"Labor Mobility and Capital Misallocation in the Mutual Fund Industry"

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Abstract

This paper studies whether fund managers’ mobility across mutual fund firms affects the efficiency in the allocation of capital across managers. I exploit exogenous shocks to fund managers’ mobility via state-level legislation changes increasing the enforceability of non-compete agreements. I find that the passage of these laws leads to a reduction by half of the propensity of fund managers to move across firms along with an increase in capital misallocation across managers by roughly 30% as well as a decline in value added of managers by more than $110 million at the state level. These results indicate that the labor market for mutual fund managers is an important channel through which capital is efficiently matched with skill.
1 Introduction

Identifying the sources of capital misallocation across an economy’s productive units is a first-order issue given the role of inputs allocation in aggregate productivity. Research in economics and finance so far has mainly focused on misallocation across establishments or firms. Assessing capital misallocation across workers is more challenging as it actually requires richer micro data and suitable settings that are scarce. In this paper, I study capital misallocation across fund managers, exploiting unique features of the mutual fund industry: the observability of workers’ productivity and amount of capital under control. The mutual fund sector manages about one fourth of all financial assets of U.S. households (i.e., almost $20 trillion) and has grown threefold over the last two decades. As fund managers vary in skills and amounts of capital under management, the value created by this industry is likely to be tied to the allocation of capital across managers.

The asset management literature has mostly emphasized the role of investors’ fund flows in reallocating capital across fund managers, i.e., capital goes to managers. However, the match between managers and capital could also occur by managers going to capital. Indeed, Berk et al. (2017) document an effective reallocation of capital through mutual fund firms’ internal labor markets: through promotions and demotions, mutual fund firms do reallocate managers across their funds and thus assign them more or less capital to manage. In this paper, I study the external labor market as another channel through which managers go to capital: by moving across mutual fund firms, managers end up running larger or smaller funds, and thus managing more or less capital. My contribution is to explicitly identify that mutual fund managers’ mobility across firms is an important channel through which capital is efficiently reallocated across managers.

In frictionless markets, as both capital and labor are perfectly mobile, which channel operates to reach the optimal allocation of capital across managers with heterogeneous skills is irrelevant. For instance, investors’ fund flows alone, i.e. capital reallocation across funds and thus across managers, might ensure that higher skilled managers manage more capital (cf., Berk and Green,

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1See Restuccia and Rogerson (2017) for a review of the recent literature on capital misallocation.
2The ICI’s Investment Company Fact Book reports 18.75 trillions of total net assets for mutual funds in the United States in 2017 and 5.53 in 1998.
3An 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).
However, there is evidence that capital may not flow efficiently across managers. If investors’ capital reallocation across funds and thus across managers is imperfect, managers reallocation across mutual fund firms can possibly improve capital allocation and the matching between managers’ skill and capital.

To study the allocative efficiency of capital across fund managers, I build on the literature on resource misallocation. Consider several managers with different skills and decreasing return to scale of assets under management (AUM). Absent frictions, capital would be efficiently allocated across managers so that their marginal products of capital would be equalized. Suppose now that capital allocation across managers’ funds is imperfect. Berk et al. (2017) show that if all managers work in the same mutual fund family firm, the latter can still reallocate capital between them to equalize marginal productivity. However, if the managers work in different firms, capital reallocation within a given firm is limited to the managers it employs and bounded by the amount of capital investors provide initially. Because capital is segmented between firms, there can still be a wedge between the different marginal products of capital in the economy. Using a simple model, I show that frictionless mobility of fund managers across mutual fund firms can result in the equalization of marginal products of capital across all managers, therefore offsetting any initial capital misallocation. On the other hand, the model spotlights that frictions in the labor market prevent equalization of marginal products of capital through this channel.

The empirical investigation of whether managers’ external mobility is a key determinant of the efficiency of capital allocation in the mutual fund industry poses three challenges. First, it is crucial to have rich fund manager-level data that allow one to follow managers over time and across firms and to track capital under management. Second, assessing capital misallocation across fund managers requires modeling managers’ value added as a function of AUM and measuring managers’ skill. Third, in order to mitigate the concern that fund managers’ mobility across firms is endogenous to many outcomes, one needs to rely on plausibly exogenous and well-defined variations in the intensity of managers’ mobility.

One reason is that investors learn imperfectly about managers’ ability. See Choi et al. (2016) for evidence of imperfect learning about manager skills. Bailey et al. (2011) relates imperfect learning to behavioral biases, Reuter and Zitzewitz (2006) and Kaniel and Parham (2017) to financial media’s recommendations, and Roussanov et al. (2018) to mutual funds’ marketing. A second reason is that investors know less about fund managers’ ability than mutual fund firms (Berk et al., 2017) and managers themselves (Ibert, 2018). A third reason is that investors learn imperfectly about managers’ ability than mutual fund firms (Berk et al., 2017) and managers themselves (Ibert, 2018).

See Restuccia and Rogerson (2008); Alfaro et al. (2008); Hsieh and Klenow (2009); Bartelsman et al. (2013) on the misallocation of resources across plants and countries, David et al. (2016) on the link between misallocation and imperfect information, and David et al. (2018) on its link with investment risk premia.
To address the first challenge, I build a novel manager-level panel of almost 4,000 different managers with their employment history from 2005 to 2018, using two databases. First, I rely on the CRSP Survivorship Bias Free Mutual Fund Database to obtain fund-level data and extract the names of portfolio managers and management companies. Then, I match the latter with employees and companies in S&P Capital IQ - People Intelligence, which gathers the profiles of professionals linked to unique individual identifiers, together with company affiliation. This allows me to identify managers and track their employment history as well as amount of capital under management. About one third of fund managers change employer at least once during the sample period. These moves tend to involve a large change in the manager’s AUM: over $600 million on average ($150 million for the median).

To overcome the second challenge, I rely on recent contributions studying the nature of returns to scale in active management. Following Berk and Van Binsbergen (2015), I compute a manager’s value added as the product of gross alpha and AUM. Then, assuming gross alpha decreases linearly with AUM, I estimate the skill parameters (first dollar alpha and decreasing returns to scale) of each manager using econometric procedures developed by Pástor et al. (2015) and Zhu (2018). This allows me to calculate each manager’s optimal AUM (maximizing value added) and marginal return on capital given current AUM. Regression analysis indicates that underfunding (i.e., the extent to which a manager manages less capital than optimally) is a strong predictor of the occurrence of departure to a new firm. Furthermore, I establish that the distance to the manager’s estimated optimal level of AUM drops by 22% on average when changing employer. These first observations suggest that managers’ mobility across mutual fund firms may improve capital allocation across fund managers.

For the third empirical challenge of addressing the endogeneity of fund managers’ mobility, I rely on exogenous variations in managers’ ability to change employer and estimate the effect on the efficiency in capital allocation across managers. My empirical strategy exploits staggered state-level variations in the enforceability of non-compete clauses (NCC) as exogenous shocks to mobility costs. In practice, NCC preclude employees from moving to a competing firm for a period of time after leaving their employer and are likely to be found in high-skill, high-paying jobs and industries, such as finance. Staggered NCC enforceability reinforcements introduced

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6Cf. Chen et al. (2004); Barras et al. (2018); Pastor et al. (2019) for additional empirical evidence regarding diseconomies of scale in the mutual fund industry.

7See Starr et al. (2018) for survey data on the occurrence of NCC in different industries. Several legal disputes in recent years involving asset managers suggest that NCC are pervasive in the finance sector. See for instance the cases of Frank Russell Investment Management Company and Wellington Management Company (1998),
by state governments or supreme courts have been shown to restrict the mobility of workers.\footnote{See for instance Marx et al. (2009); Bishara (2010); Garmaise (2011); Starr (2018); Ewens and Marx (2017); Jeffers (2018).}

To start with, I test whether state-level changes in NCC enforceability do indeed affect the mobility of mutual fund managers. I use the office addresses of professionals provided by S&P Capital IQ - People Intelligence to identify each fund manager’s state of employment and thus which managers are potentially affected by NCC law changes. Using a difference-in-difference setting, I find that stronger NCC enforceability halves the probability that an affected manager moves to another mutual fund firm, compared to unaffected managers. This result is confirmed when I aggregate observations at the state level. Indeed, the fraction of managers switching employer each quarter in the treated states drops significantly compared to control states after NCC become more enforceable.

I then test whether NCC enforceability changes affect capital misallocation and value added of mutual fund managers. I compute capital misallocation at the state level as the sum over managers of the differences between managers’ observed AUM and estimated optimal AUM. I show in a difference-in-difference setting that, after NCC become more enforceable, capital misallocation rises by almost 30% in treated states compared to control states. Consistent with this result, I also find that the dispersion of managers’ marginal products of capital increases substantially following stricter NCC regulation. The interpretation is that a greater dispersion of marginal products of capital reflects greater capital misallocation. Lastly, I establish that state-aggregated value added of fund managers decreases by more than $110 million in treated states. These results suggest that limiting the mobility of managers across firms has a negative impact on the efficiency of capital allocation in the mutual fund industry and thus that the labor market for fund managers is an important channel through which capital is efficiently matched with skill.

This paper relates to several strands of literature. Its first contribution is to show conceptually that, on top of capital mobility, labor mobility across firms is an alternative channel to reach an efficient capital allocation across fund managers. Berk et al. (2017) show that mutual fund firms can create value by reallocating managers among funds through internal labor markets. I directly complement their framework and highlight that studying the matching efficiency between capital and talent in the mutual fund industry requires a complete view of external labor movements across firms. As such, this paper also contributes to the literature studying the Graham Capital, Moore Capital, Tudor Investment Corporation and recently Brevan Howard and Rokos (2015).
career outcomes of investment managers (Khorana, 1996; Chevalier and Ellison, 1999; Barber et al., 2017; Ellul et al., 2019) and emphasizes the role of external mobility.9

Second, the paper adds to the literature studying the matching between capital and managerial talent (Gabaix and Landier, 2008; Tervio, 2008; Eisfeldt and Kuhnen, 2013) and the potential mismatch between the two (Caselli and Gennaioli, 2013; Buera and Shin, 2013), by exploiting the characteristics of the asset management sector: the observability of workers’ productivity and amount of capital under control. It also contributes to the literature on labor market frictions as a factor affecting resource allocation across plants and firms (e.g. Hopenhayn and Rogerson, 1993; Lagos, 2006) and labor productivity (Bryan and Morten, 2019). A novelty of this paper is to quantify misallocation across workers instead of firms thanks to the level of transparency that the mutual fund sector offers.

Finally, this paper is also related to the discussion on the effects of lengthened workers’ tenure in corporate finance. Several papers suggest that longer workers’ tenure can be beneficial regarding firm investment (Acemoglu and Shimer, 1999; Jeffers, 2018) and managers incentives (Gibbons and Murphy, 1992; Holmström, 1999).10 Regarding the asset management industry, Acharya et al. (2016) present a model in which fund managers are risk averse and employers need time to learn about managers’ talent. In that configuration, limiting managers’ mobility can be beneficial for learning and improve capital allocation across managers. My empirical results do not provide support for this theory but are rather in line with the existence of frictions preventing investors to directly allocate capital efficiently across managers (e.g., due to search costs as in Sirri and Tufano, 1998; Gârleanu and Pedersen, 2018), making the labor market for managers a relevant channel to improve capital allocation.

The paper proceeds as follows. Section 2 introduces a model to highlight the role of managers’ mobility across firms in the capital allocation process. Section 3 presents the data. Section 4 discusses the identification strategy. Section 5 describes the procedure I use to estimate managers’ valued added functions. Section 6 presents the results. Section 7 concludes.

9Kisin and Hamilton (2017) study fund managers mobility between mutual funds and hedge funds through the lens of a model of supply and demand for heterogeneous sector-specific skills and document potential inefficiencies in the allocation of skill and capital.

10For a focus on the mutual fund sector, cf. Cici et al. (2018).
2 Conceptual framework

This section presents a simple model featuring investors, asset managers and mutual fund family firms to illustrate the equivalent role of capital mobility and labor mobility in the process of efficiently allocating capital across managers. I enrich the framework developed in Berk et al. (2017) by considering several firms and allowing managers to change employer.

I assume investors are endowed with a total amount of capital $K$. 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. Specifically, 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:

$$v_m(k) = \frac{k}{\text{capital (AUM)}} \times \alpha_m(k)$$

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, as in Berk and Green (2004) but with manager-specific rates.\footnote{Decreasing return to scale can be due, for instance, to the fact that strategies apply only to few stocks or that prices move if large trades are executed. Cf. Chen et al. (2004); Pastor et al. (2015); Zhu (2018); Barras et al. (2018); Pastor et al. (2019) for empirical evidence regarding diseconomies of scale in the mutual fund industry.}

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 (described below).\footnote{The labor literature (cf., in particular Abowd et al., 1999; Graham et al., 2011) suggests that firm effects, while important, are not as important as person effects in worker compensation.}

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 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 $\alpha_m$ is known, the optimal amount of capital $k_m^*$ manager $m$ should be managing to maximize $v_m(k)$ is given by the condition

$$v_m'(k_m^*) = \alpha_m(k_m^*) + k_m^* \alpha_m'(k_m^*) = 0.$$  

(2)
Figure 1 shows the gross alpha and value added function of the manager when the function $\alpha_m$ 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. Let $W_m$ refers to the compensation of manager $m$. For a given 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 can be expressed as follows:

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

2.1 Perfect capital mobility

First, I assume the market is frictionless. In particular, all agents know the function $\alpha_m$ for all $m \in [0, M]$. In this case, firm internal capital reallocation and managers’ mobility across firms are 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

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

subject to

$$\int_0^M \mu(i)k_i di \leq K. \quad (5)$$

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

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

where $\lambda$ 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 in this economy. However, in order to highlight differences with respect to the results of the next section, I explicitly describe firms’ optimization procedure. 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 \(m \in [0,M]\)

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

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 (7), 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 \(m \in [0,M]\):

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

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).\(^{14}\) 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).

\(^{13}\)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).

\(^{14}\)This result is similar to Berk and Green (2004).
The last part of the overall equilibrium relates to managers.\footnote{I assume implicitly that each manager inelastically provides one unit of labor and thus necessarily “produces” according to the function in equation (1).} 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.

### 2.2 Imperfect investors’ capital allocation

I now consider a version of the model in which investors do not provide the optimal amount of capital to each manager directly, i.e., investors provide capital to each manager such that the condition (6) is not verified.\footnote{One way to motivate this is to assume that investors do not know the functions \( \alpha_m \) 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.} As shown by Berk et al. (2017), through internal reallocation by employers, marginal returns on capital are equalized across managers within each firm. Furthermore, I show that, because managers can switch between employers freely, 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.

To make my point clear, I assume that investors provide an exogenous amount of capital to each manager. This implies that each firm has an exogenous amount of capital to manage, denoted \( K(f) \) for firm \( f \), corresponding to the capital provided by investors to managers initially in the firm, and such that

\[
\int_0^F K(f) df = K.
\]

#### 2.2.1 Firm problem: internal capital allocation and labor demand

As described above, firms maximize profits over two dimensions that are internal capital reallocation and labor demand. Again, the optimization procedure separates into two stages. First, for all \( m \in [0, M] \), firm \( f \) chooses the amount of capital \( k_m(f) \) to be managed by managers with
type $m$, taking $W_m$ and $L_m(f)$ as given:

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

subject to

$$
\int_0^M L_i(f) k_i(f) di \leq K(f),
$$

where $K(f)$ is the total AUM of firm $f$ provided by outside investors.$^{17}$ The first order conditions with respect to $k_m(f)$, for all $m \in [0, M]$, are:

$$
v'_m(k_m(f)) = \lambda_f,
$$

where $\lambda_f$ is the Lagrange multiplier associated with (9) for firm $f$. Thus, the marginal returns on capital are equalized across the different managers working in the firm.

As before, let denote $V(L(f))$ the solution to problem (8), where $L(f)$ refers to the 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:

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

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

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

Using the result in equation (10) and the expression of the derivative with respect to $L_m(f)$ of the (binding) constraint (9), equation (12) gives

$$
W_m = v_m(k_m(f)) - \lambda_f k_m(f),
$$
i.e., manager $m$ compensation is set such that marginal labor cost equalizes marginal labor productivity.$^{18}$

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

$$
\int_0^M L_i(f) \lambda_f k_i(f) di = \lambda_f K(f).
$$

$^{17}$ Note that, through the inequality in the constraint (9), 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.

$^{18}$ Note that, even in that case, labor income of the manager is still 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).
Therefore, the firm’s profit is non zero and is proportional to its total AUM and internal marginal return on capital. The more severe the binding constraint (9), the higher its “shadow value”, the greater is the value created by the firm through internal reallocation and its profit.

### 2.2.2 Manager 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.,

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

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 (13):

$$f_m = \arg \max_f v_m(k_m(f)) - \lambda_f k_m(f),$$

(15)

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 (15) combined with (10) gives:

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

(16)

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

Note that condition (16) 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). But crucially, condition (16) 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.

### 2.3 The effect of introducing 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 2.1, frictions preventing managers to move freely across employers have no effect on the efficiency of capital allocation. Indeed,

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19It can be easily shown that one obvious equilibrium outcome is $L_m(f) = \mu(m)\frac{K(f)}{K}$, i.e., each firm employs a fraction of each type of managers, proportionally to its relative size.
investors allocate the optimal amount of capital to each manager, independently of employers. On the other hand, in the framework of section 2.2, managers’ mobility across firms is crucial in order to obtain the optimal capital allocation. Hence, as I show below, frictional labor mobility leads to capital misallocation if investors do not allocate capital perfectly across managers.

Formally, keeping the same configuration as in section 2.2, 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 an initial matching between firms and managers took place and managers now face a positive cost to move to any firm that is not the initial employer.

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 (15), now given by

$$f_m = \arg \max_f v_m(k_m(f)) - \lambda_f k_m(f) - c_m(f).$$

If $\lambda_f > 0$, (17) and (10) gives the following first order condition:

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

That is, in equilibrium, the marginal gain to change firm (AUM times the variation in marginal return on capital) equates its marginal cost.

By multiplying both sides of equation (18) by $L_m(f_m)$ and integrating over $m$, one obtains, using equation (9)

$$\frac{\partial \lambda_f}{\partial f} = -\frac{C(f_m)}{K(f_m)}$$

where

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

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

The key implication of (19) is that, in equilibrium, a firm to which it is more (less) costly to move, i.e., positive (negative) $C(f)$, has a lower (higher) internal marginal return on capital $\lambda_f$. 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 $\lambda_f$ 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.
2.4 Empirical predictions

The main conclusion from the simple 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 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, restricting 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 AUM deviates from her optimal amount of capital under management). This can be summarized by the two following predictions (denoting $k_m$ the amount of capital managed by manager $m$ and $k^*_m$ the optimal amount manager $m$ should be managing):

**Prediction 1**: Capital misallocation in the economy is positively related to managers’ mobility costs. That is, the aggregated misallocation $M$, defined by

$$M = \int_0^M \mu(m)|k_m - k^*_m|dm,$$

increases when managers’ moving costs increase.

**Prediction 2**: The total value added of managers is negatively related to managers’ mobility costs. That is, the aggregated value added $V$, defined by

$$V = \int_0^M \mu(m)v_m(k_m)dm,$$

decreases when managers’ moving costs increase.
3 Data

The mutual fund industry reporting requirements allow to observe each quantity of interest appearing in the model above. Indeed, in practice, one can collect funds’ performance and fees, assets under management and identity of the managers and employers. For my empirical analysis, I build a manager-level dataset combining two databases, the CRSP Survivorship Bias Free Mutual Fund Database and the S&P Capital IQ - People Intelligence Database, which gathers profiles of professionals with individual identifiers and company affiliations.

The first step is to clean the CRSP Mutual Fund Database, reporting fund-level information. I consider only funds with at least one observation after January 1998, which is the date S&P Capital IQ coverage begins. My sample ends in September 2018. 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. I discard money market funds. I identify the latter using either fund name (if the latter contains the case insensitive character “money market”) 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 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) and funds without information on holding composition.

As explained below, I use the code and name of management companies as well as portfolio manager names provided by CRSP to identify the manager(s) in charge of the management of the fund. Because this information is crucial for my analysis and not perfectly reported by CRSP, for each fund, 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. I run the same procedure for the managers’ name. Regarding funds’ AUM, I replace any missing fund’s observation by the most recent observation in the past and I adjust for the effect of inflation by restating all AUM observations in January 1, 2000 dollars. Finally, I also collect monthly funds’ returns and quarterly expense ratios. As for AUM, I replace any missing expense ratio by the most recent observation in the past. I merge the different sub-classes of a fund using the CRSP Class Group code, which is a unique identifier for the different classes of a fund provided by

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15
Finally I drop any fund observations before the fund’s (inflation adjusted) AUM reached $5 million. I end up with a total of 10,370 funds.

The second step corresponds to the computation of alpha and value added of each fund. I follow Berk and Van Binsbergen (2015) and Berk et al. (2017) and define 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 gross alpha of the fund is defined as

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

where $R_{i,t}^B$ 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.\(^{21}\) 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 $R_{i,t}^B$ is computed as:

$$R_{i,t}^B = \sum_{k=1}^{n(t)} \beta_{i}^{k} R_{k,t},$$

where $n(t)$ is the total number of index funds offered by Vanguard at time $t$, $R_{k,t}$ is the return of the index fund $k$ at time $t$ and the coefficients $\beta_{i}^{k}$ are obtained from the projection of $i$th active mutual fund onto the set of orthogonalized Vanguard index funds as described in Berk and Van Binsbergen (2015). The realized value added of fund $i$ is then defined as

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

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

The final step is to build a panel at the manager level. To this end, I use manager names provided by CRSP at the quarterly frequency in the “Fund Summary” section. I assume that the manager(s) stated as being managing the fund at the end of the quarter was employed in

\(^{21}\)Vanguard was the first company to offer self-proclaimed index fund of each type.
this occupation during the full quarter. Because the manager names provided by CRSP are not recorded consistently over time and across funds, I combine fund level information from CRSP with data from S&P Capital IQ - People Intelligence, which gathers profiles of professionals with their company affiliations and individual identifiers. Indeed, in CRSP, due to spelling differences and format changes, “different names” can refer to the same manager (e.g., because first and middle names are differently abbreviated or even excluded). For the same reason, identical last names, appearing in different funds or different periods, can refer to different managers. To track managers carefully, I rely on the “person id” provided by Capital IQ. To achieve this, 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.\textsuperscript{22} Once I have a list of company identifiers in Capital IQ, I download all data on professionals that have ever had an “affiliation” with those corporations. On top of information on the job functions, these data include first name, middle name, last name, prefix, suffix and office address. Each professional has also a unique identifier called “person id”. I match the manager names provided by CRSP with professionals’ full names provided by Capital IQ and the corresponding person identifiers as follows. For a given fund, for each observation, I look for the (potentially incomplete) manager name(s) reported by CRSP 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 fund’s observation in CRSP. This allows me to track carefully each manager with a unique “person id”. I am able to identify about 70% of manager names provided by CRSP in Capital IQ using this procedure.

Then, I merge all observations with the same person id and date, following the procedure of Berk et al. (2017). I keep in my sample only managers with at least two years of data. 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:

\[
k_{m,t} = \sum_{i \in \Omega_{m,t}} \frac{k_{i,t}}{n_{i,t}},
\]

where \( \Omega_{m,t} \) is the set of funds managed by manager \( m \) at time \( t \) and \( n_{i,t} \) is the number of

\textsuperscript{22}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.
managers managing fund $i$ at time $t$. Similarly, manager’s $m$ value added is the sum:

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

where $v_{i,t}$ is the value added of fund $i$ at time $t$. Finally, I define the gross alpha of a manager as her value added divided by lagged AUM

$$\alpha_{m,t} = \frac{v_{m,t}}{k_{m,t-1}}.$$ 

On top of the management company code attached to the funds allowing me to track manager employer changes, I also record the following additional variables at the manager level through time: number of funds, experience, tenure and state of employment (according to office address). To compute the number of managed funds, I count the number of different CRSP Class Group codes (aggregating the different share classes of funds) she is associated with at a given period. Experience is the number of elapsed years since the first observation of a manager in the sample. Tenure is the number of years with the current employer, i.e., the length of the current job spell in the sample. Finally, the state of location is defined using the state identifier of the primary office address provided by Capital IQ.

Figure 2 shows the final number of managers in my sample each quarter. Capital IQ coverage starts in 1998 but it is only after 2000 that a significant number of managers appears to be identified. Because in my empirical analysis of capital misallocation I aggregate data at the state level, I decide to focus only on the period 2005-2018, in order to have a reasonable number of workers in each state. The number of managers is about 1,750 at the beginning of this subsample and around 2,000 at the end, with, in total, 3,815 distinct managers over the period. Figure 3 reports the average number of managers in each state. I identify managers in 48 different states. New York and Massachusetts are the states that are the most represented in my sample with respectively 359 and 252 managers on average over the period 2005-2018.

Table 1 presents summary statistics for the managers in my sample. The unit of observation is manager-quarter. The average manager has 8 years of experience and 6 years of tenure with her employer. The average AUM is about $1 billion. The distribution is highly skewed as evidenced by the median ($209 million) and the top 5% of AUM (above $4.4 billion). Managers run on average two funds. They produce a slightly negative average gross alpha (-0.5%) while the median is zero. This is in line with an average negative value added of -$1.1 million and median equal to zero. Slightly more than a third of managers change employer at least once. I discuss this point in more detail in section 6.
4 Empirical strategy

4.1 Non-compete agreements

The goal of my empirical analysis is to determine whether fund managers’ mobility across firms contributes to the allocative efficiency of capital across managers. A direct procedure would be to estimate a regression with as dependent variable a measure of capital misallocation across managers, and as independent variable the intensity of managers’ mobility across firms. Obviously, the mobility of managers is endogenous with respect to many outcomes and such regression may suffer from omitted variable bias. It could be that managers change employer more often when more information regarding manager skills is provided to investors and firms. If so, one could falsely attribute capital allocation efficiency to labor mobility.

To overcome the issue regarding the endogeneity of managers’ mobility, I exploit staggered changes in US states’ labor laws, affecting the ability of managers to change employer. Specifically, I use state-level variations in the enforceability of non-compete clauses (NCC), as exogenous shocks to costs faced by managers when changing employer. NCC are special agreements in labor contracts preventing employees from moving to a competing firm for a period of time after leaving their employer. These clauses are governed at the state level.\textsuperscript{23} This setting allows to test whether fund managers’ mobility affects the efficiency of capital allocation, eliminating concerns regarding the endogeneity of managers’ mobility. Indeed, it allows me to compare variations in capital misallocation caused by exogenous shocks to labor mobility frictions, between affected and unaffected states.

According to a survey on more than 11,000 labor force participants in the US, Starr et al. (2018) document that nearly one in five labor force participants were bound by NCC in 2014. Furthermore, their results indicate that NCC 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, these 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 NCC and thus state-level legislation changes.\textsuperscript{24}

\textsuperscript{23}For instance California bans the use of NCC.

\textsuperscript{24}For legal disputes, see for instance the cases of 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 NCC for several investment management firms on Glassdoor.com for instance.
The typical investment manager NCC 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].”

The main hypothesis I exploit in my empirical analysis is that an increase (resp. decrease) in NCC enforceability should negatively (resp. positively) impact managers’ mobility across fund family firms as stronger NCC enforcement should deter workers from switching employers. Indeed, failures to comply with the clauses are more likely to result in cases brought to court if NCC are more enforceable. I test empirically that managers’ mobility is affected by NCC changes. My results, presented in Section 6, validate this claim.

Ewens and Marx (2017) record eleven state-level changes during my sample period (2005-2018) that correspond to state Supreme Court rulings and state legislature changes. Increase in enforceability concerns Vermont (2005 Q3), Idaho (2008-Q2), Wisconsin (2009-Q3), Georgia (2011-Q2), Colorado (2011-Q2), Illinois (2011-Q2) and Texas (2011-Q4) while decrease in enforceability affects 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. In order to determine the current state of a manager and whether she is affected by a NCC reversal, I use the state identifier of the primary office address for each manager provided by Capital IQ. On Figure 3, I flag states that passed an increase or a decrease in NCC enforceability respectively with (+) and (−). Clearly, large treated states (in terms of number of managers) are Illinois, Colorado, Texas, Georgia and Wisconsin, which are all concerned by changes in favor of stronger NCC.

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 the asset management industry, justifying the exogeneity assumption of NCC law changes in my study. In other words, none of these laws targeted specifically the investment management sector. 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.

Table 2 compares characteristics of managers and states that are affected by changes in NCC enforcement (“treated”) and others (“control”). The statistics correspond to the period 2005-Q3, i.e., the last quarter before any enforceability shock occurs. Panel A presents means,
at the manager level, of AUM, number of funds, number of employer changes at that time, experience and tenure. It also provides $t$ statistic of differences in means relative to control managers. Most of the $t$-stats indicate insignificant differences, except for the number of funds per managers but the difference does not seem economically large (1.66 for control versus 1.87 for treated). Furthermore, treated managers seem to have slightly higher average AUM ($1.3$ billion versus $994$ million) and slightly less experience (5.8 versus 6.2 years) but averages do not diverge very much. The number of employer changes are very similar between treated and control (respectively 0.43 and 0.45) although states that passed a change in favor of weaker NCC displays a lower mean (0.25).

Panel B of Table 2 compares statistics at the state level. The $t$-stat of differences in means between control and treated are much lower in magnitude compared to Panel A, given the number of observations. One notices that a slightly lower number of managers are recorded on average in treated states (28) with respect to control states (30). The average number of firms are virtually the same (10.7 versus 11.1). Regarding AUM, one sees that, as few managers are recorded in states that eventually decrease NCC enforceability, the total amount of AUM in those states is much lower than in control states ($1.1$ billion versus $32$ billion). This observation does not hold for states that eventually increase NCC enforceability ($38$ billion versus $32$ billion).

One might be concerned that managers that are affected by stronger NCC substitute within-state employer changes with out-of-state changes. Nevertheless, this seems unlikely according to law firms reports. Indeed, usually, 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. However 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. Hence it is likely that NCC in the mutual fund industry are less bounded by “local restrictions” and prevent managers to move to any employer employing similar investment strategies even in another US state.

On top of this fact, I show that employer changes in my sample display a “home bias”. In other words, managers disproportionately change firm within a given state, thus are likely to be affected by NCC law changes even if it restricted to within state employer changes. To

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25 Only two state-observations are recorded in the “Decrease” category because no managers are identified in South Carolina nor Kentucky in 2005-Q3.

establish this result, I present in Table 3 the percentage of employer changes taking place within a state (as opposed to across states), conditional on the number of firms in the state of the initial employer. Indeed, as states have different supplies of outside options, the proportion of “local” switches might vary across states. The baseline proportion of local employer changes is 79%. This percentage increases monotonically as I consider only states with a certain number of managers. In particular, there are 84% of employer changes that take place within state borders when there are at least 50 firms. This fraction jumps to 92% if there are at least 100 firms.

4.2 Methodology

First, I establish the validity of my approach, i.e., I verify that NCC law changes have a significant impact on managers’ propensity to change employer. My empirical strategy is to test, using a generalized difference-in-difference specification, whether managers working in states strengthening (weakening) NCC enforceability move less (more) across firms after NCC become more enforceable, compared to managers working in states without legislation changes.\(^{27}\)

The specification is as follows:

\[
\text{Depart}_{m,t} = \beta \{Treated \times Post\}_{m,s,t} + \gamma_1 X_{m,t-1} + \gamma_2 Y_{s,t-1} + \lambda_m + \theta_s + \delta_t + \epsilon_{m,t},
\]

where the dependent variable \(\text{Depart}\) is, for manager \(m\) working in state \(s\) at time \(t\), a dummy indicating whether the manager departs from her current employer to another one at the end of period \(t\). \(\{Treated \times Post\}_{m,s,t}\) is an indicator taking the value 1 (resp. -1) if manager \(m\) works in a state \(s\) where an increase (resp. decrease) in NCC enforceability has been passed by time \(t\), and zero otherwise. \(X_{m,t-1}\) includes control variables at the manager level. \(Y_{s,t-1}\) includes control variables aggregated at the state level. Control variables are lagged in order to avoid the “bad control” criticism discussed by Angrist and Pischke (2008). \(\lambda_m, \theta_s\) and \(\delta_t\) are respectively manager fixed effects, state fixed effects and time fixed effects. Standard errors are clustered at the state level, because that is the level of treatment.

Equation (23) accounts for the fact that there are several NCC law reversals staggered over time. Hence, the control group is not restricted to managers in states that never pass a change. Equation (23) uses as the control group all managers in 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 NCC law changes, managers’
mobility in the treated states would have changed in the same way as in the control group.

If stronger NCC enforcement negatively affects managers’ mobility, one should observe $\beta < 0$ in (23). To further confirm the validity of my approach, I also estimate a similar generalized difference-in-difference at the state level, which corresponds to the level of treatment. The specification is similar to equation (24) below, with as dependent variable the percentage of managers in the state changing employer next period. One should also observe $\beta < 0$ in this specification if managers’ mobility is negatively affected by stronger NCC enforceability.

The second stage of my empirical analysis is to evaluate whether NCC 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) NCC enforceability display an increase (decrease) in capital misallocation and a decrease (increase) in value added of managers, after NCC become more enforceable, compared to control states without legislation changes. The specification is as follows:

$$ Y_{s,t} = \beta \{\text{Treated} \times \text{Post}\}_{s,t} + \gamma_1 X_{s,t-1} + \theta_s + \delta_t + \epsilon_{s,t}, \quad (24) $$

where the dependent variable $Y_{s,t}$ is for state $s$ at time $t$ a measure of either the misallocation across managers or total value added of managers. $\{\text{Treated} \times \text{Post}\}_{s,t}$ is an indicator that is 1 (resp. -1) if an increase (resp. decrease) in NCC enforceability has been passed by time $t$ in state $s$. $X_{s,t-1}$ includes lagged control variables at the state level. $\theta_s$ and $\delta_t$ are respectively state fixed effects and time fixed effects. Standard errors are clustered at the state level.

The theoretical framework presented in section 2 suggests that, 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 NCC enforceability decreases the ability of managers to move across firms, one should observe $\beta > 0$ in (24) 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.

5 Manager skills and returns to scale

Examining capital misallocation through the lens of the model introduced in section 2 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’ alpha. In my empirical analysis, I follow the
literature studying the relationship between fund size and performance: I use a reduced form specification assuming that gross alpha decreases linearly with AUM. Namely, I assume

$$\alpha_m(k) = a_m - b_m k.$$  \hspace{1cm} (25)

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 her value added given by $v_m(k) = k \times \alpha_m(k)$:

$$k_m^* = \frac{a_m}{2b_m},$$  \hspace{1cm} (26)

as well as the expression for manager’s marginal return on capital when running a fund of size $k$:

$$v_m'(k) = a_m - 2b_m k.$$  \hspace{1cm} (27)

Second, as discussed below, I can re-use the econometric procedures developed to study returns to scale in active management, in a linear regression framework. Note however that one has to acknowledge that by estimating manager’s skill assuming this linear functional form, inferences depend on the assumption that the relation between a manager’s gross alpha and her dollar AUM is linear.

Several papers have focused on the estimation of the effect of fund size on fund alpha (see Chen et al., 2004, for an early reference). 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. 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. These methodologies are mainly developed to estimate a slope common across all funds. However, as made explicit in the model of section 2 and acknowledged 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.\textsuperscript{28} 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: I adapt Zhu (2018)’s procedure to managers instead of funds and I estimate manager-specific parameters $a_m$ and $b_m$. That is, I sort the mutual fund managers in twenty 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 ventile 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 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 summarize this procedure below:

1. I sort managers into 20 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.\textsuperscript{29} 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 $t$ given by (22). 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 $\bar{\alpha}_{m,t-1}^*$:

\[
\bar{\alpha}_{m,t} = b_g \bar{\alpha}_{m,t-1}^* + u_{m,t}.
\]

\textsuperscript{28}Despite the overall trend of decreasing returns to scale, Zhu (2018) finds that 29% of the sampled funds 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.

\textsuperscript{29}Following most papers estimating decreasing return to scale, I exclude manager-month observations with lagged AUM below $15$ million.
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:

$$\hat{a}_m = \frac{1}{T_m} \sum_{t=1}^{T_m} (\alpha_{m,t} + \hat{b}_m k_{m,t} - 1).$$

Two points regarding my dataset deserve clarification. First, even if manager names are provided at the quarterly frequency in CRSP, fund returns are actually available at the monthly frequency. To maximize the number of observations used to estimate manager skills, I assign to a given manager the 3 monthly returns and AUM of funds to which she is attached in a given quarter. Therefore, quantities in equations (20), (21) and (22) are defined at the monthly frequency and can be used to run the estimation procedure described above. Second, even if my sample of analysis goes from 2005 to 2018, several managers have track records going back to pre-2005 period. To reduce estimation error as much as possible, for each manager identified in my sample, I use the longest possible time series of gross alpha and AUM, even if it involves data before 2005.

Table 4 reports summary statistics of the estimated skill parameters. The positive estimates of $b_m$ suggest that the relation between a manager’s AUM and its gross alpha is negative in each AUM-sorted group. This coefficient is significantly positive in most ventiles according to the values of t-stats. 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 $1.8 \times 10^4$. As AUM are reported in $\$\text{million}$, this means that one more million of assets under management leads to a decrease in monthly gross alpha of almost 2 basis points. At the other extreme, in group 20, $b_m$ has a value of $0.001 \times 10^4$, i.e., it requires $\$1 \text{ billion}$ 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 4 also reports summary statistics of the estimates of $a_m$ (monthly gross alpha on the first dollar) 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 30 bps, it decreases up to zero in group 11 and then increases again. The variations in $a_m$ are large, with standard deviations between 1 and 10 times the mean value. The main conclusion is that managers with high AUM are not running investment strategies with the largest alpha on the first dollar but instead more scalable strategies than others.
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 (26). 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.\footnote{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.}

Panel A of Figure 4 presents the overall distribution of $\hat{a}_m$ in my sample of managers. It shows that slightly less than one quarter of managers fails to generate a positive alpha on the first dollar they manage. Panel B of Figure 4 reports the corresponding distribution of $k^*_m$. Its shape suggests that the density of optimal AUM is geometrically decreasing from 0 to about $3$ billion.

Statistics regarding the distribution of $k^*_m$ in each group of managers are presented in Table 4. It reveals that the average value of $k^*_m$ is clearly increasing from group 1 to group 20, as is the actual average AUM in each group. However, when comparing the mean $k^*_m$ and mean AUM across groups, one can notice an important trend. While managers in group 1 have on average $22$ million of AUM, the corresponding theoretical average value of $k^*_m$ is about $9$ million, suggesting managers in this group are on average significantly overfunded, i.e., they manage more capital than optimally. The same observation remains valid up to group 11. This trend is then reversed in most remaining groups. In particular, the top group appears to be severely underfunded with actual average AUM of $7.6$ billion and theoretical optimal AUM of $16.8$ billion. These first descriptive statistics already suggest that there exist some capital misallocation in the mutual fund industry according to the estimated skill parameters.

6 Empirical results

6.1 Misallocation and fund managers’ decision to change employer

First, I provide a set of statistics and tests in order to highlight the role of the labor market for fund managers. Figure 5 presents the distribution of the number of employer changes (recorded before exiting the sample) in the cross-section of managers. About one third of managers change employer at least once. Indeed, 20% of managers switch once, 5% switch twice and slightly more than 5% switch more than twice. Figure 6 reports the evolution of the fraction of managers changing employer each year, from 2005 to 2018. One sees a clear spike at 12% in 2007, while
the proportion of switching managers is around 4% each year after 2010.

I establish two main empirical regularities. First, the extent of misallocation at the manager level appears to predict the occurrence of an employer change. More precisely, a higher underfunding with respect to theoretical optimal AUM is associated with a greater likelihood of changing employer. Second, in the event of an employer switch, the manager’s AUM varies by more than $640 million while misallocation drops by 22%, on average.

To analyze managers mobility across employers, I use the manager-panel described above. As the manager-firm association is only available at the quarterly frequency in CRSP, I focus on quarterly data. I define a dummy variable $\text{Depart}_{m,t}$ set to one if there is an employer change for manager $m$ next quarter at time $t + 1$, i.e., manager $m$ departs from her current employer at the end of period $t$. An employer change corresponds to a change in the Management Company Code provided by CRSP as well as a full change of the set of funds’ identifiers associated to the manager. The unconditional mean of the variable $\text{Depart}$ is 1.6% in the sample.

As a first step, I regress the dummy $\text{Depart}$ on a set of variables defined at the manager and state level. Formally, I present in Table 5 the results of the estimation of the following specification for manager $m$, working in state $s$, at quarter $t$:

$$\text{Depart}_{m,t} = \gamma_1 X_{m,t} + \gamma_2 Y_{s,t} + \lambda_m + \theta_s + \delta_t + \epsilon_{m,t}, \quad (28)$$

where $X_{m,t}$ includes the following variables at the manager level: AUM, number of managed funds, value added, flow, gross alpha, (firm) tenure, experience and their squares and $Y_{s,t}$ includes variables aggregated at the state level in my sample: the number of managers in the state, the number of management family firms in the state, the total AUM of managers in the state and their squares. All regressions include manager fixed effects $\lambda_m$, state fixed effects $\theta_s$ and time fixed effects $\delta_t$. Table 5 shows that the number of managed funds appears to be significantly positively correlated with the probability to change employer, although the corresponding square term reveals a concave effect. The same can be said of the tenure with employer, while experience appears to have a negative effect. I do not find that the state-level number of firms, managers and AUM have a significant effect.

I turn now to the analysis of the correlation between misallocation and the event of employer change. For this purpose, I define several measures of misallocation building on the theoretical framework presented in section 2. The first measure relates to the notion of marginal product of capital (MPK). Indeed, a manager $m$ managing her optimal level of assets $k^*_m$, defined in (26),
has a marginal return on capital equal to zero:

\[ a_m - 2b_m k_m^* = 0. \]

On the other hand, if the manager is underfunded (overfunded), i.e., manages an amount of assets below (above) \( k_m^* \), her MPK is positive (negative). A prediction from section 2.2 is that, if manager mobility plays a role in reaching an efficient capital allocation, employer changes should allow managers to reach a common value of MPK, as close to zero as possible. Hence, intuitively, a manager with a high value of MPK should be more likely to change employer compared to a manager with a low value.

In order to tease out whether manager moves are driven by a potential wedge between the actual amount of capital under management and the hypothetical optimal amount of AUM, I test whether the marginal product on capital of a manager actually correlates with the event of a departure of that manager to another firm, controlling for the variables discussed above and present in Table 5. To compute the value of MPK, I use the estimates of the parameters \( a_m \) and \( b_m \) obtained in section 5. Each quarter \( t \), I compute for each manager \( m \) her marginal product as

\[ MPK_{m,t} = \hat{a}_m - 2\hat{b}_m k_{m,t}, \tag{29} \]

where \( \hat{a}_m \) and \( \hat{b}_m \) are the estimated parameters for manager \( m \) and \( k_{m,t} \) is the current amount of assets under management of the manager.

Specifically, in a first regression I consider the absolute value of \( MPK_{m,t} \) as independent variable on top of the set of regressors discussed above and present in specification (28):

\[ \text{Depart}_{m,t} = \beta|MPK_{m,t}| + \gamma_1 X_{m,t} + \gamma_2 Y_{s,t} + \lambda_m + \theta_s + \delta_t + \epsilon_{m,t}. \tag{30} \]

The intuition being that a large underfunding or overfunding should be associated with a large (absolute) marginal product of capital and a greater likelihood of changing employer for the corresponding manager. To further capture the potential asymmetric effect of under and overfunding, in a second regression, I replace the absolute value of \( MPK_{m,t} \) in (30) by the two terms of the decomposition of \( MPK \): \((MPK)^+ = \max(MPK, 0)\) (positive when the manager is underfunded, zero otherwise) and \((MPK)^- = -\min(MPK, 0)\) (positive when the manager is overfunded, zero otherwise).

Regressions (1) and (2) in Table 6 present the results. Clearly, \(|MPK|\) appears to be positively correlated with the event of employer change. The magnitude of the coefficient is about 1.5. Given that the unconditional average probability to leave for another firm is 1.6% and
the standard deviation of $|MPK|$ is about 0.004, a two-standard deviation increase in $|MPK|$ appears to be associated with a rise of 50%, relative to the mean, in the propensity to change employer. The correlation is statistically significant and robust, even in the presence of other determinants of departure such as number of funds, tenure and experience. When the two terms $(MPK)^{+}$ and $(MPK)^{-}$ are considered as regressors instead of $|MPK|$, both corresponding coefficients are statistically significant. However, one clearly sees that the magnitude of the coefficient on $(MPK)^{+}$ (2.83), i.e., the marginal product of capital when the manager is underfunded is twice as large as the magnitude of the coefficient when the manager is underfunded (1.47). This points toward a greater effect of underfunding on the likelihood of departing.

It is fair to say that the estimates of regression coefficients related to the notion of marginal product of capital might be difficult to interpret. In order to alleviate that concern, I consider a second set of similar regressions using a more readable measure of misallocation. Formally, using again the estimates of the parameters $a_m$ and $b_m$ obtained in section 5, I compute the theoretical amount of assets maximizing the value added of each manager, defined as $k^{*}_m = \hat{a}_m/2\hat{b}_m$. As in section 5, I set $k^{*}_m$ to zero for managers who have a negative estimate $\hat{a}_m$. Then, for managers with positive $\hat{a}_m$, I compute a percentage misallocation as follows:

$$%Misallocation_{m,t} = 100 \times \frac{|k_{m,t} - k^{*}_m|}{k^{*}_m},$$

where $k_{m,t}$ is the current amount of assets under management of the manager. I re-estimate regression (37), with $|MPK|$ replaced by $%Misallocation$. I also consider a specification with asymmetric effects of underfunding and overfunding, by replacing $%Misallocation$ by the two terms of its decomposition: $%Underfunding$ (positive when the manager is underfunded, zero otherwise) and $%Overfunding$ (positive when the manager is overfunded, zero otherwise).

The results correspond to regressions (3) and (4) in Table 6. $%Misallocation$ does not seem to be significantly correlated with Depart as the corresponding coefficient is virtually zero. Nevertheless, when the effect of $%Underfunding$ and $%Overfunding$ are estimated separately, one sees that the impact of the former is significantly positive. The magnitude of the coefficient on $%Underfunding$ is 0.0001, meaning that a 50% underfunding raises the likelihood of employer change by 0.005, which corresponds to almost one third of the unconditional mean of the dependent variable. The coefficient on $%Overfunding$ is virtually zero.

The results described above, using two measures of misallocation, suggest that a larger underfunding with respect to her theoretical optimal AUM significantly raises the likelihood for a manager to change employer. Yet, two caveats have to be discussed. First, one has to
acknowledge that the positive and significant estimates may be due to reverse causality. Indeed, it could be that the AUM of the manager decreased in response to her willingness to leave the firm, raising mechanically \((MPK)^+\) and \(\%\text{Underfunding}\). Second, to be fully rigorous I should adjust or bootstrap standard errors of coefficients of interest, given that the misallocation measures I use are generated independent variables.

The second part of this section presents summary statistics of key variables in the event of an employer change. The goal is to show that one observes large capital reallocation and a reduction in misallocation when managers move across firms. Table 7 presents experience and tenure as well as variations of AUM, performance and misallocation conditioning on the occurrence of an employer change. On average, switching managers have nine years of experience and five years of tenure. The amount of AUM does not seem to move systematically in one direction in the event of a switch. Indeed AUM increases on average by $760,000 ($6.65 million for the median), although this can correspond to large AUM growth. The mean of the absolute value of AUM variation is large though. On average, an employer change is associated with a variation of AUM, either positive or negative, of $644 million. This result suggests that the magnitude of capital reallocation following a manager move can be severe. The variations of the employer’s AUM, number of funds and managers do not seem to be considerable, but it is fair to say that this might be due to the fact that my sample does not cover all funds proposed by a given provider.

Value added over one year and average (quarterly) gross alpha over one year appear to rise in the event of an employer change, respectively by $3.9 million and 3.6%. Regarding misallocation, I focus on the variations of the two measures defined above: \(|MPK|\) and \(\%\text{Misallocation}\). The former drops on average by 0.24 in case of a switch. In addition, the reduction of more than 22% in \(\%\text{Misallocation}\), on average, clearly suggests that there is a reduction in misallocation in case of a switch. In dollar term, the misallocation is reduced by an average of $1.6 million. These results constitute a first indication that manager mobility across employers is a potential channel through which capital reallocation can occur and, at the same time, misallocation be reduced.

6.2 The effect of stronger non-compete agreements enforceability on the mobility of managers

I present the estimation results of the specifications discussed in section 4 presenting my empirical strategy to address the concern that fund managers’ mobility is endogenous to many outcomes. First, to validate my approach, I confirm that changes in NCC enforcement act as shocks that
affect the ability of managers to move across firms. My hypothesis is that an increase (decrease) in NCC enforceability should decrease (increase) the mobility of labor, i.e., of managers in the affected states. To test this, I use a generalized difference-in-difference approach, with changes in NCC enforcement as the main independent variable. Formally, I estimate the following specification, for manager $m$, working in state $s$, at quarter $t$:

$$\text{Depart}_{m,t} = \beta \{\text{Treated} \times \text{Post}\}_{m,s,t} + \gamma_1 X_{m,t-1} + \gamma_2 Y_{s,t-1} + \lambda_m + \theta_s + \delta_t + \epsilon_{m,t}, \quad (32)$$

where $\text{Depart}_{m,t}$ is, as above, a dummy variable taking the value one when there is a change in manager $m$’s employer in quarter $t + 1$. Therefore, $\text{Depart}$ is only equal to one when the manager stays in the sample and changes firm at the end of quarter $t$. $\{\text{Treated} \times \text{Post}\}_{m,s,t}$ is an indicator taking the value 1 (resp. -1) if manager $m$ works in a state $s$ where an increase (resp. decrease) in NCC enforceability has been passed by time $t$, and zero otherwise. $X_{m,t-1}$ and $Y_{s,t-1}$ act as control for outside options of managers. I use lagged controls in order to avoid the “bad control” criticism discussed by Angrist and Pischke (2008). $X_{m,t-1}$ includes lagged control variables at the manager level: AUM, number of managed funds, value added, flow, gross alpha, (firm) tenure, experience, and their squares. $Y_{s,t}$ includes the following lagged control variables aggregated at the state level in my sample: the number of managers in the state, the number of management family firms in the state, the total AUM of managers in the state, and their squares. The regression includes manager fixed effects $\lambda_m$, state fixed effects $\theta_s$ and time fixed effects $\delta_t$. Standard errors are clustered at the state level, because that is the level of treatment.

Regressions (1) and (2) in Table 8 present the results of the estimation, with and without state-level controls. Clearly the effect of stronger NCC enforceability on the propensity of managers to change employer is negative. The coefficient $\beta$ in equation (32) is significantly different from zero and its magnitude is between -0.7% and -0.8%, depending on the specification. Given that the average of the variable $\text{Depart}$ is about 1.6%, this corresponds to a decrease of about fifty percent with respect to the sample average.

To alleviate concerns that managers could have anticipated NCC law changes, and to assess the effect of the latter through time, I present in Figure 7, the estimates of coefficients $\beta_k$ in the following specification:

$$\text{Depart}_{m,t} = \sum_k \beta_k \{\text{Treated} \times \text{year k to treatment}\}_{m,s,t} + \gamma_1 X_{m,t-1} + \gamma_2 Y_{s,t-1} + \lambda_m + \theta_s + \delta_t + \epsilon_{m,t}, \quad (33)$$
where \( \{Treated \times year\ k \ to \ treatment\}_{m,s,t} \) is a specific indicator that is equal to 1 (or -1) if manager \( m \) works in a state \( s \) that is eventually treated and if the period \( t \) corresponds to one of the four quarters in a year \( k \) before or after the NCC law change. As made clear in Figure 7, the two years before the enforceability change, the estimated difference between the treatment and control groups is virtually zero. Following the change, the likelihood to change employer in the treatment group drops significantly relative to the likelihood in the control group. The effect appears to be sizable two years after the change (-1.1%) and is persistent even after more than five years, suggesting long-lasting effects on manager mobility.

To evaluate the potential asymmetric effect of stronger versus weaker NCC, regressions (3) and (4) in Table 8 presents the results of the estimation of specification (32), where the regressor \( \{Treated \times Post\}_{m,s,t} \) is decomposed between a separate indicator for managers in states where enforcement has increased \( \{Strengthened \times Post\}_{m,s,t} \) and where it has decreased \( \{Weakened \times Post\}_{m,s,t} \). I obtain very similar magnitude and significance for estimates of the effect of stronger NCC, when comparing to the bundled coefficients in regressions (1) and (2). For \( \{Weakened \times Post\}_{m,s,t} \), the estimate has a slightly larger magnitude but with the sign flipped and not statistically significant. The lack of statistical significance is not surprising given the much fewer observations in this group, as discussed before.

To confirm this result, I estimate a similar generalized difference-in-difference at the state level, which corresponds to the level of treatment. For this purpose I estimate the following regression:

\[
DepartureRate_{s,t} = \beta \{Treated \times Post\}_{s,t} + \gamma_{1} X_{s,t-1} + \theta_{s} + \delta_{t} + \epsilon_{s,t}, \tag{34}
\]

where

\[
DepartureRate_{s,t} = 100 \times \frac{\#Departures_{s,t}}{\#Managers_{s,t}}
\]

is, for a given state \( s \), the percentage of managers changing employer in quarter \( t + 1 \). The independent variable \( \{Treated \times Post\}_{s,t} \) is an indicator that is equal to 1 (resp. -1) if an increase (resp. decrease) in NCC 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 number of managers in the state, the number of management family firms in the state, the total AUM of managers in the state, and their squares. The regression includes state fixed effects \( \theta_{s} \) and time fixed effects \( \delta_{t} \). Standard errors are clustered at the state level.

Table 9 shows the results of the estimation. The aggregation of manager moves at the state level leads to a sharp reduction in the number of observations. Specification (34) corresponds to
regression (1) in Table 9. The coefficient on \{(Treated \times Post)\} is negative and has a magnitude around -0.42, but is not statistically different from zero. Note though that the direct estimation of specification (34) leads to coefficients that are calculated considering that each state has the same weight. Given the obvious difference in terms of number of managers in each state (which is the denominator of DepartureRate), as shown in Figure 3, I also present the results of two other regressions. In regression (3) in Table 9, I only consider state observations for which the current number of managers is larger than 10. Indeed, all observations with departure rate above 30% correspond to states with at most 5 recorded managers, which is likely to generate extreme and unrepresentative observations. In regression (4), observations are weighted by the average number of managers in the state across the sample period. Both specifications lead to similar estimates of the effect of stronger NCC enforceability on the propensity of managers to change employer. The corresponding coefficient is significantly different from zero and its magnitude is between -0.72% and -0.63%. Given that the corresponding average of the variable DepartureRate is about 1.5% (1.4% with observations with at least 10 managers), this corresponds to a decrease of slightly less than fifty percent with respect to the sample average.

I also present the estimates of the effect each specific year before and after the law changes. Figure 8 shows the coefficients \(\beta_k\) in the following specification, dropping observations with less than 10 managers:

\[
\text{DepartureRate}_{s,t} = \sum_k \beta_k \{\text{Treated} \times \text{year k to treatment}\}_{s,t} + \gamma_1 X_{s,t-1} + \theta_s + \delta_t + \epsilon_{s,t}. \tag{35}
\]

where \{\text{Treated} \times \text{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 one of the four quarters in a year \(k\) before or after the NCC law change. As in Figure 7, one sees that the coefficients corresponding to the two years before the enforceability change are virtually zero. Following the change, the departure rate in the treatment group declines significantly relative to the rate in the control group. Again, the effect appears to be sizable two years after the change (-1%) and is persistent even after more than five years.

As discussed previously, I re-estimate specification (34) at the state level, where the term \{\text{Treated} \times Post\}_{s,t} is decomposed between a separate indicator for states where enforcement has increased \{\text{Strengthened} \times Post\}_{s,t} and where it has decreased \{\text{Weakened} \times Post\}_{s,t}. Regression (2) in Table 9 presents the estimates without weighting observations. The coefficient capturing the effect of stronger NCC is negative (-0.99) and highly significant, while for \{\text{Weakened} \times Post\}_{s,t} it has the wrong sign but the standard error is three times as large as
the estimate. Again, the lack of statistical significance is not surprising given the much fewer observations in this group. Regression (5) presents the results when observations are weighted by the average number of managers in the state (the specific effect of weaker NCC cannot be estimated when dropping observations with less than 10 managers). It shows that the coefficient on \{$Strenghtened \times Post\}_{s,t}$ is significantly negative (-0.75) and a bit larger than the blended coefficient in regression (4). The coefficient for \{$Weakened \times Post\}_{s,t}$ is virtually zero but the standard error is thirty times as large as the estimate.

In conclusion, the results presented above are consistent with the hypothesis that stronger NCC enforceability deters managers from changing employer, and as a consequence acts as a negative shock on manager mobility across firms.

6.3 The effect of restricting managers’ mobility on capital misallocation and value added of managers

The last part of my analysis regards the effect of stronger NCC enforceability on capital mis-allocation. As NCC are governed at the state level, my unit of observation is state-quarter. Following the spirit of Hsieh and Klenow (2009) and guided by the theoretical framework developed in section 2, I use as a first indicator of misallocation the dispersion of marginal products on capital across managers. The intuition being that the extent of capital misallocation is worse when there is a greater dispersion of marginal products. Specifically, for each quarter and each state, I compute two measures of dispersion related to the variable \(MPK\) defined in equation (29). 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 quarter \(t\). The second one, denoted \(MPK\) 90 – 10, is the ratio of the 90th and 10th percentiles of the \(MPK\) of managers employed in state \(s\) in quarter \(t\). Furthermore, I also construct a measure of misallocation similar to (31), at the state level, using the estimated theoretical optimal amount of AUM of each manager. Formally, I define \(\%Misallocation_{s,t}\), for a state \(s\) at period \(t\) as

\[
\%Misallocation_{s,t} = 100 \times \frac{\sum_{m \in M_{s,t}} |k_{m,t} - k^*_m|}{\sum_{m \in M_{s,t}} k^*_m},
\]

(36)

where \(M_{s,t}\) is the set of managers working in state \(s\) at time \(t\), \(k_{m,t}\) is the amount of AUM of manager \(m\) at time \(t\) and \(k^*_m\) is the estimated optimal amount of AUM of manager \(m\) (set to zero if \(\hat{a}_m < 0\)). In words, this measure computes the misallocation in a given state relative to the estimated optimal amount of assets that should be managed in that state.

The specification I study to evaluate the relationship between manager mobility and the
efficiency of capital allocation is designed to assess the impact of stronger NCC enforceability on misallocation. I use again a generalized difference-in-difference approach with changes in NCC enforcement as my main independent variable. Formally, I estimate the following specification for state $s$ at quarter $t$:

$$M_{s,t} = \beta \{Treated \times Post\}_{s,t} + \gamma_1 X_{s,t-1} + \theta_s + \delta_t + \epsilon_{s,t},$$  \hfill (37)

where $M_{s,t}$ is one of the misallocation measures described above, i.e., $\sigma(MPK)_{s,t}$, $MPK \ 90 - 10$ or $\%Misallocation_{s,t}$. $\{Treated \times Post\}_{s,t}$ is an indicator defined as in regression (34), that is 1 (resp. -1) if an increase (resp. decrease) in NCC enforceability has been passed by time $t$ in state $s$. $X_{s,t-1}$ includes lagged control variables at the state level: the number of managers in the state, the number of management family firms in the state, the total AUM in the state and their squares. The regressions include state fixed effects $\theta_s$ and time fixed effects $\delta_t$. Standard errors are clustered at the state level. Given that measures of dispersion are not indicative with too few managers, I drop all state observations with less than 10 managers.

The results are shown in Table 10. Regression (1) displays the coefficients when the dependent variable is $\sigma(MPK)_{s,t}$. The coefficient corresponding to $\{Treated \times Post\}_{s,t}$ is positive, suggesting an increase in misallocation, but not significant. Regarding the magnitude, the point estimate of 0.0003 represents 10% of the sample mean of $\sigma(MPK)_{s,t}$. Regression (2) presents the estimates when the dependent variable is $MPK \ 90 - 10$. In that case, the coefficient $\beta$ in regression (37) appears to be significantly different from zero at the 10% level and positive. Given that the sample mean of $MPK \ 90 - 10$ is of the order of 0.35, the estimated coefficient of 0.19 is sizable. Finally, the results when $\%Misallocation$ is used as dependent variable correspond to regression (3). Again, the coefficient on $\{Treated \times Post\}_{s,t}$ is positive and significantly different from zero at the 10% level. The point estimate of more than 28 suggests that it is economically significant, implying a rise in misallocation of almost 30% in treated states after implementing stronger NCC, relative to the control group. The conclusion, according to the results presented in Table 10 is that restricting labor mobility of managers between firms seems to have a detrimental effect on the allocative efficiency of capital.

Furthermore, in order to assess the evolution of misallocation several years before and after NCC reversals, Figure 9 presents the estimates of coefficients $\beta_k$ in the following specification:

$$\%Misallocation_{s,t} = \sum_k \beta_k \{Treated \times year \ k \ to \ treatment\}_{s,t} + \gamma_1 X_{s,t-1} + \theta_s + \delta_t + \epsilon_{s,t},$$  \hfill (38)

where $\{Treated \times year \ k \ to \ treatment\}_{s,t}$ is defined as in regression (35), i.e., it is a specific indicator equal to 1 (or -1) if state $s$ is eventually treated and if the period $t$ is one of the four
quarters in a year $k$ before or after the NCC law change. Figure 9 suggests that misallocation rises gradually in treated states with respect to the control group following NCC law reversals. A lack of statistical power does not allow to observe statistically significant coefficients but the magnitude of misallocation ex-post is economically large. Indeed, the effect appears to be sizable even after more than five years (almost 40%), which is compatible with the effect of NCC changes on labor mobility presented in Figure 8, suggesting long-lasting effects on capital misallocation.

The last test I implement concerns the effect of stronger NCC enforceability on the value added of managers. Indeed, the conceptual framework of section 2 shows that an increase in misallocation implies a decrease in value added. Figure 1 illustrates this point. When the distance to $k^*_m$ rises, the value added drops. Therefore, if the misallocation increases in treated states following changes in favor of stronger NCC, one should expect the total value added of managers in those states to shrink relative to other states. To evaluate this effect, I re-estimate specification (37) with the aggregate value added at the state level $V_{s,t}$ as dependent variable, where $V_{s,t}$ is defined as

$$V_{s,t} = \sum_{m \in M_{s,t}} v_{m,t},$$  \hspace{1cm} (39)$$

where $M_{s,t}$ is the set of managers working in state $s$ at time $t$ and $v_{m,t}$ is the value added of manager $m$ at time $t$ defined in equation (21). Note that this measure is independent of the estimates of manager skills and decreasing returns to scale discussed in section 5.

The estimated coefficients are presented in regression (4) of Table 10. The effect of stronger NCC appears to be negative and significant at the 10% level. It suggests that the total value added at the state level is reduced by more than $110$ million after a change in favor of stronger NCC, relative to states in the control group. Given that the sample mean of $V_{s,t}$ is $-75$ million, this is highly economically significant.

A final point regarding investor capital allocation deserves special attention. According to the simple theoretical framework developed in section 2, the effect of labor market frictions should be respectively positive and negative on misallocation and value added, if investors do not directly equalize marginal products of capital across managers through asset flows. To ensure that my results are not driven by a change in investor behavior regarding capital allocation following NCC reversals, I estimate a final regression at the manager level. Specifically, I estimate regression (32) with the manager capital flow as dependent variable. The coefficient on \( \{\text{Treated} \times \text{Post}\}_{m,s,t} \) captures the difference in capital provided by investors to managers in treated states relative to managers in the control group, controlling for a range of variables including the lagged values.
of AUM, number of funds, value added, flow, gross alpha, tenure, experience and their squares. The corresponding estimate (unreported in Tables) is equal to 10 with a standard error of 8, i.e., not significant. This suggests that investors do not systematically provide more or less capital to managers in treated states (controlling for other determinants of flows) in order to potentially compensate the reduction in labor mobility following NCC reversals. Hence, my results regarding misallocation discussed above are unlikely to be driven by a worse allocation of capital by investors ex-post.

The conclusion is that capital mobility by investors is likely to be imperfect and such that misallocation worsens if manager mobility is restricted. The potential reasons are multiple but an obvious one could be that it is extremely difficult for investors to have a good sense of the skill and decreasing return to scale of each manager. Overall, these results are compatible with the existence of search cost faced by investors to find and evaluate asset managers, as modeled by Gärleanu and Pedersen (2018).

7 Concluding remarks

This paper studies the link between mutual fund managers’ mobility across firms and the efficiency in capital allocation across managers. My analysis relies on the simple theoretical argument that, in the absence of frictions preventing either capital to go to managers or managers to go to capital through mobility across firms, revenue productivity from investment, i.e. marginal products of capital, would be equalized across managers. My contribution is to demonstrate that managers’ mobility across firms has an important role in efficiently reallocating capital across managers, suggesting that capital mobility, i.e., investors’ fund flows, do not directly equalize marginal products.

My empirical analysis uses staggered changes in non compete clauses (NCC) enforceability in different states, as shocks to managers’ ability to change employer, in order to test the relevance of the external labor market in efficiently reallocating capital across managers. I find that stronger NCC enforceability significantly reduces the propensity of managers to change employer and significantly increases the misallocation of capital across managers. These results suggest that restricting the mobility of managers across firms leads to a worse capital allocation in the mutual fund sector. These findings indicate that the external labor markets for fund managers is an important channel through which capital is efficiently reallocated across managers.
Table 1: Summary statistics in the pool of managers: This table reports summary statistics for the main variables at the quarterly frequency at the manager level in my sample from 2005 to 2018. Tenure corresponds to the number of years spent with the current employer. When a fund is co-managed by $N$ managers, I attribute $(1/N)$th of the fund’s AUM to each of its managers. AUM are expressed in January 2000 dollars.
Table 2: **Ex-ante manager and state characteristics**: This table reports ex-ante (2005-Q3) means of characteristics. Panel A focuses on mutual fund managers working for firms located in states where NCC enforcement does not change, and for states where NCC enforcement changes during the sample period. Panel B reports ex-ante characteristics at the state level. $t$ corresponds to a $t$-test statistic of differences relative to the “Control” observations. The treated states are broken down into states for which NC enforcement eventually increases and eventually decreases. Only two state observations are recorded for the latter because no managers are identified in South Carolina nor Kentucky in 2005-Q3.

### Panel A: Manager level

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Table 3: **Average of the fraction of switching managers moving to an employer in the same state conditional on the number of firms in the state**: This table reports the average fraction of manager employer changes taking place within a given state (as opposed to across states). Each line corresponds to the mean of the ratio $\frac{\text{#Departures within state}}{\text{#Departures}}$, given that the denominator is positive (i.e., there is at least one departure in the state) and that the number of firms in the state is larger than a certain threshold.
Table 4: 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 twenty groups (ventile) 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 $k^*_m = \frac{\hat{a}_m}{2\hat{b}_m}$. $k^*_m$ is set to zero if the manager has a negative estimate $\hat{a}_m$. 

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<th>$t(b_m)$</th>
<th>$a_m$ ($\times 10^4$)</th>
<th>$k_m^*$ (millions)</th>
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<tr>
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<td>0.10</td>
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Table 5: **Effect of variables on manager departure**: This table presents the results of regression estimations with a dummy variable indicating departure from the current employer as the dependent variable. The independent variables consist of a set of contemporaneous manager level and state level variables. All regressions include manager fixed effects, state fixed effects and time fixed effects. Standard errors in parentheses are clustered at the state level. Data frequency is quarterly. * p<.10; ** p<.05; *** p<.01.
Table 6: Effect of Marginal Return on Capital (MPK) and capital misallocation on manager departure: This table presents the results of regression estimations with a dummy variable indicating departure from the current employer as the dependent variable and measures of capital misallocation as main independent variables.

\[ \text{Depart}_{m,t} = \beta M_{m,t} + \gamma_1 X_{m,t} + \gamma_2 Y_{s,t} + \lambda_m + \theta_s + \delta_t + \epsilon_{m,t}. \]

In regression (1), \( M_{m,t} \) corresponds to the absolute value of the Marginal Return on Capital (MPK) of manager \( m \) at time \( t \), i.e., \(|a_m - 2b_m k_{m,t}|\), where \( a_m \) and \( b_m \) are estimated and \( k_{m,t} \) is manager \( m \)'s AUM at time \( t \). In regression (2) \( M_{m,t} \) corresponds to the two terms of the decomposition of MPK: \( (MPK)^+ = \max(MPK, 0) \) (positive when the manager is underfunded, zero otherwise) and \( (MPK)^- = \min(MPK, 0) \) (positive when the manager is overfunded, zero otherwise). In regression (3), \( M_{m,t} \) corresponds to the (absolute value) percentage deviation of current AUM with respect to the theoretical optimal level of AUM defined by \( a_m/2b_m \) (which is set to zero for managers with \( a_m < 0 \)). In regressions (4) \( M_{m,t} \) corresponds to the two terms of the decomposition of \%Misallocation: \%Underfunding (positive when the manager is underfunded, zero otherwise) and \%Overfunding (positive when the manager is overfunded, zero otherwise). \( X_{m,t} \) (Manager Controls) includes control variables at the manager level: AUM, number of managed funds, value added, flow, gross alpha, (firm) tenure, experience and their squares. \( Y_{s,t} \) (State Controls) includes control variables at the state level: the number of managers in the state, the number of management family firms in the state, the total AUM of managers in the state and their squares. All regressions include manager fixed effects \( \lambda_m \), state fixed effects \( \theta_s \) and time fixed effects \( \delta_t \). Standard errors in parentheses are clustered at the state level. Data frequency is quarterly. * \( p<.10 \); ** \( p<.05 \); *** \( p<.01 \).
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<th>25%</th>
<th>50%</th>
<th>75%</th>
<th>95%</th>
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<td>4.00</td>
<td>8.00</td>
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<td>20.00</td>
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<td>4.42</td>
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<td>14.17</td>
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<td>-143.27</td>
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<td>(mill)</td>
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<td>633.12</td>
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<td>-0.18</td>
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<td>$</td>
<td>MPK</td>
<td>(×10^4)</td>
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<td>114.04</td>
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Table 7: Summary statistics when managers change employer: This table reports summary statistics for the main variables conditioning on the occurrence of an employer change. ∆ corresponds to the difference of the variable between the first quarter after the employer change and the last quarter before. Value added (VA) and Flow are summed over one year before and after the change, alpha corresponds to the average over one year before and after the change. MPK corresponds to the marginal return on capital, i.e., $a_m - 2b_m k_{m,t}$, according to estimated values of $a_m$ and $b_m$. %Misallocation and $\$Misallocation$ correspond respectively to the (absolute value) percentage and dollar deviation of current AUM with respect to the theoretical optimal level of AUM defined by $a_m/2b_m$ (which is set to zero for managers with $a_m < 0$).
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<th>(2)</th>
<th>(3)</th>
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<td>-0.0080**</td>
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<td></td>
<td>(0.0026)</td>
<td>(0.0033)</td>
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</tr>
<tr>
<td><strong>Strengthened × Post</strong></td>
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<td>-0.0069**</td>
<td>-0.0080**</td>
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<tr>
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<td>(0.0026)</td>
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</tr>
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<td>Yes</td>
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<td>Yes</td>
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<td>Yes</td>
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<tr>
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<td>Yes</td>
<td>Yes</td>
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</tr>
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<td>79,651</td>
<td>79,651</td>
<td>79,651</td>
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<td>0.12</td>
<td>0.12</td>
<td>0.12</td>
<td>0.12</td>
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</tbody>
</table>

Table 8: **Effect of changes in Non-Compete enforceability on manager departure:** This table presents the results of difference-in-difference estimations with a dummy variable indicating departure from the current employer as the dependent variable

$$\text{Depart}_{m,t} = \beta \{Treated \times Post\}_{m,s,t} + \gamma_1 X_{m,t-1} + \gamma_2 Y_{s,t-1} + \lambda_m + \theta_s + \delta_t + \epsilon_{m,t}.$$  

In regressions (1) and (2), $\{Treated \times Post\}_{m,s,t}$ is an indicator that is 1 (resp. -1) if manager $m$ works in a state $s$ where an increase (resp. decrease) in NCC enforceability has been passed by time $t$, zero otherwise. In regressions (3) and (4), $\{Treated \times Post\}_{m,s,t}$ is decomposed between a separate indicator for managers in states where enforcement has increased $\{Strenghtened \times Post\}_{m,s,t}$ and where it has decreased $\{Weakened \times Post\}_{m,s,t}$. $X_{m,t-1}$ (Manager Controls) includes lagged control variables at the manager level: AUM, number of managed funds, value added, flow, gross alpha, (firm) tenure, experience and their squares. $Y_{s,t-1}$ (State controls) includes lagged control variables at the state level: the number of managers in the state, the number of management family firms in the state, the total AUM of managers in the state and their squares. All regressions include manager fixed effects $\lambda_m$, state fixed effects $\theta_s$ and time fixed effects $\delta_t$. Standard errors in parentheses are clustered at the state level. Data frequency is quarterly. * $p<.10$; ** $p<.05$; *** $p<.01$. 

46
Table 9: **Effect of Non-Compete on state departure rate**: This table presents the results of difference-in-difference estimations with the ratio $\text{DepartureRate} = \frac{\#\text{Departures}}{\#\text{Managers}}$ at the state level, i.e., percentage of managers leaving their employer, as the dependent variable $\text{DepartureRate}_{s,t} = \beta \{Treated \times Post\}_{s,t} + \gamma_1 X_{s,t-1} + \theta_s + \delta_t + \epsilon_{s,t}$.

In regressions (1), (3) and (4), $\{Treated \times Post\}_{s,t}$ is an indicator that is 1 (resp. -1) if an increase (resp. decrease) in NCC enforceability has been passed by time $t$ in state $s$, zero otherwise. In regressions (2) and (5), $\{Treated \times Post\}_{s,t}$ is decomposed between a separate indicator for states where enforcement has increased $\{Strengthened \times Post\}_{s,t}$ and where it has decreased $\{Weakened \times Post\}_{s,t}$. $X_{s,t-1}$ includes lagged control variables at the state level, indicated in the table: the number of managers in the state, the number of management family firms in the state, the total AUM in the state and their squares. In regression (3), only observations of states with at least 10 identified managers are included (the asymmetric effect of increasing versus decreasing NCC enforceability cannot be identified given the reduced sample). In regression (4) and (5), observations are weighted by the average number of managers in the state across the sample period. All regressions include state fixed effects $\theta_s$ and time fixed effects $\delta_t$. Standard errors in parentheses are clustered at the state level. Data frequency is quarterly. * $p<.10$; ** $p<.05$; *** $p<.01$. 

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<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
</tr>
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<tr>
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<td>(3) %Misallocation</td>
<td>(4) Value Added</td>
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<td>(0.0951)</td>
<td>(15.9141)</td>
<td>(58.5563)</td>
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<td>-0.0062</td>
<td>-1.5227**</td>
<td>1.5848</td>
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<td></td>
<td>(0.0000)</td>
<td>(0.0051)</td>
<td>(0.5767)</td>
<td>(2.8128)</td>
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<td>Nb. Firms State</td>
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<td>-1.0523</td>
<td>28.0797*</td>
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<td></td>
<td>(0.0001)</td>
<td>(0.0182)</td>
<td>(2.1289)</td>
<td>(16.0120)</td>
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<tr>
<td>AUM State (bn)</td>
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<td>0.0040</td>
<td>0.6109**</td>
<td>-3.8834***</td>
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<td>(0.0000)</td>
<td>(0.0010)</td>
<td>(0.2354)</td>
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<td>0.0016*</td>
<td>-0.00105</td>
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<td></td>
<td>(0.0000)</td>
<td>(0.0000)</td>
<td>(0.0008)</td>
<td>(0.0035)</td>
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<tr>
<td>(Nb. Firms State)$^2$</td>
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<td>0.0001</td>
<td>0.0077</td>
<td>-0.1784**</td>
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<td></td>
<td>(0.0000)</td>
<td>(0.0001)</td>
<td>(0.0162)</td>
<td>(0.0736)</td>
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<tr>
<td>(AUM State)$^2$</td>
<td>-0.0000</td>
<td>0.0000</td>
<td>-0.0004</td>
<td>0.0072***</td>
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<td></td>
<td>(0.0000)</td>
<td>(0.0000)</td>
<td>(0.0002)</td>
<td>(0.0012)</td>
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<td>Only nb. managers $\geq$ 10</td>
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<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td></td>
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<tr>
<td>Time FE</td>
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<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
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<td>State FE</td>
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<td>Yes</td>
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<td>$R^2$</td>
<td>0.74</td>
<td>0.37</td>
<td>0.53</td>
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Table 10: **Effect of Non-Compete on capital misallocation and value added**: This table presents the results of difference-in-differences estimations with different measures of capital misallocation as well as value added, at the state level, as dependent variables

$$M_{s,t} = \beta \{Treated \times Post\}_{s,t} + \gamma_1 X_{s,t-1} + \theta_s + \delta_t + \epsilon_{s,t}.$$  

$\{Treated \times Post\}_{s,t}$ is an indicator that is 1 (resp. -1) if an increase (resp. decrease) in NCC enforceability has been passed by time $t$ in state $s$. In regression (1), the dependent variable is the standard deviation of the Marginal Return on Capital ($MPK$) across managers in a given state in a given quarter. In regression (2), the dependent variable is the ratio between the 90th and the 10th percentiles of the latter variable. In regression (3), the dependent variable is the percentage misallocation, i.e., the sum over all managers in a given state in a given quarter of the (absolute) dollar deviation of current AUM with respect to their theoretical optimal level of AUM, divided by the sum of the theoretical optimal levels of AUM. In regression (4), the dependent variable is the total value added of managers summed at the state level. $X_{s,t-1}$ includes lagged control variables at the state level, indicated in the table: the number of managers in the state, the number of management family firms in the state, the total AUM in the state and their squares. Only observations of states with at least 10 identified managers are included. All regressions include state fixed effects $\theta_s$ and time fixed effects $\delta_t$. Standard errors in parentheses are clustered at the state level. Data frequency is quarterly. * $p<.10$; ** $p<.05$; *** $p<.01$. 

48
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 number of asset managers in the sample**: This chart reports the time series of the number of identified mutual fund managers in the sample at each date from 1998 to 2018. All Figures and Tables are based on the sample 2005-2018. Throughout this period, 3,815 distinct managers are identified.
Figure 3: **Average number of managers in each state**: This chart reports the average number of managers in each state in my sample from 2005 to 2018. (+) and (-) denote states that respectively strengthened and weakened the enforceability of employee non-competes clauses (NCC) over the period 2005 to 2018.
Panel A: Distribution of the estimates of $a_m$

Panel B: Distribution of the estimated $k^*_m$

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 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.
Figure 5: **Distribution of the number of employer changes**: This chart reports the distribution of the number of employer changes recorded for each manager at the end of her career, i.e., the last date she is in the sample.

Figure 6: **Evolution of the proportion of asset managers changing employer each year**: This chart reports the time series of the fraction of identified mutual fund managers changing employer in a given year from 2005 to 2018.
Figure 7: Effect of changes in Non-Compete enforceability on manager departure: This figure presents the coefficient estimate $\beta_k$ against year to treatment, from the equation below with a dummy variable indicating departure from the current employer as the dependent variable. The estimate represents the difference between the treated and control observations, before and after the change in enforcement of NCC.

$$\text{Depart}_{m,t} = \sum_k \beta_k \{\text{Treated } \times \text{ year } k \text{ to treatment}\}_{m,s,t} + \gamma_1 X_{m,t-1} + \gamma_2 Y_{s,t-1} + \lambda_m + \theta_s + \delta_t + \epsilon_{m,t}.$$  

$X_{m,t-1}$ (Manager Controls) includes lagged control variables at the manager level: AUM, number of managed funds, value added, flow, gross alpha, (firm) tenure, experience and their squares. $Y_{s,t-1}$ (State controls) includes lagged control variables at the state level: the number of managers in the state, the number of management family firms in the state, the total AUM of managers in the state and their squares. The regression includes manager fixed effects $\lambda_m$, state fixed effects $\theta_s$ and time fixed effects $\delta_t$. Standard errors are clustered at the state level. Data frequency is quarterly.
Figure 8: Effect of changes in Non-Compete enforceability on state departure rate: This figure presents the coefficient estimate $\beta_k$ against year to treatment, from the equation below with the ratio $\text{DepartureRate} = 100 \times \frac{\# \text{Departures}}{\# \text{Managers}}$ at the state level, i.e., percentage of managers leaving their employer, as the dependent variable. The estimate represents the difference between the treated and control observations, before and after the change in enforcement of NCC.

$$\text{DepartureRate}_{s,t} = \sum_k \beta_k \{Treated \times k \text{ to treatment}\}_{s,t} + \gamma_1 X_{s,t-1} + \theta_s + \delta_t + \epsilon_{s,t}.$$ 

$X_{s,t-1}$ includes lagged control variables at the state level: the number of managers in the state, the number of management family firms in the state, the total AUM in the state and their squares. The regression includes state fixed effects $\theta_s$ and time fixed effects $\delta_t$. Only observations of states with at least 10 identified managers are included. Standard errors are clustered at the state level. Data frequency is quarterly.
Figure 9: Effect of changes in Non-Compete enforceability on capital misallocation: This figure presents the coefficient estimate $\beta_k$ against year to treatment, from the equation below with the variable $\%\text{Misallocation}$ at the state level as the dependent variable, i.e., the sum over all managers in a given state in a given quarter of the (absolute) dollar deviation of current AUM with respect to their theoretical optimal level of AUM, divided by the sum of the theoretical optimal levels of AUM. The estimate represents the difference between the treated and control observations, before and after the change in enforcement of NCC.

$$\%\text{Misallocation}_{s,t} = \sum_k \beta_k \{\text{Treated} \times \text{year } k \text{ to treatment}\}_{s,t} + \gamma_1 X_{s,t-1} + \theta_s + \delta_t + \epsilon_{s,t}.$$  

$X_{s,t-1}$ includes lagged control variables at the state level: the number of managers in the state, the number of management family firms in the state, the total AUM in the state and their squares. The regression includes state fixed effects $\theta_s$ and time fixed effects $\delta_t$. Only observations of states with at least 10 identified managers are included. Standard errors are clustered at the state level. Data frequency is quarterly.
References


Ibert, M. (2018). What do mutual fund managers’ private portfolios tell us about their skills? *Available at SSRN 3068656*.


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