average in treated states than in control states (27 versus 38). Logically, one sees that, the total amount of assets (TNA) in treated states is lower than in control states ($28 billion versus $45 billion) as in the number of funds (26 versus 35). The average number of firms are very similar (17 versus 20). I do not observe large ex-ante differences in terms of percentage of switching fund managers.

Comparing states that do experience changes in the enforceability of NCCs with states that do not to study managers' mobility and capital misallocation requires that US states operate as independent "fund manager markets". In other words, although fund managers employed in a given state could move to firms located in other states, NCCs enforceability changes should have an effect only if fund managers disproportionately move across firms in the same state where they are located. To establish that there exists such a "home bias", I count the proportion of switching fund managers that remain in the same state. Out of the 964 cases of manager changing firm, 741 (77%) correspond to switching managers remaining in the same state. If I focus on state-level observations featuring at least one manager switching firm, I observe that the fraction of switches occurring within the state (versus out of state) has a mean of 78% and a median of 100%. These observations confirm that there are very few fund managers moving across states.

One might still be concerned that managers that are affected by stronger NCCs substitute within-state employer changes with out-of-state changes. Nevertheless, for the purpose of enforcing NCCs, the relevant jurisdiction is the place where the economic activity takes place, i.e., where the worker is located (Lester and Ryan, 2009). Hence it is unlikely that fund managers in treated states would tend to move more out of the state where they are located.[39]

4.6 Specifications to study the effect of changes in the enforceability of non-compete agreements on managers' mobility and capital misallocation

First, I establish the validity of my approach, i.e., I verify that NCCs law changes have a significant impact on managers' propensity to change mutual fund firm. My empirical strategy is to test, using a generalized difference-in-difference specification, whether states strengthening (weakening) NCCs enforceability see a decrease (increase) in managers' mobility across firms after the NCCs law change, compared to states without legislation change.[40] The specification I use is the following :

$$\%Switchers_{s,t} = \beta \left\{Treated \times Post\right\}_{s,t} + \gamma X_{s,t-1} + \theta_s + \delta_t + \epsilon_{s,t}, \tag{30}$$

where $\%Switchers$ is the percentage of managers in state s at time t changing employer next period $t+1$ and is defined in (29). The independent variable $\{Treated \times Post\}_{s,t}$ is an indicator that is equal to 1 (resp. -1) if an increase (resp. decrease) in NCCs enforceability has been passed by time t in state s, and zero otherwise. $X_{s,t-1}$ includes lagged control variables at the state level: the (log) number of managers, the (log) number of management firms, the (log) total AUM of managers and the (log) number of funds. Control variables are lagged in order to avoid the "bad control" criticism discussed by Angrist and Pischke (2008). The regression includes state fixed effects θ_s and time fixed effects δ_t that absorb the usual $Treated$ and $Post$ terms present in standard difference-in-difference specifications. Standard errors are clustered at the state level because that is the level of treatment.

[39] Furthermore, in order to be enforceable, a non-compete clause has to specify a reasonable geographic scope, for instance prohibiting the employee from becoming employed in a firm proving similar products in similar areas. Several law firms affirm that the reasonableness of the geographic scope of a covenant has become less significant in the asset management industry, because this business is usually global. See for instance the article by Schulte Roth & Zabel: https://www.hflawreport.com/2542751. Hence it is likely that NCCs in the mutual fund industry are less bounded by "local restrictions".

[40] The generalized difference-in-difference specification I use is similar to the one used in Bertrand and Mullainathan (2003), who focus on the assessment of the effects of anti-takeover law changes.

Specification (30) accounts for the fact that there are several NCCs law reversals staggered over time. Hence, the control group is not restricted to states that never pass a change. Equation (30) uses as the control group all states that have not passed a law change at time t, even if they will be affected by a change later on. The common trends assumption underlying this specification is that, in the absence of NCCs law changes, managers' mobility in the treated states would have changed in the same way as in the control group. If stronger NCCs enforcement negatively affects managers' mobility, one should observe $\beta < 0$ in (30).

The second stage of my state-level analysis is to evaluate whether NCCs law changes affect capital misallocation across managers and thus value added of managers. My strategy is to test, using a similar generalized difference-in-difference specification, whether states strengthening (weakening) NCCs enforceability display an increase (decrease) in capital misallocation and a decrease (increase) in value added of managers, after the NCCs law change, compared to control states without legislation change. The specification is the same as in equation (30):

$$Y_{s,t} = \beta \left\{Treated \times Post\right\}_{s,t} + \gamma X_{s,t-1} + \theta_s + \delta_t + \epsilon_{s,t}, \tag{31}$$

where the dependent variable $Y_{s,t}$ is for state s at time t a measure of the misallocation across managers or total value added of managers, described in Section 4.5. If managers' mobility across firm is an important channel that contributes to improve capital allocation, preventing managers from moving across firms should worsen capital allocation. Therefore, if stronger NCCs enforceability decreases the ability of managers to move across firms, one should observe $\beta > 0$ in (31) when the dependent variable $Y_{s,t}$ is a measure of misallocation and $\beta < 0$ when $Y_{s,t}$ is a measure of value added of managers.

To study the timing of the effect of NCCs enforceability changes, I also estimate the following specification with the same dependent variables as in equations (30) and (31):

$$Y_{s,t} = \sum_k \beta_k \left\{Treated \times year\ k\ to\ treatment\right\}_{s,t} + \gamma X_{s,t-1} + \theta_s + \delta_t + \epsilon_{s,t}, \tag{32}$$

where $\left\{Treated \times year\ k\ to\ treatment\right\}_{s,t}$ is a specific indicator equal to 1 (or -1) if state s is eventually treated and if the period t is part of year k before or after the NCCs law change.

Because New-York, Massachusetts and California appear to be larger than other states in terms of average number of fund managers during the sample period and might be outliers in the control group, I also estimate all the state-level regressions discussed above when observations for each of these three states are removed.

5 Empirical results

5.1 Capital misallocation as a predictor of fund managers' mobility

I start my analysis by showing the estimation results of the manager-level regression (26) in which the dependent variable is a dummy set to one if the manager switches firm next period. The unconditional mean of the dependent variable is 0.00168.

I first estimate equation (26) without any misallocation measure as independent variable, in order to quantify the effect of control variables. The results are presented in Table 6 without and with firm fixed effects respectively in columns 1 and 4. It shows that the amount of assets under management and the number of funds are significantly negatively correlated with the probability that the manager switches firm next period. The number of comanagers does not seem to have a significant impact. The coefficient on tenure with the firm is statistically significant and positive, while the coefficient on experience in the mutual fund industry is significantly negative. It is important to note that the indicator variable for whether the manager has incurred an internal capital reallocation in the firm has a sizable positive impact. This can be interpreted in two ways. By adding a fund to or taking away a fund from the manager's set, the firm might have either attempted to reduce the manager's misallocation internally as documented by Berk et al. (2017), or worsen the manager's misallocation if the firm decision was not optimal. Finally, the fraction of funds with a retail share class and the assets flow do not seem to severely impact managers' decision to switch.

Columns 2 and 5 of Table 6 reports the estimation results of (26) respectively without and with firm fixed effects when I use as misallocation measure the (log) absolute value of the manager's marginal product of capital (MPK). The coefficients on the misallocation variable are positive and both statistically and economically significant. Column 2 indicates that doubling a manager's MPK raises the likelihood of the manager switching firm by 0.0003 ($0.0004 \times \log(2)$), which corresponds to 18% of the unconditional mean of the dependent variable.

The results when I use the (log) dollar misallocation as main independent variable are reported in columns 3 and 6 of Table 6, respectively without and with firm fixed effects. The sign and magnitude of the coefficients on the misallocation measure remain similar with respect to the results discussed above and suggest that doubling a manager's misallocation raises the likelihood of the manager switching firm by 0.0002 ($0.0003 \times \log(2)$), which corresponds to 12% of the unconditional mean of the dependent variable.

In Table A1 in Appendix B, I present results of regressions in which I modify the dependent variable with respect to equation (26) to acknowledge that managers can switch firm by leaving the mutual fund industry and thus exit my sample. Namely, I define the dependent variable $Depart_{m,t}$ as a dummy equal to one if manager m switches mutual fund firm next period $t+1$ or if she drops out of the sample (before December 2018) and is less than 55 years old (if the manager's birth date if available from S&P Capital IQ) or has less than 25 years of experience in the mutual fund industry.[41] The magnitude and significance of the coefficients on proxies for misallocation remain very stable and if anything are larger with respect to Table 6.

These first results establish one main empirical regularity. Namely, the extent of misallocation at the fund manager level appears to predict the occurrence of a firm change. In other words, a manager incurring a high capital misallocation is more likely to switch mutual fund firm with respect to an otherwise similar manager with a lower misallocation. The correlation is statistically significant and robust, even in the presence of time, manager, style and firm fixed effects. However, one has to acknowledge that the positive and significant estimated coefficients on misallocation in regression (26) may be due to reverse causality. Indeed, for instance it could be that the AUM of the manager decreased in response to her willingness to leave the firm, raising potentially misallocation.

5.2 The effect of switching firm on managers' capital misallocation and value added

Summary statistics presented in Table 2 and discussed in Section 3.4 show that manager moves across firms involve large AUM variations (about \$500 million on average). In Table 7, I report manager-level regressions (27), investigating the variations in misallocation and value added after a manager switches mutual fund firm.

Panel A of Table 7 presents the estimation results of (27) when the dependent variable is the (log) absolute value of manager's marginal product of capital (MPK). All the specifications include time, manager and style fixed effects. Columns 1 and 2 correspond to regressions without firm fixed effects, respectively without and with the manager's (log) experience in the mutual fund industry as control. Columns 5 and 6 correspond to regressions with firm fixed effects, respectively without and with the manager's (log) experience as control. The coefficients on the indicator $\{Switch \times Post\}$ of whether the manager has changed firm are negative and are both statistically and economically significant. They indicate that after a manager switches mutual fund firm, the magnitude of her MPK drops by between 24% ($\exp(-0.28)-1$) and 27%

[41] The 55 years old and 25 years of experience thresholds are from Barber et al. (2017).

$(\exp(-0.32)-1)$, with respect to non switching managers' MPK. Note that when firm fixed effects are included in columns 5 and 6, the magnitude of the coefficient decreases slightly but remains highly statistically and economically significant. This suggests that the drop in misallocation is not driven by managers moving to "better" firms in which the average managers' misallocation is lower.

Columns 3-4 and 7-8 reports the estimation results when I split the main independent variable into two separate indicators $\{SwitchHighRetail \times Post\}$ and $\{SwitchLowRetail \times Post\}$, distinguishing whether the switching manager managed a majority of funds in the initial firm with a retail share class or not. I observe that the coefficients are significantly negative for both types of indicators. However, the coefficient on $\{SwitchHighRetail \times Post\}$ are much larger, ranging from -0.31 to -0.40, with respect to the coefficients on $\{SwitchLowRetail \times Post\}$ between -0.13 and -0.21. Hence a fund manager moving away from a firm where she managed mainly retail funds sees a larger relative drop in misallocation with respect to switching managers with a minority of retail funds. If retail investors tend to allocate capital across mutual funds for reasons unrelated to manager skills leading to larger misallocation levels, one can interpret these results as suggesting that managers incurring a larger misallocation in their initial firm "benefit" more from a firm change.

Panel B of Table 7 presents the estimation when the dependent variable is the (log) dollar misallocation. The results are very consistent with those in Panel A discussed above. Across the different specifications in columns 1-2 and 5-6, the coefficients on the indicator of whether the manager has changed firm range between -0.28 and -0.40. They indicate that the dollar misallocation of switching managers drops significantly between 24% (exp(-0.28)-1) and 33% (exp(-0.40)-1) after the firm change with respect to non switching managers. When I split the independent variable to distinguish whether the switching manager managed a majority of funds in the initial firm with a retail share class, I observe that the results discussed above remain valid and if anything sharper. Indeed, the coefficients on $\{SwitchLowRetail \times Post\}$ are negative but no longer significant, while the coefficients on $\{SwitchHighRetail \times Post\}$ are even larger than in Panel A (between -0.35 and -0.53) and are both statistically and economically significant.

If misallocation drops when managers switch firm then one should also observe an increase in switching managers' value added. Panel C of Table 7 presents the estimation results of (27) when the dependent variable is the manager's value added computed in (20). In line with the results in Panels A and B, the coefficients on the indicator of whether the manager has changed firm are positive and both statistically and economically significant. Columns 1-

2 and 5-6 indicate that after a fund manager switches firm, monthly value added increases by between \$0.82 million and \$0.93 million depending on the specification, relative to non switching managers' value added. This corresponds to the 74th percentile of the manager's value added distribution reported in Table 1. In columns 3-4 and 7-8, when I split the independent variable into $\{SwitchLowRetail \times Post\}$ and $\{SwitchHighRetail \times Post\}$, I observe that the coefficients on the latter are much larger (between \$1.01 and \$1.09 million) than the coefficients on the former (between \$0.41 and \$0.59 million). Thus a fund manager moving away from a firm where she managed mainly retail funds sees a larger relative increase in value added, consistent with a larger relative drop in misallocation, with respect to switching managers with a minority of retail funds.

Finally, to identify that the drop in misallocation and the increase in value added documented in Table 7 are due to the AUM variation associated with the firm change, and not to other factors affecting these variables later in the future, I implement the specification (28). Figure 6 plots the estimates β_k, i.e., the coefficients on $\{year\ k\ to\ firm\ change\}$ together with 95% confidence intervals against k years to treatment. The omitted time period is one year prior to the firm change. Five or more years pre- and post-firm change are grouped.

Panel A in Figure 6 presents the coefficient estimates β_k when the dependent variable is the (log) absolute value of manager's marginal product of capital (MPK). Prior to the mutual fund firm change, the estimated difference between the switching and non switching managers is indistinguishable from zero. If anything, switching managers incur a larger misallocation, which is in line with the results discussed in Section 5.1. However, immediately after the firm change, the misallocation of switching managers drops significantly relative to the misallocation of non switching managers. The pattern is further amplified after several years and does not reverse. The fact that the coefficient β_k is significantly negative just after the firm change supports the view that it is the variation in AUM implied by the move that is causing the drop in misallocation and not other factors at play later in the new firm.

If misallocation drops immediately when a manager changes mutual fund firm then one should observe an immediate increase in the manager's value added. Panel B in Figure 6 presents the coefficient estimates β_k in (28) when the dependent variable is the manager's value added. The dynamics of the coefficient remarkably mirrors the one in Panel A. Before the mutual fund firm change, the difference in value added between the switching and non switching managers is indistinguishable from zero but immediately after the firm change, the value added of switching managers increases significantly relative to the value added of non switching managers. The pattern does not reverse after several years.

Overall, the results presented above corroborate the claim that the large changes in AUM that accompany managers' moves across firms, documented in Section 3.4, involve large relative increase in value added and large relative decrease in capital misallocation at the manager level.

5.3 The effect of changes in the enforceability of non-compete agreements on the mobility of fund managers

To validate the identification strategy aiming at providing more macro evidence on the role of managers' mobility and described in section 4.4, I confirm that changes in non-compete enforceability act as shocks to inter-firm managers' mobility frictions. I present the estimation results of the regression at the state-level discussed in section 4.6, to investigate the causal impact of changes in NCCs on the actual mobility of funds managers across firms. Table 8 reports the results of the estimation of the generalized difference-in-difference specification (30) in which the dependent variable is the percentage of managers in the state changing mutual fund firm next period.

Column 1 in Table 8 presents the results without including any state-level controls. The coefficient on the indicator $\{Treated \times Post\}$ indicates that after an increase in NCCs enforceability is passed, fund managers' mobility rate drops by 0.042 relative to the rate in control states, which represents 40% of the sample mean (0.104) of the dependent variable. The effect is both statistically and economically significant. Looking at column 2, when New-York, Massachusetts and California are removed from the sample, I observe that the impact is similar, with a statistically and economically significant coefficient of -0.046 representing -47% of the average rate (0.097).

Column 3 in Table 8 presents the results when state-level control variables are included in the regression. The coefficient on the indicator $\{Treated \times Post\}$ is very similar to the one in column 1 and if anything larger in magnitude. It indicates that controlling for the (log) values of the number of fund managers, firms, funds and amount of assets under management, managers' mobility rate drops by 0.049 relative to control states after an increase in NCCs enforceability. This represents 47% of the sample mean (0.104) of the dependent variable. When New-York, Massachusetts and California are removed from the sample, the estimated coefficient is equal to -0.053 in column 4, which represents -55% of the mean rate in this sample (0.097).

The results presented in Table 8 confirm the hypothesis that an increase (resp. decrease) in NCCs enforceability decreases (resp. increases) the inter-firm mobility of mutual fund managers in the affected states, with respect to managers' mobility in control states. To alleviate concerns that managers could have anticipated NCCs law changes, and to assess the effect of the latter over time, I present in Figure 7 the estimates of coefficients β_k in specification (32), in which the dependent variable is the percentage of fund managers changing firm at the end of the period. The omitted time period is one year prior to the effective change in NCCs enforceability. Five or more years pre- and post-treatment are grouped. Figure 7 shows that there was no anticipation or differential trend between treated and control states prior to the treatment, in terms of fund managers' mobility rate. Prior to the enforceability change, the estimated difference between the treatment and control groups is very close to zero. Following the change in enforceability, the mobility rate in the treatment group drops relative to the mobility rate in the control group and does not seem to revert back.

In conclusion, the results presented above are consistent with the claim that stronger NCCs enforceability deters managers from changing mutual fund firm, and as a consequence acts as a negative shock to managers' mobility across firms.

5.4 The effect of restricting managers' inter-firm mobility on capital misallocation and value added

I estimate the generalized difference-in-difference specification (31) to study the effect of changes in NCCs enforceability on state-level measures of capital misallocation across managers and value added developed in section 4.5. Table 9 reports the results.

In column 1 of Table 9, the dependent variable is a measure of the dispersion of marginal products on capital across managers, namely the standard deviation of the marginal products of capital of managers employed in the state in that month. The coefficient on the indicator $\{Treated \times Post\}$ indicates that after an increase in NCCs enforceability is passed, capital misallocation increases by 0.021 relative to the misallocation in control states, which represents 12% of the sample mean (0.175) of the dependent variable. The effect is both statistically and economically significant. Looking at column 2, when New-York, Massachusetts and California are removed from the sample, I observe that the impact is virtually unchanged.

In column 3 and 4 of Table 9, the dependent variable is another measure of the dispersion of marginal products on capital across managers, namely the difference between the 75th and 25th percentiles of the marginal products on capital of managers employed in the state in that month. The results are consistent with the previous ones discussed above. The coefficient on the indicator $\{Treated \times Post\}$ is 0.045. It indicates that after an increase in NCCs enforceability is passed, capital misallocation increases by 9% of its sample mean (0.516), with respect to the misallocation in control states. Again, the effect is both statistically and economically significant. When New-York, Massachusetts and California are removed from the sample, the coefficient remains very stable and equal to 0.046.

The results in Table 9 discussed so far suggest that restricting the mobility of managers across firms increases the dispersion of marginal product on capital across managers and therefore have a detrimental effect on the allocative efficiency of capital. The next question is whether this translates into a lower aggregated value added of managers in states that strengthen NCCs enforceability. Columns 5 and 6 of Table 9 reports estimation results of specification (31) when the dependent variable is the sum of the value added of managers employed in the state that month. I observe that the coefficient on the indicator $\{Treated \times Post\}$ is -\$26.94 million. It is both statistically and economically significant and corresponds to the 79th percentile of the state-level distribution of value added. When New-York, Massachusetts and California are removed from the sample, the coefficient remains very stable and equal to -\$25.86 million.

Finally, in order to assess the evolution of state-level misallocation several years before and after NCCs enforceability changes, I estimate specification (32) in which the dependent variables are state-level measures of capital misallocation. Figure 8 presents the estimates of the coefficients β_k against year to/after the NCCs change. The omitted time period is one year prior to the effective change in NCCs enforceability. Five or more years pre- and post-treatment are grouped. In Panel A, the dependent variable is the standard deviation of the marginal products on capital of managers employed in the state in that month. One observes that prior to the enforceability change, the estimated difference between the treatment and control groups is very close to zero. Following the change in enforceability, the misallocation in the treatment group rises gradually relative to the misallocation in the control group. The effect appears to be sizable even after four years and slightly reverts after more than five years. This suggests long-lasting effects of NCCs law changes on capital misallocation in treated states with respect to the control group. The conclusion remains similar when the dependent variable is an alternative measure of capital misallocation, namely the difference between the 75th and 25th percentiles of the marginal products on capital of managers employed in the state in that month. The estimates of the corresponding coefficients β_k are presented in Panel B of 8.

Taken jointly with the results in the previous section, the results discussed above show, first, that NCCs enforceability changes directly affect fund managers' mobility across firms. Second, in states that strengthen the enforceability of NCCs and experience a relative drop in the percentage of switching managers, proxies for capital misallocation across managers increase significantly relative to misallocation in other states. Finally, at the same time the total value added of fund managers in the treated states decrease significantly relative to managers' value added in control states. Overall, the results provide direct evidence that NCCs enforceability changes affect fund managers' mobility and have real consequences as they lead to a workforce with lower productivity in the mutual fund industry.

5.5 Robustness checks

According to the stylized theoretical framework developed in section 2, larger inter-firm mobility frictions should increase capital misallocation across fund managers if investors do not equalize marginal products of capital across managers through asset flows. To confirm the interpretation of the results in the previous two sections, I explore whether investors change their behavior regarding capital allocation following NCCs law changes. I estimate specification (31), in which the dependent variable is the (log) sum of the absolute value of asset flows of managers in the state in that month. If investors react to the changes in NCCs, it should be reflected in the magnitude of asset flows. Table A2 reports the results in columns 1 and 2. The coefficients on the indicator $\{Treated \times Post\}$ are slightly negative and not significant. This suggests that investors do not systematically reallocate more or less capital across managers through fund flows in treated states following NCCs enforceability changes. Therefore, the results regarding misallocation discussed in the previous section are unlikely to be driven by a worse or a more sticky allocation of capital by investors after NCCs enforceability changes.

Another concern is that the composition of the set of managers in treated or control states might change after NCCs law changes. To rule out manager composition as the driver of my main result, I estimate specification (31), in which the dependent variable is the (log) sum of the optimal AUM of managers in the state in that month.[42] The intuition is that if the drop in value added in states that strengthen NCCs is driven by a worse set of managers after the law change, the sum of managers' optimal AUM should drop relative to the sum in control states. The results are reported in columns 3 and 4 of Table A2. The coefficients on the indicator $\{Treated \times Post\}$ are not statistically significant, indicating that the composition of the set of fund managers is unlikely to be the drivers of the results discussed in the previous section.

[42] I add one to the state-level sum of the optimal AUM of managers to deal with observations of states that only feature managers with zero optimal AUM.

6 Conclusion

The paper studies the relation between the mobility of fund managers across mutual fund firms and the efficiency of the allocation of capital in the mutual fund industry. Capital can go to managers through investors' asset flows. However, by moving across fund family firms, managers can end up running larger or smaller funds and as a consequence more or less capital. Therefore if investors' capital does not come to managers, managers can go to capital.

First, I illustrate the role of fund managers' mobility across firms in a stylized model featuring managers, firms and investors. The model predicts that inter-firm mobility constraints affect the efficiency of the capital allocation across managers if investors do not allocate capital efficiently through asset flows. Then, I show empirically that fund managers' mobility across mutual fund firms is a key channel through which capital is efficiently reallocated across managers.

Using a rich dataset of manager-level data from CRSP, Morningstar and S&P Capital IQ as well as econometric procedures developed in the literature studying the returns to scale in active asset management, I estimate capital misallocation of managers. The latter is defined as the extent of the mismatch between a manager's actual amount of assets under management (AUM) and the optimal AUM according to the manager's skill and return to scale. My results show that i) the capital misallocation incurred by a manager is a robust predictor of the manager's move to a new firm. ii) Manager moves across mutual fund firm involve large changes in managers' AUM (on average \$497 million, at the median \$107 million). iii) After a manager switches firm, her misallocation drops by more than 24% and her monthly value added (return in excess of the benchmark times that manager's AUM) increases by more than \$0.8 million, relative to non switching managers. This set of empirical findings are consistent with manager moves across mutual fund firms being a channel through which capital misallocation is reduced.

Then, I examine how inter-firm manager mobility frictions affect the efficiency of capital allocation across fund managers at a more macro level. To address concerns about causality, I use a series of legal changes to the enforceability of non-compete clauses (NCCs) in various US states. I combine these with detailed data on fund managers' office addresses from S&P Capital IQ to conduct an analysis at the state level.

I show that changes in NCCs enforceability affect the mobility of fund managers across firms and the allocative efficiency of capital. My results indicate that i) the percentage of managers changing firm declines in states that strengthen NCCs enforceability, relative to control states. ii) The misallocation of capital across fund managers increases in states that strengthen NCCs, relative to the misallocation in control states. iii) The total value added of fund managers in states that strengthen NCCs decreases relative to the value added in control states.

Overall, my set of empirical findings provide direct evidence that inter-firm mobiliy frictions have real consequences as they lead to a larger mismatch between skill and scale among mutual fund managers and thus to a workforce with lower productivity in the mutual fund industry. These results point to an important role for labor mobility across firms in the allocation of capital in the mutual fund industry. This raises potential questions over the link between labor mobility and labor productivity in other industries.

Tables

	Obs	Mean	Sd	5%	25%	50%	75%	95%
TNA (mill)	573,154	1,029.3	3,054.6	10.3	50.2	197.3	734.9	4,765.8
#Funds	573,154	2.1	2.0	1.0	1.0	1.0	2.0	5.0
#Comanagers	573,154	3.7	5.6	0.0	1.0	2.0	4.0	14.0
Gross alpha (%)	573,154	-0.0	1.7	-2.3	-0.7	-0.0	0.6	2.2
Value Added (mill)	573,154	-0.8	16.4	-20.5	-1.3	-0.0	1.0	16.1
Flow (mill)	573,154	0.5	116.1	-35.6	-3.9	-0.3	1.1	29.1
Experience (years)	573,154	8.2	6.1	1.1	3.3	6.8	11.8	20.0
Tenure (years)	573,154	4.9	4.5	0.3	1.5	3.5	6.8	14.1

Table 1: **Summary statistics at the manager level**: This table reports summary statistics for the main variables at the monthly frequency at the manager level in my sample from 2000 to 2018. Experience corresponds to the number of years spent in the mutual fund industry. Tenure corresponds to the number of years spent with the current mutual fund firm. When a fund is co-managed by N managers, I attribute $(1/N)$th of the fund's AUM to each of its managers. Dollar amounts are expressed in January 2000 dollars.

	Mean	Sd	5%	25%	50%	75%	95%
Experience (years)	6.24	4.57	1.08	3.00	5.08	9.00	15.08
Tenure (years)	3.29	3.07	0.25	1.00	2.33	4.50	9.50
Flow over past month (mill)	-3.67	26.70	-23.10	-2.82	-0.42	0.12	8.86
Flow over past year (mill)	-28.93	234.04	-265.49	-37.93	-4.82	3.77	138.12
Gross alpha over past month (%)	-0.10	2.09	-3.12	-0.88	-0.05	0.62	2.63
Mean gross alpha over past year (%)	-0.11	0.83	-1.02	-0.33	-0.07	0.17	0.69
Value Added over past month (mill)	-0.59	10.68	-8.68	-0.68	-0.01	0.40	6.71
Value Added over past year (mill)	-10.96	63.22	-83.52	-6.22	-0.26	1.11	23.87
TNA (mill)	388.01	1,161.55	4.78	21.20	81.42	251.13	1,575.45
Mean TNA over past year (mill)	491.20	1,372.47	5.76	32.32	112.05	346.49	2,026.17
#Funds	1.30	0.83	1.00	1.00	1.00	1.00	3.00
Mean #Funds over past year	1.45	0.88	1.00	1.00	1.00	1.75	3.00
Liquidated fund	0.00	0.00	0.00	0.00	0.00	0.00	0.00
TNA var. over next month (mill)	-101.16	1,341.38	-1,308.47	-139.80	-9.93	77.59	1,066.25
Abs. TNA var. over next month (mill)	496.65	1,250.05	2.89	27.71	106.82	381.85	2,127.06

Table 2: **Characteristics of managers when switching mutual fund firm**: This table reports summary statistics of the main characteristics of managers changing mutual fund firm in the sample (964 cases). The values represent the manager's characteristics just before the firm change. The past month and past year correspond respectively to the last month and last year before the employer change. Liquidated fund corresponds to a dummy set to one if one of the manager's funds was liquidated just before the employer change and zero otherwise. TNA variation over next month corresponds to the difference between the manager TNA just after and just before the employer change. Absolute TNA variation corresponds to the absolute value of TNA variation.

Group	Avg. AUM	#Mgrs	Obs	$b_m(\times 10^4)$	$t(b_m)$	a_m $(\times 10^4)$							k^*_m (millions)						
						mean	std.	5%	25%	50%	75%	95%	mean	std.	5%	25%	50%	75%	95%
1	27	559	32,107	0.612	2.81	8.30	45.79	-28.97	1.91	14.04	22.33	38.85	12	12	0	2	11	18	32
2	48	559	42,481	0.208	3.74	7.56	17.39	-17.04	0.22	8.13	13.86	33.33	25	33	0	1	20	33	80
3	78	559	46,219	0.131	3.59	6.69	23.77	-27.08	0.55	8.71	15.95	33.69	44	51	0	2	33	61	129
4	123	558	49,878	0.051	4.16	3.26	20.53	-29.11	-3.24	4.90	11.74	27.07	80	139	0	0	48	115	264
5	186	559	56,594	0.036	4.04	2.09	19.32	-25.76	-5.31	3.63	10.08	29.37	102	158	0	0	50	138	402
6	280	559	58,969	0.026	4.51	3.26	19.98	-26.38	-5.52	4.42	11.74	31.43	160	253	0	0	84	222	595
7	423	558	60,126	0.021	4.34	3.65	20.04	-30.70	-3.24	6.15	13.16	30.12	211	275	0	0	146	313	715
8	676	559	65,363	0.016	7.47	6.36	18.22	-25.94	0.37	8.33	14.25	30.42	308	338	0	11	254	435	929
9	1,220	559	68,009	0.007	5.95	4.62	15.97	-20.76	-1.24	5.77	11.93	26.28	597	758	0	0	427	883	1,946
10	4,984	558	79,044	0.003	4.09	9.69	18.66	-19.90	0.11	9.11	18.41	38.40	2,235	2,681	0	20	1,625	3,282	6,845

Table 3: **Summary statistics of the skill parameters**: This table reports summary statistics for the estimated parameters a_m, b_m in the gross alpha production function of each manager $\alpha_m(k) = a_m - b_m k$, where k is the amount of AUM. Managers are sorted into ten groups (decile) by average AUM, b_m is estimated using the panel estimator of Zhu (2018) in each group. The reported values of b_m correspond to the decrease in monthly gross alpha (in bps) due to one more \$million of AUM. Manager-specific a_m is estimated as: $\hat{a}_m = \frac{1}{T_m}\sum_{t=1}^{T_m}(\alpha_{m,t} + \hat{b}_m k_{m,t-1})$, where T_m is the number of observations for manager m. k^*_m is the implied optimal AUM which maximizes the value added of the manager and is defined $k^*_m = \hat{a}_m/2\hat{b}_m$. k^*_m is set to zero if the manager has a negative estimate $\hat{a}_m$.

	Obs	Mean	Sd	5%	25%	50%	75%	95%
#Managers	9,488	60.3	104.7	2.0	5.0	20.0	64.0	297.0
#Firms	9,488	20.0	30.1	1.0	3.0	8.0	22.0	81.0
TNA (bill)	9,488	62.1	150.2	0.1	0.9	9.7	48.0	365.1
#Funds	9,488	50.0	88.3	1.5	4.2	16.4	56.3	209.4
Value Added (mill)	9,488	-48.0	382.9	-466.2	-51.2	-0.7	14.4	238.6
#Switches	9,488	0.1	0.5	0.0	0.0	0.0	0.0	1.0
100 × (#Switches/#Managers)	9,488	0.2	1.8	0.0	0.0	0.0	0.0	0.4

Table 4: **Summary statistics at the state level**: This table reports summary statistics for the main variables at the state level in my sample, from 2000 to 2018 at the monthly frequency. Dollar amounts are expressed in January 2000 dollars.

	Control		Treated		
	Obs	Mean	Obs	Mean	t
#Managers	312	38.1	120	27.1	1.87
#Firms	312	19.6	120	16.9	0.97
TNA (bill)	312	44.6	120	28.3	1.84
#Funds	312	35.1	120	26.4	1.56
Value Added (mill)	312	82.4	120	61.6	0.70
#Switches	312	0.2	120	0.1	0.92
100 × (#Switches/#Managers)	312	0.5	120	0.3	0.98

Table 5: **Ex-ante state-level characteristics**: This table reports ex-ante (in the year 2000) means of characteristics of states where NCCs enforcement does not change and where NCCs enforcement does change during the sample period. t corresponds to a t-test statistic of differences relative to the "Control" observations.

	Switch					
	(1)	(2)	(3)	(4)	(5)	(6)
$\log \lvert MPK \rvert$		0.0004^{***}			0.0003^{***}	
		(0.0001)			(0.0001)	
$\log(\$Misallocation)$			0.0003^{***}			0.0003^{***}
			(0.0001)			(0.0001)
log(TNA)	-0.0003^{**}	-0.0004^{***}	-0.0004^{***}	-0.0005^{***}	-0.0006^{***}	-0.0006^{***}
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
log(#Funds)	-0.0037^{***}	-0.0038^{***}	-0.0038^{***}	-0.0036^{***}	-0.0036^{***}	-0.0036^{***}
	(0.0005)	(0.0005)	(0.0005)	(0.0006)	(0.0006)	(0.0006)
log(#Comanagers)	-0.0003	-0.0002	-0.0002	-0.0002	-0.0001	-0.0002
	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)
Flow	-0.0000	-0.0000	-0.0000	-0.0000	-0.0000	-0.0000
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
log(Tenure)	0.0021^{***}	0.0022^{***}	0.0022^{***}	0.0021^{***}	0.0021^{***}	0.0021^{***}
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
log(Experience)	-0.0030^{***}	-0.0029^{***}	-0.0029^{***}	-0.0023^{***}	-0.0023^{***}	-0.0023^{***}
	(0.0004)	(0.0004)	(0.0004)	(0.0003)	(0.0003)	(0.0003)
Internal.Realloc	0.0044^{***}	0.0044^{***}	0.0044^{***}	0.0041^{***}	0.0041^{***}	0.0041^{***}
	(0.0004)	(0.0004)	(0.0004)	(0.0005)	(0.0005)	(0.0005)
Retail.Share	0.0009	0.0009^{*}	0.0009^{*}	0.0007	0.0007	0.0007
	(0.0006)	(0.0005)	(0.0005)	(0.0006)	(0.0006)	(0.0006)
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Manager FE	Yes	Yes	Yes	Yes	Yes	Yes
Style FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	No	No	No	Yes	Yes	Yes
Observations	573,152	573,152	573,152	573,015	573,015	573,015
R^2	0.02	0.02	0.02	0.04	0.04	0.04

Table 6: **Determinants of mutual fund firm changes**: This table reports results for regressions investigating the drivers of a fund manager' decision to switch mutual fund firm. The dependent variable is a dummy variable equal to one if the manager switches mutual fund firm next period $t+1$, zero otherwise (the sample mean of the dependent variable is 0.00168). The main independent variables consist of proxies for capital misallocation: MPK is the marginal product of capital of the manager and $\$Misallocation$ is the dollar spread between the actual AUM of the manager and her optimal level of AUM computed in Section 4.2. Internal.Realloc is a dummy indicating whether the manager has incurred an internal capital reallocation in this firm. Retail.Share is the share of manager's funds with a retail share class. Standard errors in parentheses are clustered at the firm level. * p<.10; ** p<.05; *** p<.01.

Panel A

	log $\lvert MPK\rvert$							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$Switch \times Post$	-0.314*** (0.050)	-0.322*** (0.050)			-0.275*** (0.055)	-0.283*** (0.055)		
$SwitchLowRetail \times Post$			-0.134* (0.072)	-0.145** (0.072)			-0.196** (0.082)	-0.206** (0.082)
$SwitchHighRetail \times Post$			-0.396*** (0.055)	-0.403*** (0.055)			-0.312*** (0.062)	-0.319*** (0.062)
log(Experience)		0.071*** (0.018)		0.070*** (0.018)		0.048** (0.019)		0.047** (0.019)
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Manager FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Style FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	No	No	No	No	Yes	Yes	Yes	Yes
Observations	573,153	573,153	573,153	573,153	573,016	573,016	573,016	573,016
R^2	0.44	0.44	0.44	0.44	0.53	0.53	0.53	0.53

Panel B

	log($\$Misallocation$)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$Switch \times Post$	-0.382*** (0.068)	-0.397*** (0.068)			-0.281*** (0.069)	-0.297*** (0.070)		
$SwitchLowRetail \times Post$			-0.086 (0.099)	-0.107 (0.099)			-0.142 (0.104)	-0.163 (0.104)
$SwitchHighRetail \times Post$			-0.517*** (0.074)	-0.528*** (0.074)			-0.345*** (0.076)	-0.359*** (0.077)
log(Experience)		0.127*** (0.021)		0.125*** (0.021)		0.091*** (0.021)		0.091*** (0.021)
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Manager FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Style FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	No	No	No	No	Yes	Yes	Yes	Yes
Observations	573,153	573,153	573,153	573,153	573,016	573,016	573,016	573,016
R^2	0.75	0.76	0.75	0.76	0.80	0.80	0.80	0.80

Panel C

	Value Added							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$Switch \times Post$	0.912*** (0.152)	0.932*** (0.154)			0.818*** (0.157)	0.838*** (0.162)		
$SwitchLowRetail \times Post$			0.564*** (0.168)	0.592*** (0.168)			0.405** (0.197)	0.431** (0.199)
$SwitchHighRetail \times Post$			1.070*** (0.179)	1.086*** (0.180)			1.010*** (0.184)	1.027*** (0.188)
log(Experience)		-0.171** (0.074)		-0.169** (0.074)		-0.116 (0.081)		-0.114 (0.081)
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Manager FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Style FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	No	No	No	No	Yes	Yes	Yes	Yes
Observations	573,153	573,153	573,153	573,153	573,016	573,016	573,016	573,016
R^2	0.03	0.03	0.03	0.03	0.04	0.04	0.04	0.04

Table 7: **Effect of mutual fund firm changes on manager's misallocation and value added**: This table reports estimation results for the following specification:

$$Y_{m,t} = \beta Switch_{m,t} + Controls_{m,t-1} + \delta_t + \lambda_m + \eta_{style} + \theta_f + \epsilon_{m,t}.$$

In Panel A, the dependent variable is the log of the absolute value of the marginal product of capital of the fund manager. In Panel B, the dependent variable is the log of misallocation (absolute value of the dollar spread between the current manager's TNA and her optimal level of capital). In Panel C, the dependent variable is the manager's value added (measured in January 2000 \$millions/month). $\{Switch \times Post\}_{m,t}$ is an indicator that is 1 if manager m has switched mutual fund firm by time t. Standard errors in parentheses are clustered at the firm level. * p<.10; ** p<.05; *** p<.01.

	$100 \times (\#Switches/\#Managers)$			
	(1)	(2)	(3)	(4)
$Treated \times Post$	-0.042**	-0.046**	-0.049***	-0.053***
	(0.016)	(0.017)	(0.018)	(0.018)
log(#Managers)			0.036	0.038
			(0.024)	(0.023)
log(#Firms)			0.060**	0.057**
			(0.025)	(0.025)
log(TNA)			-0.008	-0.009
			(0.011)	(0.011)
log(#Funds)			-0.040	-0.038
			(0.027)	(0.027)
Drop NY, MA, CA	No	Yes	No	Yes
Time FE	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes
Observations	9,488	8,804	9,451	8,770
R^2	0.14	0.13	0.14	0.13

Table 8: **Effect of changes in non-compete enforceability on state-level managers' mobility rate**: This table presents the results of difference-in-difference estimations with the ratio $\%Switchers_{s,t} = 100 \times \frac{\#Switches_{s,t}}{\#Managers_{s,t}}$ at the state level, i.e., percentage of managers in state s changing firm at the end of month t, as the dependent variable

$$\%Switchers_{s,t} = \beta \left\{Treated \times Post\right\}_{s,t} + \gamma X_{s,t-1} + \theta_s + \delta_t + \epsilon_{s,t}.$$

The independent variable $\{Treated \times Post\}_{s,t}$ is an indicator that is equal to 1 (resp. -1) if an increase (resp. decrease) in NCCs enforceability has been passed by time t in state s, and zero otherwise. $X_{s,t-1}$ includes lagged control variables at the state level: the (log) number of managers, the (log) number of management firms, the (log) total AUM of managers and the (log) number of funds. The regression includes state fixed effects θ_s and time fixed effects δ_t. Standard errors in parentheses are clustered at the state level. In regressions (2) and (4), the observations corresponding to the states of New-York, Massachusetts and California are dropped from the estimation. * p<.10; ** p<.05; *** p<.01.

	$100 \times \sigma(MPK)$		$100 \times (MPK\ 75-25)$		Value Added	
	(1)	(2)	(3)	(4)	(5)	(6)
$Treated \times Post$	0.021^{**}	0.021^{**}	0.045^{***}	0.046^{***}	-26.940^{**}	-25.860^{**}
	(0.009)	(0.009)	(0.015)	(0.015)	(12.799)	(11.708)
log(#Managers)	-0.024	-0.024	-0.073^{**}	-0.074^{**}	16.327	10.306
	(0.022)	(0.022)	(0.028)	(0.029)	(17.916)	(11.072)
log(#Firms)	0.034	0.034	0.052	0.053	0.213	-9.063
	(0.023)	(0.023)	(0.035)	(0.035)	(12.743)	(7.090)
log(TNA)	0.024^{*}	0.024^{*}	0.029	0.029	-15.058^{*}	-8.151^{**}
	(0.014)	(0.014)	(0.020)	(0.020)	(8.847)	(3.951)
log(#Funds)	-0.002	-0.002	0.006	0.006	-2.423	-5.820
	(0.023)	(0.023)	(0.029)	(0.030)	(9.197)	(5.833)
Drop NY, MA, CA	No	Yes	No	Yes	No	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	9,451	8,770	9,451	8,770	9,451	8,770
R^2	0.61	0.61	0.54	0.54	0.17	0.17

Table 9: **Effect of changes in non-compete enforceability on state-level capital misallocation and value added**: This table presents the results of difference-in-difference estimations with different measures of capital misallocation across managers as well as value added, at the state level, as dependent variables

$$Y_{s,t} = \beta \left\{Treated \times Post\right\}_{s,t} + \gamma X_{s,t-1} + \theta_s + \delta_t + \epsilon_{s,t}.$$

The independent variable $\{Treated \times Post\}_{s,t}$ is an indicator that is equal to 1 (resp. -1) if an increase (resp. decrease) in NCCs enforceability has been passed by time t in state s, and zero otherwise. $X_{s,t-1}$ includes lagged control variables at the state level: the (log) number of managers, the (log) number of management firms, the (log) total AUM of managers and the (log) number of funds. The regression includes state fixed effects θ_s and time fixed effects δ_t. Standard errors in parentheses are clustered at the state level. In regressions (1) and (2), the dependent variable is (100 times) the standard deviation of the marginal products of capital of managers employed in the state in that month. In regressions (3) and (4), the dependent variable is (100 times) the difference between the 75th and 25th percentiles of the marginal products of capital of managers employed in the state in that month. In regressions (5) and (6), the dependent variable is the sum of the value added of managers employed in the state in that month. In regressions (2), (4) and (6) the observations corresponding to the states of New-York, Massachusetts and California are dropped from the estimation. * p<.10; ** p<.05; *** p<.01.

Figures

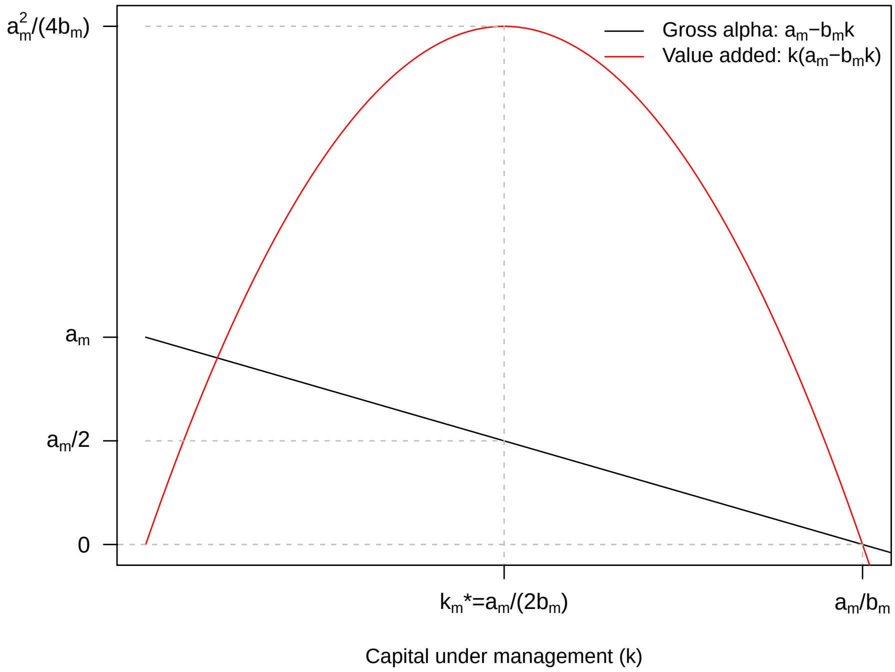


Figure 1: **Gross alpha and value added**: This chart reports the gross alpha and value added as functions of the manager's amount of capital under management, assuming that the gross alpha is linear in capital under management, i.e., $\alpha_m(k) = a_m - b_m k$, where a_m and b_m are positive constant parameters. The value added is given by $v_m(k) = k \times \alpha_m(k)$.

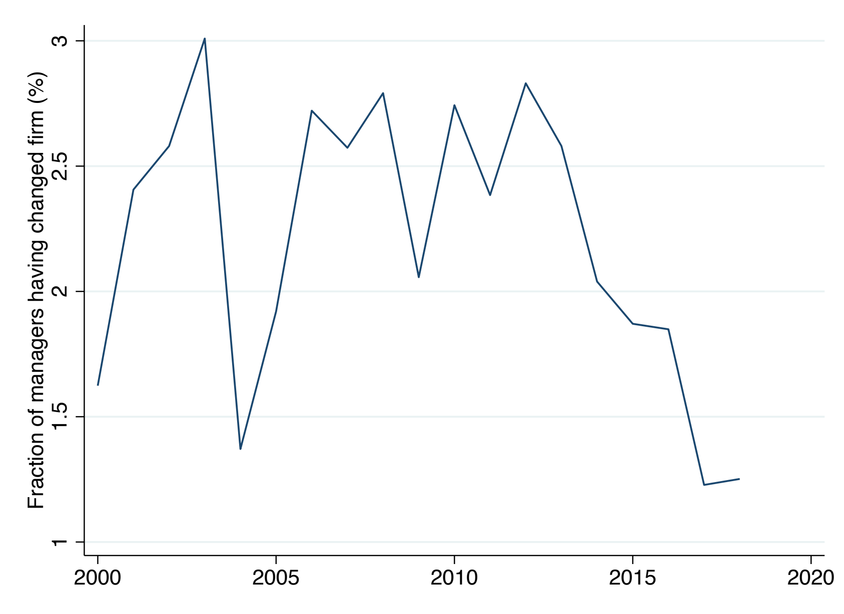


Figure 2: **Evolution of the fraction of asset managers changing firm each year**: This chart reports the time series of the fraction of mutual fund managers I identify as having switched firm in a given year from 2000 to 2018.

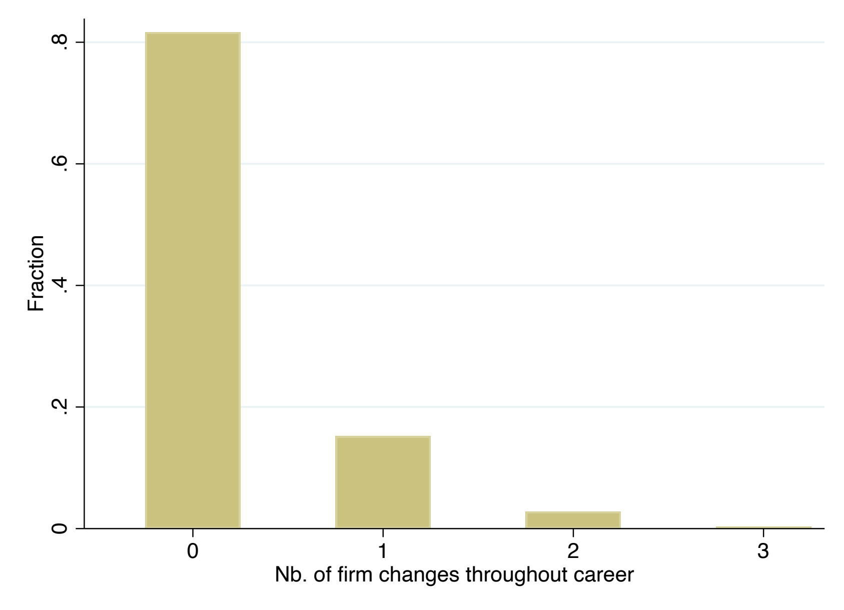
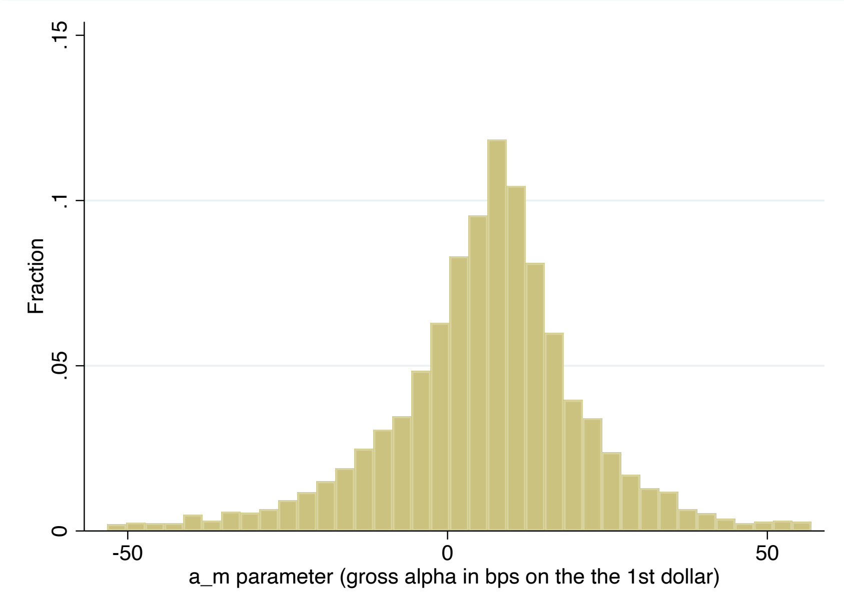


Figure 3: **Distribution of the number of firm changes**: This chart reports the distribution of the number of employer changes recorded for each manager at the last date she is in the sample.

Panel A



Panel B

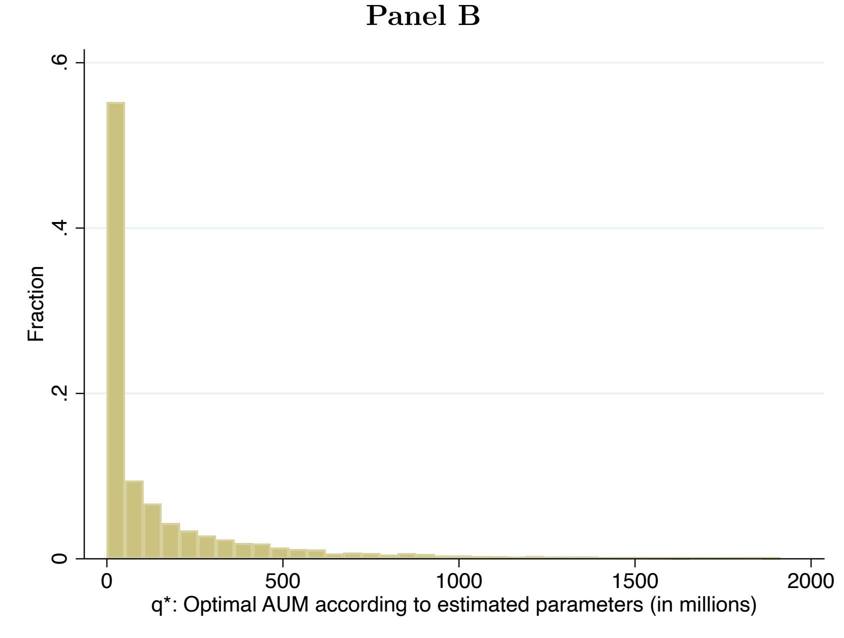
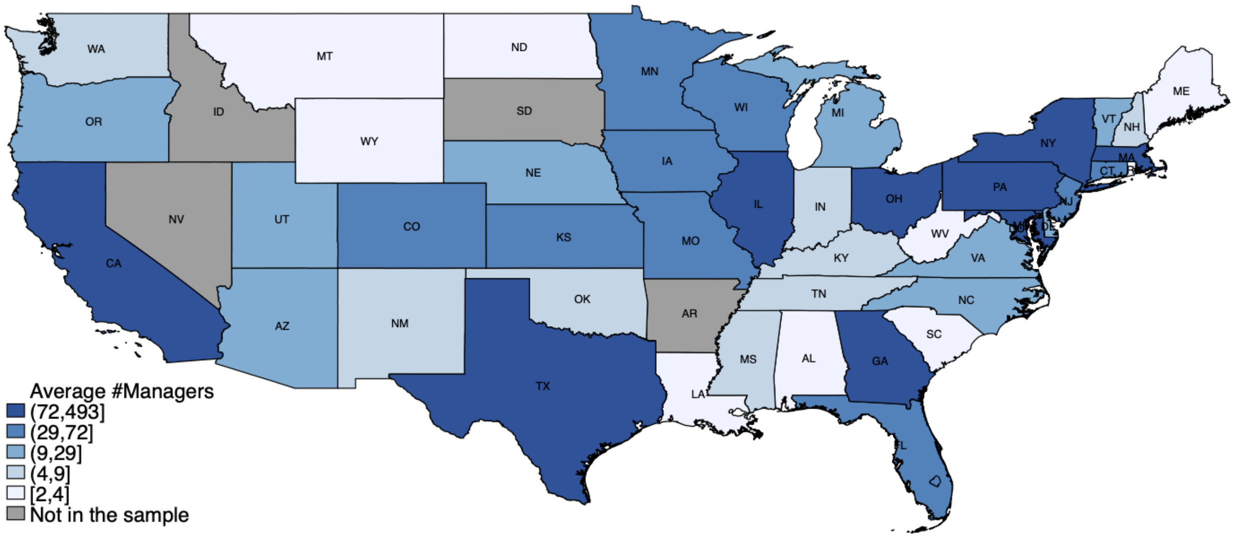


Figure 4: **Distribution of the estimated parameter a_m (alpha on the first dollar) and optimal AUM**: Panel A reports the distribution of the estimated parameters a_m in the gross alpha production function of each manager $\alpha_m(k) = a_m - b_m k$, where k is the amount of managed capital (AUM). a_m represents the monthly gross alpha (in bps) on the first dollar and is estimated as: $\hat{a}_m = \frac{1}{T_m}\sum_{t=1}^{T_m}(\alpha_{m,t} + \hat{b}_m k_{m,t-1})$, where T_m is the number of observations for manager m, $\alpha_{m,t}$ the gross alpha of manager m in period t and $\hat{b}_m$ the panel estimator developed in Zhu (2018). Top and bottom 1% of estimates are removed from the distribution in Panel A for presentation purpose. Panel B reports the distribution of the implied optimal AUM k_m^*, which maximizes the value added of the manager $k \times \alpha_m(k)$, i.e., $k_m^* = \hat{a}_m / 2\hat{b}_m$. k_m^* is set to zero if the manager has a negative estimate $\hat{a}_m$. Top 5% of estimates are removed from the distribution in Panel B for presentation purpose.

Panel A



Panel B

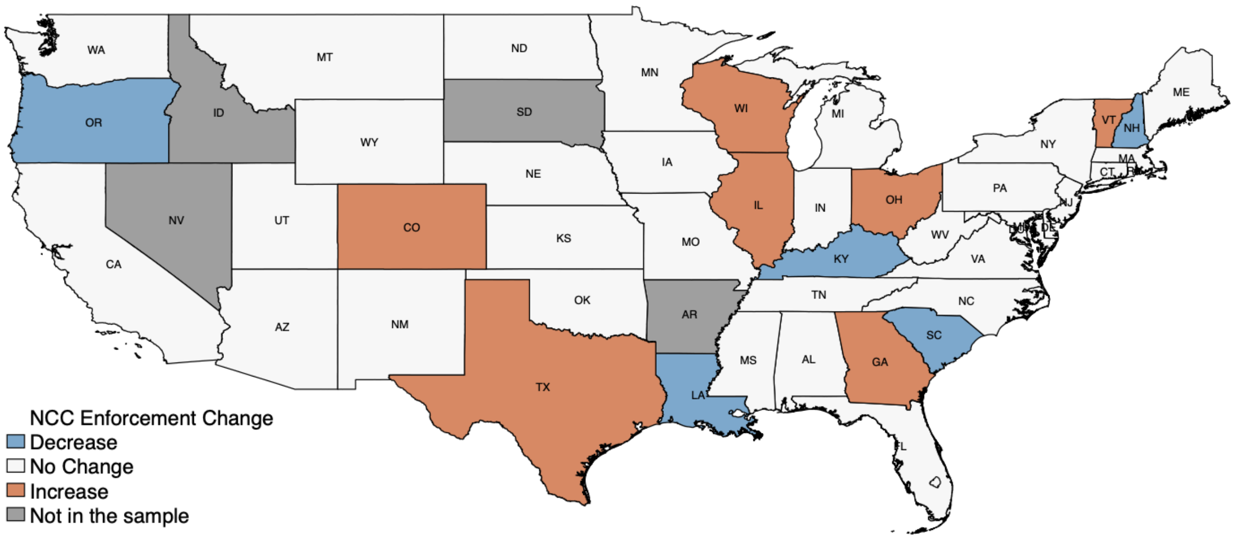
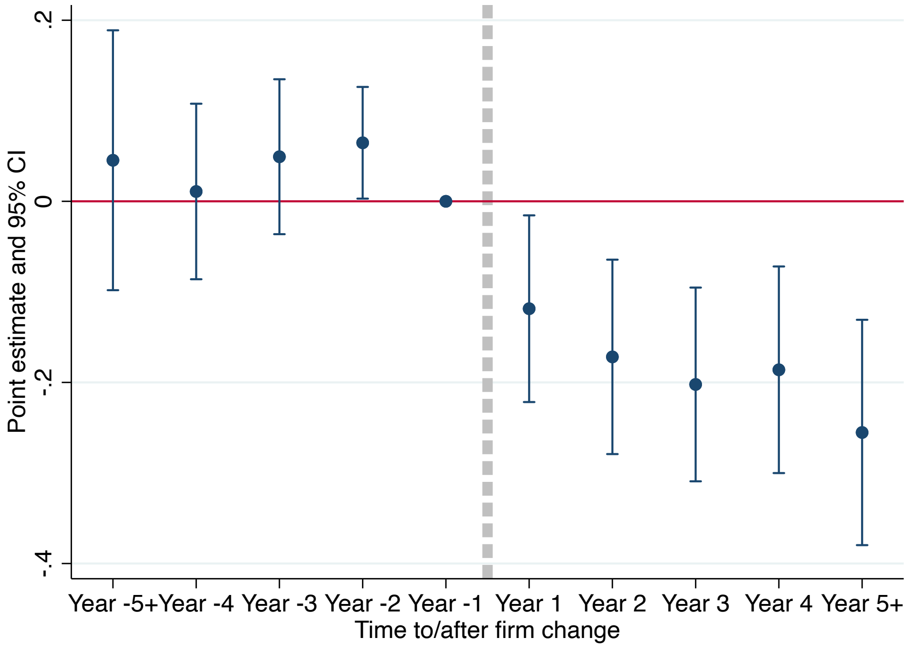


Figure 5: **Maps of average number of managers and NCCs enforcement changes**: Panel A reports the average number of managers in each state in my sample from 2000 to 2018. Panel B reports the states that are affected by a change in NCCs enforcement between 2000 and 2018.

Panel A



Panel B

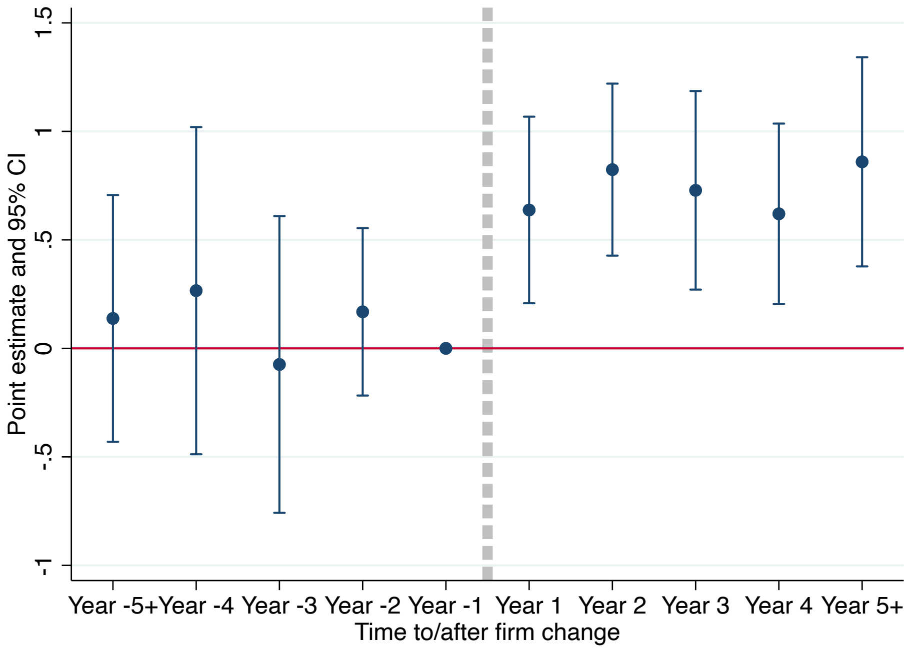


Figure 6: **Effect of mutual fund firm change on manager's marginal product of capital and value added**: This figure presents the coefficient estimates β_k and 95% confidence intervals against year to firm change in regression (28):

$$Y_{m,t} = \sum_k \beta_k \{year\ k\ to\ firm\ change\}_{m,t} + \delta_t + \lambda_m + \eta_{style} + \theta_f + \epsilon_{m,t}.$$

In Panel A, the dependent variable is the log of the absolute value of the marginal product of capital of manager m at time t computed using the parameters estimated as described in section 4.1. In Panel B, the dependent variable is the manager's value added (return in excess of the benchmark times that manager's AUM, measured in \$millions/month). Standard errors are clustered at the firm level.

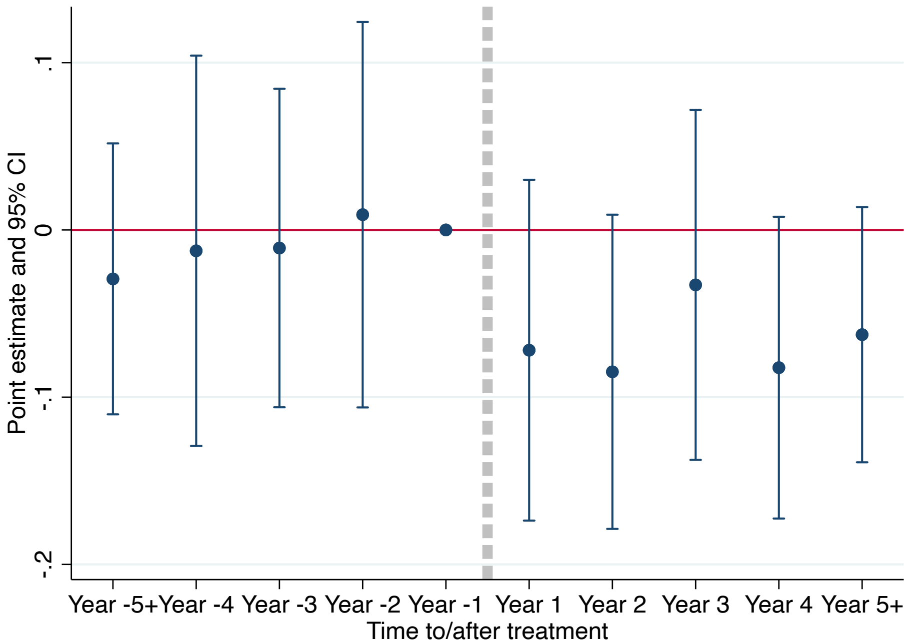


Figure 7: **Effect of changes in non-compete enforceability on state-level managers' mobility rate**: This figure presents the coefficient estimates β_k and 95% confidence intervals against year to firm change in regression (32) with $\%Switchers_{s,t}$, i.e., the percentage of managers in state s changing mutual fund firm at the end of month t, as the dependent variable:

$$\%Switchers_{s,t} = \sum_k \beta_k \left\{Treated \times year\ k\ to\ treatment\right\}_{s,t} + \gamma X_{s,t-1} + \theta_s + \delta_t + \epsilon_{s,t}.$$

The independent variable $\{Treated \times year\ k\ to\ treatment\}_{s,t}$ is a specific indicator equal to 1 (or -1) if state s is eventually treated and if the period t is part of year k before or after the NCCs law change. $X_{s,t-1}$ includes lagged control variables at the state level: the (log) number of managers, the (log) number of management firms, the (log) total AUM of managers and the (log) number of funds. The regression includes state fixed effects θ_s and time fixed effects δ_t. Standard errors are clustered at the state level.

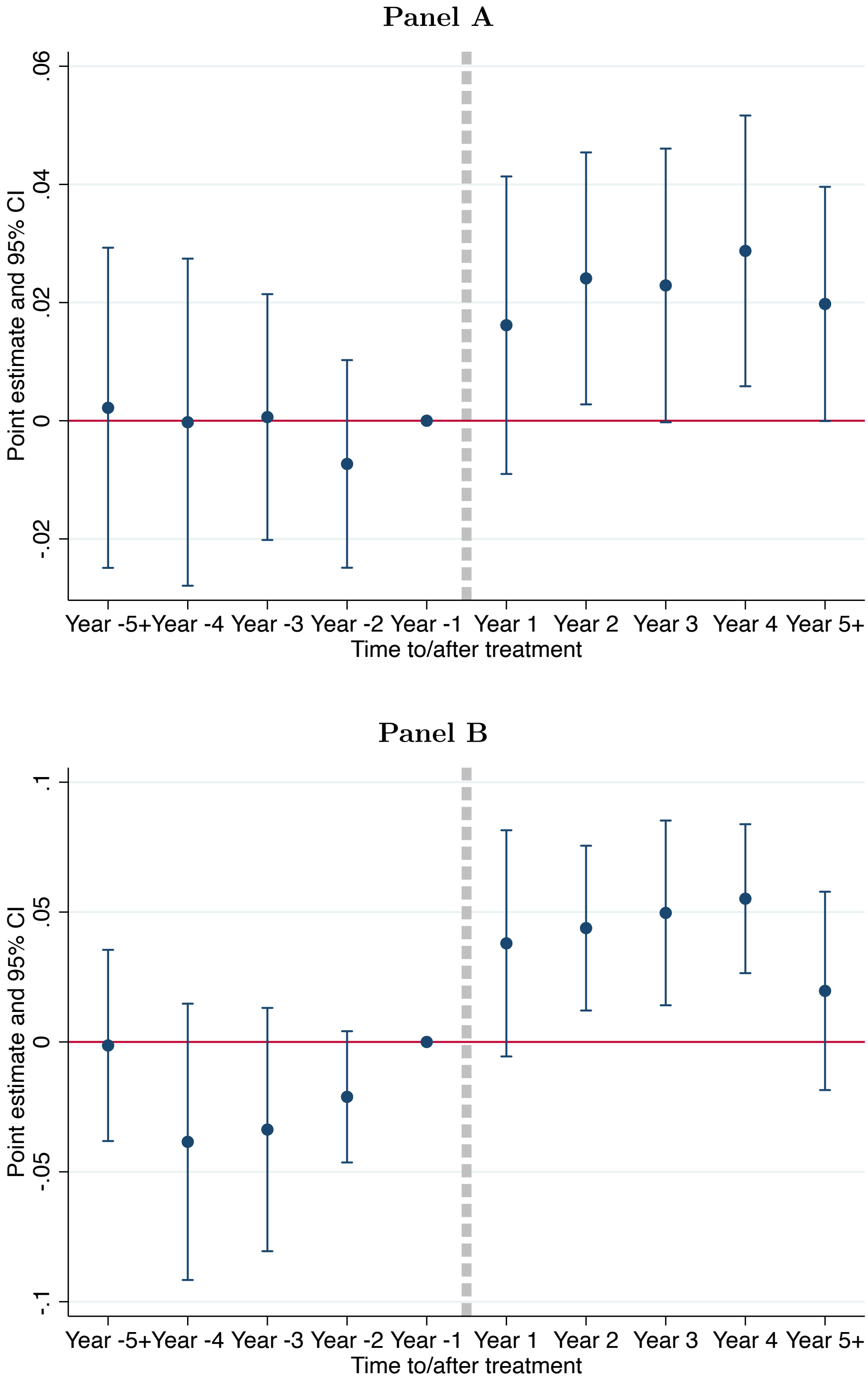


Figure 8: **Effect of changes in non-compete enforceability on state-level measures of capital misallocation across managers**: This figure presents the coefficient estimates β_k and 95% confidence intervals against year to firm change in regression (32) with state-level measures of capital misallocation as dependent variables:

$Y_{s,t} = \sum_k \beta_k \left\{Treated \times year\ k\ to\ treatment\right\}_{s,t} + \gamma X_{s,t-1} + \theta_s + \delta_t + \epsilon_{s,t}.$

In Panel A, the dependent variable is the standard deviation of the marginal products of capital of managers employed in the state in that month. In Panel B, the dependent variable is the difference between the 75th and 25th percentiles of the marginal products on capital of managers employed in the state in that month. Standard errors are clustered at the state level.

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Appendix

A Firms' and managers' problems when capital is mobile

Firms maximize profits given in equation (3) by optimizing over two dimensions. The first one is the amount of capital managed by each employee (i.e., internal reallocation), the second one is labor demand, i.e., the mass of each type of manager the firm is willing to employ. This optimization can be separated into two stages. First, for a given set of masses of employed managers $(L_m(f))_{m\in[0,M]}$, a firm can determine the optimal internal capital allocation between its different managers in order to maximize profits.[43] Second, the firm can adjust its labor demand for each type of manager, knowing the result of the first optimization procedure.

Specifically, firm f first chooses the amount of capital $k_m(f)$ to be managed by managers of type m, taking W_m and $L_m(f)$ as given. This leads to the optimization over $k_m(f)$, for all $m \in [0, M]$

$$\max_{k_m(f)} \int_0^M L_i(f)\left[v_i(k_i(f)) - W_i\right] di, \tag{33}$$

subject to

$$\int_0^M L_i(f)k_i(f)di \leq \int_0^M L_i(f)\tilde{k}_i di,$$

where $\tilde{k}_m$ is the amount of capital provided to manager m by investors. Obviously the first order conditions of this optimization are the same as for investors' problem, i.e., the firm seeks to equalize marginal products of capital across its employees. Thus, the firm cannot add any value through internal reallocation and each manager runs a fund with capital $\tilde{k}_m, m \in [0, M]$, directly provided by investors. As pointed out by Berk et al. (2017), in this world, there is no role for a firm executive.

Let denote $V(L(f))$ the solution to problem (33), where $L(f)$ refers to given masses of employed managers: $L(f) = (L_m(f))_{m\in[0,M]}$. We can now write down the firm's optimization problem regarding labor demand:

$$\max_{L(f)} V(L(f)) = \max_{(L_m(f))m\in[0,M]} \int_0^M L_i(f)\left[v_i(\tilde{k}_i) - W_i\right] di,$$

which leads to the following first order conditions for all $m \in [0, M]$:

$$W_m = v_m(\tilde{k}_m).$$

[43] In practice, a firm cannot arbitrarily move capital from one of its funds to another but it can promote (or demote) a manager by assigning her more or less funds, i.e., it decides which manager gets to manage which fund, as documented by Berk et al. (2017).

Namely, the marginal labor cost equates the marginal labor product. Note that the manager extracts the whole surplus. Therefore, investors make zero net alpha, i.e., their NPV of investing with managers is zero after fees (i.e., after managers are paid).[44] By definition of the value added function v_m, labor income of the manager is concave in the size of the funds under management, as documented empirically by Ibert et al. (2017).

The last part of the overall equilibrium relates to managers.[45] The latter can optimize regarding the "choice" of employer in order to maximize compensation. However, it is clear that for a given manager m, her wage is the same in all firms. With any employer, the manager will run a fund of size $\tilde{k}_m$ and earn $W_m = v_m(\tilde{k}_m)$. Therefore, in this world, just as there is no role for firm internal reallocation, there is no gain from external mobility of managers. Marginal products of capital are equalized across all managers directly by investors' capital allocation.

[44] This result is similar to Berk and Green (2004).

[45] I assume implicitly that each manager inelastically provides one unit of labor and thus necessarily "produces" according to the function in equation (1).

B Capital misallocation as a predictor of fund managers' departure

	Depart					
	(1)	(2)	(3)	(4)	(5)	(6)
$\log\lvert MPK \rvert$		0.0005***			0.0005***	
		(0.0002)			(0.0002)	
log($\$Misallocation$)			0.0004**			0.0003*
			(0.0002)			(0.0002)
log(TNA)	-0.0024***	-0.0026***	-0.0026***	-0.0033***	-0.0034***	-0.0034***
	(0.0002)	(0.0002)	(0.0002)	(0.0003)	(0.0003)	(0.0003)
log(#Funds)	-0.0111***	-0.0112***	-0.0111***	-0.0107***	-0.0108***	-0.0108***
	(0.0009)	(0.0009)	(0.0009)	(0.0010)	(0.0010)	(0.0010)
log(#Comanagers)	0.0006	0.0007	0.0006	0.0009	0.0009	0.0009
	(0.0004)	(0.0004)	(0.0004)	(0.0007)	(0.0007)	(0.0007)
Flow	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
log(Tenure)	0.0028***	0.0028***	0.0028***	0.0031***	0.0031***	0.0031***
	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)
log(Experience)	0.0004	0.0005	0.0005	0.0005	0.0005	0.0005
	(0.0005)	(0.0005)	(0.0005)	(0.0006)	(0.0006)	(0.0006)
Internal.Realloc	0.0090***	0.0090***	0.0090***	0.0090***	0.0090***	0.0090***
	(0.0008)	(0.0008)	(0.0008)	(0.0009)	(0.0009)	(0.0009)
Retail.Share	0.0004	0.0004	0.0004	-0.0001	-0.0000	-0.0001
	(0.0008)	(0.0008)	(0.0008)	(0.0011)	(0.0011)	(0.0011)
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Manager FE	Yes	Yes	Yes	Yes	Yes	Yes
Style FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	No	No	No	Yes	Yes	Yes
Observations	573,152	573,152	573,152	573,015	573,015	573,015
R^2	0.02	0.02	0.02	0.04	0.04	0.04

Table A1: **Determinants of managers' departure from mutual fund firm**: This table reports results for regressions investigating the drivers of a fund manager' decision to depart from a mutual fund firm. The dependent variable is a dummy variable equal to one if the manager switches mutual fund firm next period $t + 1$ or if she drops out of the sample and is less than 55 years old (if birth date if available from Capital IQ) or has less than 25 years of experience in the mutual fund industry. The main independent variables consist of proxies for capital misallocation: MPK is the marginal product of capital of the manager and $\$Misallocation$ is the dollar spread between the actual AUM of the manager and her optimal level of AUM computed in Section 4.2. Internal.Realloc is a dummy indicating whether the manager has incurred an internal capital reallocation in this firm. Retail.Share is the share of manager's funds with a retail share class. Standard errors in parentheses are clustered at the firm level. Data frequency is monthly. * p<.10; ** p<.05; *** p<.01.

C Robustness checks

	$\log\lvert Flow\rvert$		$\log(OptimalAssets)$	
	(1)	(2)	(3)	(4)
$Treated \times Post$	-0.044	-0.046	-0.136	-0.130
	(0.101)	(0.102)	(0.222)	(0.226)
log(#Managers)	0.445***	0.449***	0.889***	0.891***
	(0.121)	(0.122)	(0.254)	(0.254)
log(#Firms)	-0.146	-0.155*	-0.035	-0.028
	(0.088)	(0.088)	(0.255)	(0.258)
log(TNA)	0.714***	0.716***	0.098	0.098
	(0.038)	(0.038)	(0.141)	(0.142)
log(#Funds)	0.054	0.055	0.329*	0.324*
	(0.091)	(0.091)	(0.172)	(0.173)
Drop NY, MA, CA	No	Yes	No	Yes
Time FE	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes
Observations	9,451	8,770	9,451	8,770
R^2	0.94	0.92	0.96	0.94

Table A2: **Effect of changes in non-compete enforceability on state-level flows and manager composition**: This table presents the results of difference-in-difference estimations;

$$Y_{s,t} = \beta \left\{Treated \times Post\right\}_{s,t} + \gamma X_{s,t-1} + \theta_s + \delta_t + \epsilon_{s,t}.$$

In regressions (1) and (2), the dependent variable is the (log) sum of absolute asset flows of managers in the state in that month. In regressions (3) and (4), the dependent variable is the (log) sum of optimal AUM of managers in the state in that month (I add one before taking log). The independent variable $\left\{Treated \times Post\right\}_{s,t}$ is an indicator that is equal to 1 (resp. -1) if an increase (resp. decrease) in NCCs enforceability has been passed by time t in state s, and zero otherwise. $X_{s,t-1}$ includes lagged control variables at the state level: the (log) number of managers, the (log) number of management firms, the (log) total AUM of managers and the (log) number of funds. The regression includes state fixed effects θ_s and time fixed effects δ_t. Standard errors in parentheses are clustered at the state level. In regressions (2) and (4), the observations corresponding to the states of New-York, Massachusetts and California are dropped from the estimation. * p<.10; ** p<.05; *** p<.01.