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What Makes Fund Managers Leave Their Jobs Faster?

Michail Karoglou,[1] Jia Liu[2] and Dimitrios Stafylas[3]
[1]Centre for Business Prosperity, Aston Business School, Birmingham, B4 7ET, UK, [2]School of Accounting, Economics and Finance, University of Portsmouth, Portsmouth, PO1 3DE, UK, and [3]School for Business and Society, University of York, York, YO10 5DD, UK
Corresponding author email: m.karoglou@aston.ac.uk

We examine fund managers' mobility across different funds and the factors associated with their moving to new posts. Based on a comprehensive and unique dataset of open-ended funds of the booming Chinese mutual fund industry, we model the duration of a fund manager's service as a time-to-event counting process and examine how the prevailing market conditions, the manager's performance and the risk profile of the fund determine how long the manager will remain in post. Our study establishes that managerial performance and rising rather than falling markets are the two main factors that make managers less likely to remain in their posts. In contrast, the riskier the profile of the fund with respect to the market, the less likely it is that a manager will move. When all factors are considered, it appears that open-ended fund managers leave their posts when offered better employment prospects rather than when confronted by market adversity. Our study provides a novel insight into the optimization of investment decisions and encourages regulators to scrutinize the disclosure of appropriate information to investors regarding fund manager changes.

Introduction

The mutual fund industry has grown dramatically worldwide in recent years, reaching almost $65 trillion by the end of the first quarter of 2021, in comparison to $7 trillion in 2000. Equity funds account for almost 42% of the total (ICI Report, 2021). The very young Chinese mutual fund industry[1] has been at the forefront of this development over the last 20 years and is expected to remain so in the coming decades. And for a good reason. The recent fund market liberalization of the second largest economy in the world has made this industry extremely appealing to international investors, and it is projected that by 2025 it will be managing assets of $7.5 trillion (Financial Times, 2018). Therefore, it is hardly surprising that practitioners and policymakers demonstrate an avid and unabating interest in studying this phenomenon (e.g. Bali, Brown and Caglayan, 2019; Baquero and Verbeek, 2022; Chen, Han and Jing, 2021; Kuvandikov, Pendleton and Georgen, 2022), and that it attracts so much attention from the research community (Cheema and Nartea, 2014; Cornell *et al.* 2020; Xu *et al.*, 2013).

With the growing literature, a notable key conceptual shift occurred when a vital distinction was made between the fund manager and the fund that they serve (e.g. Andrew *et al.*, 2014; Wang and Ko, 2017). Initially, this relationship was characterized as a distinctive example of the traditional principal–agent problem (Jensen and Smith, 1985), but more recently it has been perceived to constitute a fundamental determinant of the asset allocation of each specific fund. Indeed, the principal characteristics of any fund, such as its performance and the risk–return trade-off, are governed by the decisions that its fund manager makes (e.g. Grinblatt *et al.*, 2020). Arguably, other market

[1]Closed-end funds were first introduced in 1998, and the first open-end fund in 2001.

considerations, organizational structures and norms also have a bearing on these characteristics. However, it is the manager who ultimately determines the fund investment policies.

This strong connection between the fund manager and the characteristics of the fund they manage is a relationship that market practitioners and the financial press are acutely aware of, as is vividly demonstrated by the proliferation of related news items across the media. The explanation is rather straightforward: in contrast to the departure of an upper-level manager for most other industries, the departure of a fund manager can have a profound effect on how the fund is managed, and on how its characteristics will subsequently change (Clare *et al.*, 2014). Therefore, such an event may well have far-reaching consequences, not least in terms of the fund's market valuation, for which it can herald a structural change because rational investors, speculators and noise traders will inevitably modify their assessments to account for the effect of the manager's departure. Nevertheless, there is a paucity of research in this area and has overwhelmingly focused on the US market a lacuna that this study aspires to fill.

Specifically, we examine if, and to what extent, the prevailing market conditions, the manager's performance, and the fund characteristics induce a manager to leave the fund. Using a comprehensive set of administrative data from Chinese funds, we introduce into this strand of the literature various survival analysis techniques with time-varying regressors to explore what factors contribute to the departure of a fund manager, and to what extent they do so. Our findings demonstrate that: (i) the period between the first and the third year is particularly notable as the time when fund managers change, a phenomenon that becomes even more acute during 'up' markets; (ii) during 'up' markets, fund managers are more likely to change funds compared with during 'down' markets; (iii) when a fund delivers abnormal returns and/or grows in terms of fund flows, fund managers are less likely to leave; (iv) the riskier the manager's profile, the more likely they are to remain in a fund for longer; and (v) fund managers with lower exposure to the size factor are less likely to change funds.

The remainder of this paper is structured as follows. We begin by reviewing the relevant literature and developing our hypotheses. Then, we discuss our data and methodology, and show our empirical results and robustness checks. Finally, we discuss our findings and present our concluding remarks.

Theoretical underpinnings and hypothesis development

At the heart of our work is agency theory, which acknowledges the conflict of interest between principals and agents (see e.g. Lambert, 2001) and plays a central role in corporate finance (e.g. in relation to contracts – Banker and Datar, 1989; Holmstrom, 1979; incentives – Jensen and Smith, 1985; Smith and Warner, 1979; and glass cliffs – Elsaid and Ursel, 2018; Mulcahy and Linehan, 2014). The relationship between fund managers and investors fits naturally into this framework. Together with information asymmetry and signalling theory (Brennan and Hughes, 1991; Copeland and Brennan, 1988; Myers and Majluf, 1984), it can explain the behaviour of fund managers who, compared with investors, may have better information about whether and when to leave their posts. The issue is that such an event, by its very nature, exerts a dramatic influence on the performance, characteristics and, in turn, survivability of the fund.

For the mainstream financial press, the significance of a fund manager's leaving is self-evident. But it has also been well established in several rather new albeit fast-growing strands of academic literature – despite the focus being primarily on the US market and overwhelmingly comprising event studies measuring the impact of manager change on fund performance. All the relevant research aligns with the concept that the trading norms and behaviours that a manager infuses into a fund fundamentally affects its characteristics. Therefore, when they stop working for a fund, it is natural to expect dramatic changes to the fund's characteristics. This fully justifies the avid interest of investors and media about who the fund managers are, which funds they have led in the past, and which funds they currently lead.

This section provides an overview of the relevant strands of academic literature and develops the hypotheses that we seek to test. First, we establish the importance of fund managers for the characteristics of their fund; next, we give an overview of the literature that investigates the impact of fund manager changes; and finally, we formulate our hypotheses.

The importance of a fund manager for the characteristics of their fund

The first, and well-established, strand of literature examines empirically the survivability and attrition rates of funds (e.g. Getmansky, 2012; Gregoriou, 2006). Arguably, several factors have been found to influence the mortality of funds, such as inflows, performance, liquidity constraints, asset under-management, lower skewness of returns, or even the alliance of firms during crises (Pangarkar, 2007). The relatively recent, albeit growing, phenomenon of mutual funds outsourcing many of their functions (Cumming, Schwienbacher and Zhan, 2015) is certain to complicate further any conclusions that the empirical literature has reached. However, all these factors are, to varying degrees, directly determined by the fund manager's decisions; and although Gregoriou (2002) and Baba and Goko (2009) demonstrate that the relationships are far from being clear-cut, they do signify the pivotal role that fund managers play in determining their fund features and, in turn, the importance of their leaving.

Another strand of literature indicates the importance of fund manager changes by documenting the persistent returns that funds tend to produce and explicitly linking them to the behaviour of fund managers. For example, Stulz (2007), Eling (2009) and Jagannathan, Malakhov and Novikov (2010) find both short- and long-term persistence, which indicates that fund managers trade based on specific norms and patterns of behaviour. This finding is in line with Makarov and Plantin (2015), who find that managers may waive long-term alpha-generating strategies in favour of negative-alpha trades to temporarily manipulate investors' perceptions of their skills. It is in accord with Grinblatt *et al.* (2020), who demonstrate that the superior performance of contrarian hedge fund managers exhibits persistence stemming from their stock-picking ability rather than liquidity provision. Therefore, when the manager of a fund changes, expectedly the successor's behaviour will not be identical, which may result in changes in the features of the fund.

A similar argument can also be drawn from the strand of literature concerning the value-adding market-timing and stock-picking capabilities of fund managers (Alda, 2018; Baker *et al.*, 2010; Bangassa, Su and Joseph, 2012; Feng and Johanson, 2015; Hentati-Kaffel and de Peretti, 2015; Osinga, Schauten and Zwinkels, 2021), although Kosowski *et al.* (2006) and Yi and He (2016) are sceptical as to whether Chinese fund managers have indeed such capabilities. Likewise, Caglayan, Celiker and Sonaer (2022) document twice as many disagreements than agreements between hedge funds and other institutions in their common stock trades, suggesting differences in fund managers' skills and their responsiveness to public information; and Kacperczyk and Seru (2007) find that the responsiveness of a fund manager's portfolio allocations to changes in public information are negatively related to the manager's skill. Therefore, fund manager changes are likely to entail substantial changes in the features of the fund.

Even the disposition behaviour of fund managers can adversely affect fund performance and increase fund failure rates; thus, establishing the importance of reducing the impact of such trading behaviour on stock prices (Singal and Xu, 2011). Others have also examined this disposition effect of fund managers (see Frazzini, 2006; Jin and Scherbina, 2011, among others). In all cases, however, abnormal (or otherwise) fund returns are based on fund managers' decisions; hence, their departure is bound to have a significant effect on the fund features.

The impact of fund manager changes

The literature that has explicitly examined the impact of fund manager changes is surprisingly limited, albeit of recent origin. Fund manager changes have been explicitly considered in Dangl, Wu and Zechner (2008), who find that if a fund manager underperforms, then capital outflows follow that are subsequently reversed after the manager is replaced. Similarly, Massa, Reuter and Zitzewitz (2010) find that fund flows decrease when an overperforming manager departs; and Kostovetsky and Werner (2015) find that fund flows increase after a manager change if they were underperforming. Evidently, fund sponsors cater to investors to minimize outflows or attract inflows.

The same rationale holds true for manager turnover, with a negative relationship between manager changes and fund performance having been established (Chevalier and Ellison, 1999a; Kostovetsky and Warner, 2015). Khorana (2001) is particularly indicative – he finds explicitly that manager changes lead to a performance improvement (deterioration) for recently underperforming (overperforming) funds. This is in line with Gallagher (2003) in relation to top management changes and the actual life of managed funds, and with Ding and Wermers (2014), who establish a positive cross-sectional relationship between replacement and performance. Likewise, Clare *et al.* (2014) find that the performance of the top (worst) performing funds deteriorates (improves) after their manager leaves.

Market conditions and fund manager changes

Our first hypothesis concerns the impact of market conditions on fund manager changes. Indeed, many of a fund's cross-sectional and time-series properties are attributed to market conditions as proxied by various macro and market variables. Indicative of a voluminous literature are the predictability of fund returns from the VIX index, dividend yield and default spread (Avramov, Barras and Kosowski, 2013); the positive correlation between fund returns and default risk premium, which suggests that risk premia or risky assets are negatively correlated with the current economic activity (Bali, Brown and Caglayan, 2014); and the increase in the dispersion of funds' returns due to industrial production growth, inflation and market return (Racicot and Theoret, 2016).

But the effect of market conditions on funds, and by extension on manager changes, is either channelled through or accentuated by the fund managers – which is why Agarwal, Arisoy and Naik (2017) and Stafylas, Anderson and Uddin (2018) amongst others condition their analyses on the business cycle when examining fund exposures and performance. Kacperczyk, Nieuwerburgh and Veldkamp (2011) find that fund manager skill comes from their ability to choose portfolios that anticipate macro and micro fundamentals, and their allocation depends on the state of the business cycle. Similarly, Kosowski (2011) claims that fund manager performance varies over the business cycle; and Auerbach and Gorodnichenko (2012) find that the response of fund strategies to macroeconomic shocks depends on the stage of the economic cycle. In fact, Kacperczyk, Nieuwerburgh and Veldkamp (2013), following Freson and Schadt (1996), Christopherson, Ferson and Glassman (1998) and Moskowitz (2000), go even further to argue that fund managers exhibit stock-picking skills in up-markets and market-timing skills in down-markets. Therefore, it is reasonable to expect that market conditions have a direct impact on fund returns and exposures derived from fund managers' decisions, which, in turn, are key factors in the much broader and well-established literature on what affects managerial job changes and careers (see e.g. Inkson, 1995, and references therein). Given also the literature that found that, unlike in bear markets, in bull markets there are few fund closures and a lot of new funds (Kempf, Ruenzi and Thiele, 2009; Zhao, 2005), we can assert that during favourable market conditions fund managers should have more and better opportunities for jobs elsewhere. Consequently, by adopting the predominant dichotomy of market conditions into 'up' and 'down' markets, our hypothesis related to *market conditions* is as follows:

H1 The probability of a fund manager leaving a fund is higher during 'up' markets than during 'down' markets.

Fund performance and fund manager changes

Given that (a) the characteristics and performance of funds are so tightly linked to the selection of the fund manager in charge; and (b) fund manager changes can have a remarkable effect on the fund, it is natural to expect that the fund performance affects the probability of a fund manager change. However, research on this topic is both at an embryonic stage and characterized by a lack of consensus.

On the one hand, the probability of fund manager replacement increases with the inferiority of past performance (Chevalier and Ellison, 1999b; Khorana, 1996, 2001). On the other hand, top-performing fund managers can earn a higher income either by moving to a larger fund within the same organization (Hu, Hall and Harvey, 2000) or by moving to another fund company (Kostovetsky, 2010), in accordance with the positive relationship between turnover and compensation that Deli (2002) reports. However, many mutual funds retain out-performing managers even when imposing higher management fees that reduce net returns to investors (Bryant, 2012; Deuskar *et al.*, 2011).

More recent studies also consider fund flows, which are mechanically linked to fund size, in relation to fund performance and fund manager changes. For instance, winner (loser) funds with higher (lower) net flows or a manager change exhibit a fall (rise) in subsequent performance (Bessler *et al.*, 2018). Berk and Green (2004) popularized the fund flow mechanism to argue that even with skilled managers, the inflow to previously successful funds and the outflow from underperforming funds leads to mutual fund market equilibrium with zero expected abnormal returns. And studies such as Chen *et al.* (2004) and Yan (2008) backed up this argument with empirical evidence. Given that fund companies are demonstrably eager to keep 'winners' and replace 'losers', our second hypothesis concerning the role of *fund manager performance* on the probability of staying in post is:

H2 The probability of a fund manager leaving a fund is inversely proportional to the degree of abnormal returns and/or fund flow growth that they deliver.

Fund risk profile and fund manager changes

A similar argument can be made for the relationship between the risk profile of a fund and the manager's behaviour and decisions – which, together with performance, is of vital importance to investors. However, research on linking the risk profile to fund manager changes is almost nonexistent, probably because, unlike performance, the risk profile is a multifaceted notion and therefore not easy to draw inference from. Clare *et al.* (2014) is a notable exception, suggesting that the improvement in the average post-manager-exit performance is associated with a reduction in market risk, a slight reduction to the small cap stocks exposure, and an increase to momentum and value stocks.

Nevertheless, the importance of such research is demonstrated by the fact that it is directly linked to the literature that attributes the risk profile of a fund to its manager's choices concerning the market-related risk or exposure to systemic factors (Agarwal and Naik, 2004; Bollen and Whaley, 2009; Fund and Hsieh, 2001, 2004; Giannikis and Vrontos, 2011). In fact, Agyei-Ampomah *et al.* (2015) argue that style-consistent and industry benchmarks reveal the skill level of fund managers along with the Fama and French risk factors. Also, fund managers' decisions in terms of style-shifting and use of strategies have an impact on fund risk profile as well as on performance. For instance, Jiang, Liang and Zhang (2021) show that three-quarters of funds shifted their style and that managers exhibit both style-timing ability and the skill of generating abnormal returns in new styles. Moreover, fund managers following short-term contrarian strategies with larger exposure to the liquidity provision factor provide higher abnormal returns. This is also the case in periods of low funding liquidity, suggesting that less-binding financial constraints contribute to their superior returns (Jame, 2017). Furthermore, Wang and Zheng (2022) find that dynamic momentum strategies adopted by fund managers enhance fund performance and that momentum timing skills vary considerably with fund investment styles; and managing the risk of the momentum strategy leads to extraordinary economic gains (Barroso and Santa-Clara, 2015). All these research findings, combined with the fact that exposure to risk makes it more difficult for a fund manager to credibly claim superior skills, and, in turn, be offered better job opportunities, lead to our third hypothesis regarding the role of the *fund risk profile*:[2]

H3 The probability of a fund manager leaving a fund is inversely proportional to the risk profile of the fund.

Research and design

Data and sample

For the purposes of our study, we merge data from two databases. The first one provides us with information about Chinese equity funds and fund managers; and the second one gives us information about the Chinese risk factors, which we need to determine the fund's risk profile.

[2] We acknowledge that there is an ambiguity with the definition of 'market risk'. Indeed, on the one hand, a narrow definition of the market risk implies that the beta of the market factor (denoted as MRP in our results) is a scalar that captures the fund exposure to market risk, while the scalar betas of the other factors, such as the size and profitability factors (denoted as SMB and RMW, respectively, in our results) capture its exposure to other risks. On the other hand, a broader definition of the market risk implies that the different factors are facets of the market risk, effectively capturing with a vector instead of a scalar the exposure of a fund to market risk. Given that the former viewpoint is considered to be more common in the finance literature (e.g. Carhart, 1997; Fama and French, 1993; Fama and French, 2015), we therefore adopt it and refer to the different factors collectively as the risk profile of the fund.

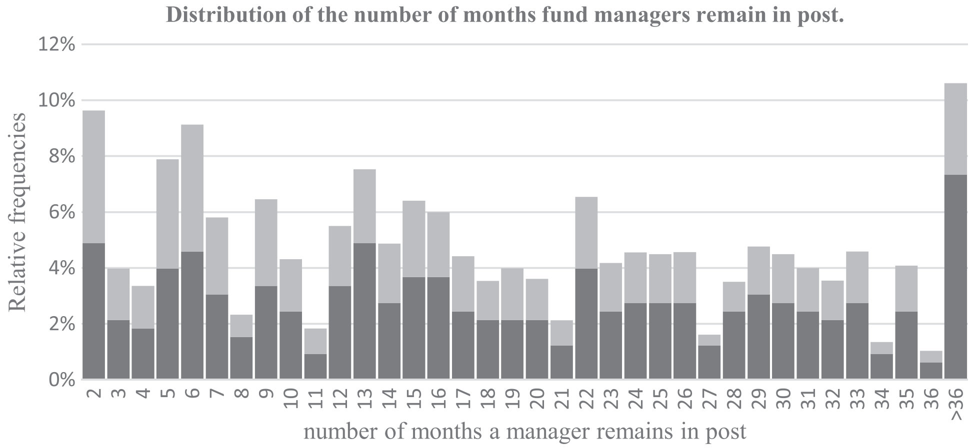

Figure 1. The actual distribution of the number of months that Chinese fund managers stay in the same fund. The bold (light) grey part of each column depicts the portion of months that the fund managers stayed in the same post during an 'up' ('down') market.

The dataset for the funds and fund managers is drawn from the *CSMAR China Funds Market Research Database*. Our sample is based on funds' net-of-fees raw returns and assets under management that span the period January 2006 to December 2017. For robustness, and in line with other relevant studies (e.g. Bessler *et al.*, 2018), we omit interim fund managers from our sample. Therefore, our sample contains 257 managers of open-ended equity funds who have, on average, delivered 1.562% returns (see Table 2 Panel A). Figure 1 gives an overview of the actual distribution of the months that Chinese managers remain in post.

The dataset with the factors is drawn from the China Asset Management Academy (CAMA). Because we make use of the predominant asset pricing models, these factors are the market factor (MRP, market risk premium); the size factor (SMB, small minus big); the book-to-market capitalization factor (HML, high minus low); the profitability factor (RMW, difference of the returns on diversified portfolios of stocks with robust and weak profitability); the investment factor (CMA, the difference of the returns on diversified portfolios of stocks of low and high investment firms – designated conservative and aggressive, respectively); and the momentum factor (MOM). Table 1 provides the variable definitions.

Table 2 provides the statistical properties. Panel A shows the key cross-sectional statistics of fund managers' returns, while Panel B shows the key statistics of the underlying risk exposures. Notably, the highest is the market exposure (1.304), the lowest (in absolute terms) is the investment exposure (0.068), and the profitability factor has a negative exposure (−0.173).

Methodology

We argue that the most direct way to determine what contributes, and to what extent, towards a fund manager change, based on administrative data,[3] is to consider the dual problem of determining what contributes, and to what extent, towards a fund manager remaining in post. To this end, we model the duration of a fund manager's service (i.e. working in the same fund) in months as a time-to-event counting process, which in turn enables us to draw our inference by applying survival analysis methods. Given that, to our knowledge, this is the first time not only that this aspect of fund manager changes has been examined but also that this modelling approach has been adopted in this strand of literature, in what follows we briefly explain it.

In particular, by treating a fund manager's duration of service as a random variable, denoted as T, the probability of them continuing to manage the same fund until time t is modelled through the

[3] By administrative data, we signify that our analysis relies on objective measures and not on survey data – which are likely to be severely misleading for such issues owing to perceptual biases, disclosure agreements and/or formal and informal firm policies.

Table 1. Variable definitions

RTNS	Funds' net-of fees raw returns
AUM	Assets under management. These are released every quarter, so to construct the monthly growth series variable we have used polynomial extrapolation of the levels
MRP	Market risk premium, which is the difference of the market return and the risk-free rate of the 3-month China bonds treasury yields
SMB	Rate of return difference of small-cap stocks and large-cap stocks based on the Fama & French method
HML	Difference between the rate of return of a portfolio with high book value ratio and a portfolio with low book value ratio based on Fama & French method
MOM	Momentum return based on the calculation method of the Carhart momentum factor
CMA	Investment factor, which is the difference between returns of conservative stock portfolios and aggressive stock portfolios
RMW	Profitability factor, which is the difference between returns of high profitability stock portfolios and low profitability stock portfolios
CLI	A composite leading indicator from OECD, which is based on selected weighted macroeconomic indicators
XP	Fund managers' experience in the industry, in years
BMXP	Binary variable denoting whether a fund manager has other relevant business experience

This table provides detailed definitions of the variables used in this study.

Table 2. Summary statistics

Panel A	Mean	Median	SD	Skew	Kurt	Min	Max
RTNS	1.562	1.616	3.032	0.027	0.227	–3.488	7.042
AUM	321,279	233,115	323,519	1.77	4.62	86,581	1,023,019
CLI	99.71	99.74	1.68	0.35	–0.08	96.04	104.26
XP	9.67	9.00	3.84	0.86	0.72	1.00	23.00
BMXP	With BS	133	No BS	124			
Panel B							
MRP	1.304	2.043	8.791	–0.409	0.992	–26.24	22.435
SMB	1.131	1.169	4.334	0.014	3.698	–17.249	20.029
HML	0.083	0.015	2.151	0.509	5.325	–8.594	10.843
MOM	0.306	0.306	5.125	–0.336	1.328	–19.915	13.100
CMA	0.068	0.051	1.278	0.052	0.499	–3.407	3.774
RMW	–0.173	–0.140	2.285	–0.180	3.260	–8.164	8.436

Panel A presents the time-series averages of the monthly cross-sectional summary statistics for net-of fees raw returns (RTNS) and flows (FLOWS) (quarterly in CNY millions). These include the average mean (Mean), median (Median), standard deviation (SD), skewness (Skew), excess kurtosis (Kurt), minimum (Min) and maximum (Max) values of the return distributions, where the average is taken across all periods in the sample. It also presents statistics for the Composite Leading Indicator (CLI), fund managers' experience in the industry (XP) (in years), and whether the managers have other relevant business experience (BMXP) (binary, for which we report the counts with and without business experience). Panel B presents the basic statistics for the Chinese risk factors under consideration, which are the market (MRP), size (SMB), book-to-market capitalization ratio (HML), momentum (MOM), investment (CMA) and profitability (RMW) factors.

survival function $S(t) = S(T = t) = P(T > t)$.[4] With this in mind, a survival analysis involves examining the properties of $S(t)$ and the factors that determine it.[5]

[4]In other words, the survival function is the complement of the cumulative distribution function; that is, $S(t) = 1 - F(T \leq 0)$.

[5]In effect, the purpose of survival analysis is to predict *how long it will take until* a fund manager leaves their post. This can be juxtaposed to probit or logit analysis that aims to predict *if* a fund manager will leave their post. In this respect, the results of the non-parametric and semi-parametric methods that we adopt here could be considered somewhat comparable to the results that one could obtain by running a sequence of probit or logit models, one for each different time period – effectively conditioning the results of such parametric models to the selection of the time period. Naturally, the latter approach, being

For many well-documented reasons, the overwhelming majority of empirical investigations based on survival analysis begin with a visual depiction of the non-parametric product-limit estimator of *S(t)*, commonly known as the *Kaplan–Meier* (KM) method (Kaplan and Meier, 1958). This is often combined with reporting the results of one or more proportional hazards regressions, generally known as the *Cox model* (aka the Cox proportional hazard model), which was first developed by Cox (1972). This is a powerful semi-parametric approach that, unlike the univariate KM method, enables us to incorporate covariates into the survival function and estimate and test their effects. In fact, this method, and its later incarnations, proved so successful that many disciplines made it almost synonymous with survival analysis.

A significant limitation of these two approaches lies in the fact that they are based on time-invariant covariates. However, in some settings, such as ours, it is essential that the covariates can vary over time. To address this issue, alternative estimators need to be considered.

The most popular non-parametric estimator, which is asymptotically equivalent to the KM estimator, first conceived by Aalen (1978), is the multiple decrements estimator or *the Nelson–Aalen* (NA) estimator of *S(t)*:

$$\tilde{S}(t) = e^{-\tilde{H}(t)}, \tag{1}$$

where $\tilde{H}(t)$ is the integrated hazard or cumulative hazard rate estimator, specified as:

$$\tilde{H}\ (t) = \sum_{t_{i \leq t}} \frac{d_i}{n_i}, \tag{2}$$

where d_i is the number of fund managers that change posts at time t_i, and n_i is the total number of fund managers at risk of changing posts at time t_i.

For the semi-parametric approach, the Cox model was extended, first by Andersen and Gill (1982), to accommodate time-varying x_i covariates:

$$S\,(t|x_1, x_2, centerdots) = S_0(t)^{\exp(\beta_1 \cdot x_1 + \beta_2 \cdot x_2 + centerdots)}. \tag{3}$$

Equation (3) is conveniently expressed through the hazard ratio as:

$$\frac{h(t|x_1, x_2, centerdots)}{h_0\,(t)} = \exp(\beta_1 \cdot x_1 + \beta_2 \cdot x_2 + centerdots) \tag{4}$$

and, estimated specifically by using the natural log of Equation (4):

$$ln\, \frac{h(t|x_1, x_2, centerdots)}{h_0\,(t)} = \beta_1 \cdot x_1 + \beta_2 \cdot x_2 + centerdots, \tag{5}$$

where *h(t)* is the hazard function, which captures the probability that a fund manager leaves the fund they are leading, given that s/he has remained with it up to time *t*. The hazard function is linked to the survival function through the identity *h(t)* = *f(t)*/*S(t)*, where *f(t)* is the probability density function of the *t* random variable.

The hazard ratio can be extended to the case of time-varying covariates, because the partial likelihood is built by considering only what happens at each 'failure time' (i.e. the time of the fund manager's movement between fund firms) and therefore, at the limit, it can account for every single time period (in our case, a month). This is why, even from its conception, this extension, which bridges the gap between survival analysis and counting processes, has been used to test the assumption of proportional hazards. Therefore, the only remaining issues for us to determine are the covariates that might accelerate or delay the fund manager change.

First, we consider *market conditions*. We measure them by making the distinction between an 'up' (aka 'bull' or 'rising') and 'down' (aka 'bear' or 'declining') market. The impact of the market conditions is captured through an 'up'-market dummy derived from the *composite leading indicator* (CLI) of China, which provides early signals of turning points in business cycles related to economic activity.[6] The reason for including such a covariate in our analysis is because it enables us to measure whether and, if so, to what extent fund managers' mobility across different funds is affected by the overall state of the market. Interestingly, unlike the other variables, because the

parametric, would be based on a much more stringent set of assumptions.

[6]See https://data.oecd.org/leadind/composite-leading-indicator-cli.htm#indicator-chart

market conditions variable is binary, it is possible to also use it with the NA estimator, thus enabling us to compare non-parametrically the survival functions of 'up' and 'down' markets.

Second, we consider the *manager's performance*. We capture it by the performance of the fund they lead, which is proxied by Jensen's measure, estimated as the alpha of each asset-pricing model that we consider, and the respective growth of the fund flows. The underlying argument is that a fund manager with superior performance will be considered to be one whose fund has achieved excess returns after accounting for the market's overall risk, size, value and so on, depending on the asset-pricing model; and also, to be one who has increased the attractiveness of their fund to investors, as evidenced by the rise in the fund inflows in comparison with its outflows. In other words, we distinguish fund manager performance from fund performance and therefore consider fund managers' risk-adjusted returns instead of funds' risk-adjusted returns. This is because fund managers may move to several different funds during their careers – a common industry practice in China too. If a fund manager manages more than one fund simultaneously, we consider the average cross-sectional performance for each monthly period, following the same process for all fund managers in our sample. Note that we also control both for the experience of the fund manager in the industry and for other related business experience that they may have.

Finally, we consider the *fund's risk profile*. We proxy it by the exposure of the fund, during the term of a fund manager, to the factors of the different asset-pricing models; hence, we measure these exposures through the corresponding beta estimates. The underlying idea is that each specific fund is based on contractual obligations to its investors and regulatory bodies that limit the scope and scale of their fund manager's trading behaviour while implementing their strategy, which we expect to be translated onto the exposure of the fund to each factor.

Note that the asset-pricing models that we use here are the predominant ones in the empirical finance literature: (a) the CAPM (Sharpe, 1964); (b) the Fama and French three-factor model (FF3) (Fama and French, 1993); (c) the Carhart four-factor model (FF3C) (Carhart, 1997); and (d) the Fama and French five-factor model (FF5) (Fama and French, 2015), as well as (e) a customized six-factor model (FF5C), which extends the Fama and French five-factor model with Carhart's momentum factor. However, any multifactor model whose factors correlate even weakly with the factors of these models will deliver a similar cross-sectional fit (Lewellen, Nagel and Shanken, 2010), which in turn will lead to the same inference. Formally, the Fama and French five-factor model outperforms the rest in China's mutual fund industry (Yezhou and Ran, 2019) but, in anticipation of our results, the comparison of all these variants shows clearly that our inference is robust to model selection.

Consequently, our main semi-parametric model is given by:

$$ln \frac{h\left(t|x_1, x_2, \ldots\right)}{h_0\left(t\right)} = f\left(\text{market conditions}, \right. \\ \left. \text{manager's performance, fund risk profile}\right),$$

where $f(.)$ is a linear function of the variables discussed above. The exponent of the coefficients of these variables shows whether, and to what extent, each variable accelerates (hazard ratio greater than 1) or delays (hazard ratio less than 1) the departure of a fund manager from their post. Because the variables depend on the underlying asset-pricing model, we derive five variants of the main model, which also serves as a natural way to test the robustness of our results and inference.[7]

Empirical results

In this section, we present first the results from the non-parametric approach and then those from the semi-parametric approach.

The non-parametric analysis

Figure 2 presents the NA estimates for fund managers managing the same fund over time.

As expected, the probability of fund managers staying in the same fund decreases over time – equivalently, the probability of them leaving increases over time. However, this probability is far

[7]Note that for robustness, we have also repeated the estimations with a reduced sample by excluding all contemporaneous observations, effectively using only lagged information, and have thus confirmed that the results remain unaffected.

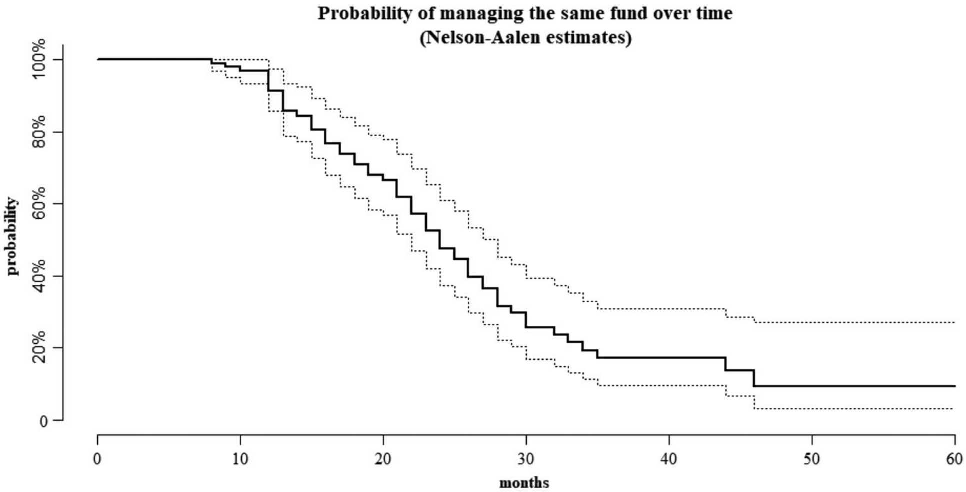

Figure 2. The probabilities of fund managers staying in the same fund as determined by the non-parametric Nelson–Aalen estimates. The grey lines indicate the 95% confidence interval.

from being linear; and most interestingly, it is vividly distinguished into three periods.

Over the first 12 months, the probability of staying in the same fund is on average more than 80% with the slope of the survival curve rather flat (0.84% negative gradient), indicating an intuitively reasonable *settling-in period*. Apparently, the fund manager seeks to settle into their new role, develop a better understanding of their working environment, and gather critical information for exploring the possibility of whether to stay in the same fund or leave. Correspondingly, the fund firm uses this period to evaluate reasonably the suitability and performance of the new fund manager.

Then, there is a period that spans approximately 12 to 36 months, during which the probability that fund managers remain in their posts, by choice or otherwise, declines from 80% to 20% – gradually again, but with a much steeper slope than before (1.86% negative gradient, more than double that before) – and which can therefore be thought of as the *stirring period*. Half of the managers remain in the same fund for about 2 years. From the fund manager's perspective, this appears to be the period during which they become more and more predisposed to decide to move, either owing to the acquisition of better information about their workplace, or owing to eventually finding better opportunities in the market. Correspondingly, fund companies have gathered sufficient evidence to reasonably judge the performance of the incumbent manager and decide whether to continue or end their collaboration.

After somewhat less than three years, the probability of working in the same fund remains more or less the same (with the slope rising to −0.4), and this may therefore be reasonably described as a *temperate period*. As we can also observe, there is a small but significant fraction of our fund managers' sample who remain in their post for more than 5 years.

Figure 3 takes the non-parametric analysis a step further and adds the distinction between 'up' and 'down' markets. Therefore, it offers an effective way to test H3 non-parametrically.

The graph depicts a clear pattern: during 'down' markets, fund managers are less likely to move from their posts compared with during 'up' markets. Indeed, after the initial 12-month period, the differences of the two curves are notable, even if not universally statistically significant. This suggests that fund managers and fund companies seem to be much more prone to making fund management changes during an 'up' market than during a 'down' market. Arguably, this may be because as the market rises there are better career opportunities that could be attributed to, say, an expansion of the investing activities of the fund companies or to fund manager departures, which allow in turn fund managers to search for more lucrative posts elsewhere, especially if they are high-flyers with a reputation for success. In contrast, as the market falls, fund management

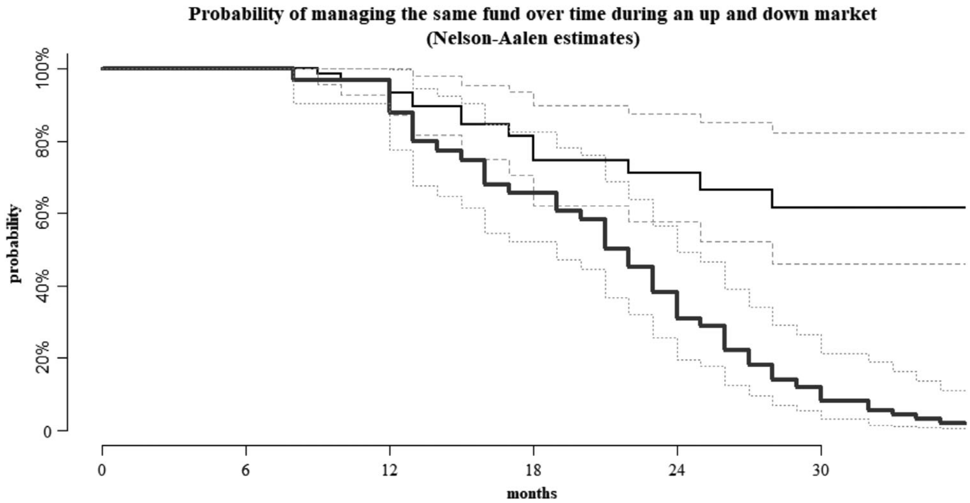

Figure 3. The probabilities of fund managers staying in the same fund as determined by the non-parametric Nelson–Aalen estimates during 'up' markets (bold line) and during 'down' markets (normal line). The 95% confidence intervals are indicated by the grey lines, dotted for the 'up' and normal for the 'down' markets.

companies offer fewer career opportunities, and managers' sense of insecurity might convince them to hold onto their jobs. It is also worth noting here that, in our sample, half of the managers remained in the same fund for slightly more than 1.5 years during an 'up' market, which is substantially shorter than the 2 years observed in Figure 1, when the median survival rate is not reached for the 'down' market.[8] Consequently, the non-parametric analysis provides evidence that supports our Hypothesis 3 (H3). In other words, based on our non-parametric analysis, the probability of a fund manager leaving a fund is higher during 'up' markets than during 'down' markets.

The semi-parametric analysis

Table 3 presents the results of our semi-parametric analysis.

One striking feature of the results is that they are surprisingly robust to the asset-pricing model specification we consider. Indeed, the variations in the signs and values of the coefficient estimates across the five model variants we use are markedly small. Moreover, there seems to be a consistent narrative across the asset-pricing models in terms of the changes that take place in the coefficient estimates, when moving from the simplest variant (the CAPM) to the most inclusive one (the FF5C). Finally, the goodness-of-fit statistics and tests (reported in Panel B) are rather clear-cut. Notably, the significance of the concordance statistic, popularized by Harrell, Lee and Mark (1996) and currently considered the dominant goodness-of-fit measure for survival models, also suggests unambiguously that the models explain our data very well.

Specifically, with regard to *market conditions*, for the period under consideration, the 'up'-market variable is statistically significant at a 1% level for all five model variants. Most importantly, the variability of the coefficient estimates across the five variants is surprisingly small, ranging from 1.39 (FF5C and FF3C) to 1.45 (FF5), corresponding to hazard ratios of approximately 4. This suggests clearly that an 'up' market accelerates notably the departure of a manager from their post, while a 'down' market delays it. In other words, the market conditions are negatively related to the length of time a manager continues to manage their fund. Consequently, the semi-parametric analysis confirms our findings from the non-parametric analysis and provides evidence that supports our Hypothesis 1 (H1) – the probability of a fund manager leaving a fund is indeed higher during 'up' markets than during 'down' markets.

With regard to *manager's performance*, the results show that for the period under consideration,

[8]This very notable difference persists even for the most conservative proxy of the 'up'-market dummy we use.

Table 3. Results based on the semi-parametric analysis

Panel A	Coefficient estimates				
	CAPM	FF3	FF3C	FF5	FF5C
Up-Market Dummy	4.12***	4.23***	4.00***	4.25***	4.00***
	[1.41]	[1.44]	[1.39]	[1.45]	[1.39]
	(0.32)	(0.33)	(0.34)	(0.34)	(0.34)
Flows	0.20**	0.23**	0.23**	0.27	0.31
	[−1.59]	[−1.48]	[−1.49]	[−1.32]	[−1.16]
	(0.65)	(0.72)	(0.73)	(0.77)	(0.81)
Alpha	0.97	0.67**	0.71**	0.74*	0.67**
	[−0.03]	[−0.41]	[−0.34]	[−0.30]	[−0.39]
	(0.14)	(0.17)	(0.17)	(0.17)	(0.17)
Beta MRP	0.66	0.14***	0.15***	0.21***	0.18**
	[−0.42]	[−1.97]	[−1.90]	[−1.54]	[−1.71]
	(0.75)	(0.74)	(0.73)	(0.75)	(0.76)
Beta SMB	-	0.39*	0.46	0.44*	0.26**
		[−0.94]	[−0.78]	[−0.83]	[−1.36]
		(0.53)	(0.53)	(0.48)	(0.55)
Beta HML	-	1.03	1.11	1.17	1.27
		[0.03]	[0.10]	[0.15]	[0.24]
		(0.27)	(0.28)	(0.20)	(0.20)
Beta MOM	-	-	0.64	-	1.68***
			[−0.45]		[0.52]
			(0.50)		(0.19)
Beta RMW	-	-	-	1.36	0.85
				[0.31]	[−0.16]
				(0.20)	(0.15)
Beta CMA	-	-	-	0.95	0.67
				[−0.05]	[−0.40]
				(0.15)	(0.45)
XP	0.99	0.97	0.97	0.99	0.98
	[−0.01]	[−0.03]	[−0.03]	[−0.01]	[−0.02]
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
BMXP	0.79	0.81	0.82	0.82	0.86
	[−0.24]	[−0.21]	[−0.20]	[−0.20]	[−0.15]
	(0.29)	(0.29)	(0.29)	(0.29)	(0.30)
Panel B					
Log-likelihood 1	–209.8	–209.8	–209.8	–209.8	–209.8
Log-likelihood 2	–194.7	–190.1	–190.7	–191	–188.3
Concordance	0.63***	0.7***	0.7***	0.69***	0.71***
	(0.06)	(0.05)	(0.05)	(0.05)	(0.05)
R^2	1.46%	1.91%	1.84%	1.82%	2.08%
	(18.52%)	(18.52%)	(18.52%)	(18.52%)	(18.52%)
Likelihood ratio test	30.16***	39.4***	38.09***	37.6***	42.99***
Wald test	26.31***	36.36***	35.71***	35.92***	42.16***
Score (log-rank) test	29.65***	40.34***	39.68***	40.41***	46.97***

Panel A presents the hazard ratios that have been derived from the coefficient estimates (in square brackets) as well as the respective standard errors (in brackets) from the semi-parametric Cox regression for each of the five asset-pricing models, namely the CAPM, FF3 (Fama and French three-factor), FF3C (Carhart model), FF5 (Fama and French five-factor model) and FF5C (custom six-factor model) model. MRP, market factor; SMB, small minus big; HML, high minus low; MOM, momentum; CMA, investment; RMW, profitability; XP, industry experience; and BMXP, other relevant business experience. '*', '**' and '***' denote statistical significance at the 10%, 5% and 1% level, respectively. Panel B presents the goodness-of-fit statistics and, where appropriate, the respective test results.

the alphas are not statistically significant at the 5% level when we use the CAPM model, but they are when we use FF3 (−0.41), FF3C (−0.34), FF5 (−0.30) and FF5C (−0.39). These correspond to hazard ratios of about 0.7, which suggests that the more positive alpha is, the longer the manager is expected to remain in the fund, whereas the more negative it is, the earlier they are likely to depart. Similarly, the fund flows are statistically significant at the 5% level for the CAPM (−1.59), FF3 (−1.48) and FF3C (−1.49) models corresponding to hazard ratios of about 0.2. This again suggests that the higher the fund flows, the longer the manager is expected to remain in the fund. In other words, the manager's performance is positively related to the length of time they manage the fund. Consequently, the semi-parametric analysis provides evidence that supports Hypothesis 2 (H2), namely that the probability of a fund manager leaving a fund is inversely proportional to the degree of abnormal returns and/or growth of the fund flows that they deliver. The industry experience (EX) and other relevant business experience (BMXP) are not significant.

Finally, with regard to the *fund risk profile*, the most notable feature that our regression analysis has identified appears to be its market beta (MRP), which is common in all five model variants. The respective coefficient estimate is statistically insignificant for the CAPM (−0.42) but significant for the FF3 (−1.97), FF3C (−1.90), FF5 (−1.54) and FF5C (−1.71) variants. These values correspond to hazard ratios between 0.14 and 0.21, which suggests that the more positive MRP is, the longer the manager remains in the fund. In contrast, when it is negative, the manager is more likely to depart earlier. In other words, the market beta feature of the fund's risk profile is positively related to the length of time the manager manages the fund. Interestingly, this effect is markedly less influential than the effect of manager's performance (0.2 vs. 0.7).

Similarly, albeit more weakly supported, our findings for the size (SMB) factor are statistically significant at the 5% level for FF3 (−0.94), FF5 (−0.83) and FF5C (−1.36), with hazard ratios 0.39, 0.44 and 0.26 accordingly, indicating that the more positive the SMB, the longer the manager will remain in the fund; and conversely, the more negative the SMB, the more likely it is that the fund manager will depart earlier. In other words, the beta of the size factor of the fund's risk profile is also positively related to the length of time the manager manages the fund.

In contrast to the previous variables, for the book-to-market capitalization ratio (HML), the hazard ratios for all model variants are greater than one, indicating that the higher its value, the earlier the fund manager departs from the fund, while the lower its value, the longer they remain in their post. However, in all cases, the variable is not statistically significant even at the 10% level. The hazard ratio of the momentum (MOM) variable in FF5C (0.52) is statistically significant, suggesting that the higher (lower) the MOM, the earlier (later) the fund manager will change their post. For the investment (CMA) and profitability (RMW) variables we have no statistically significant results.

Overall, the semi-parametric analysis provides evidence to support Hypothesis 3 (H3). However, there is substantial variation across the different risk factors. Indeed, while the results for the market and size factors support the hypothesis, the momentum factor points in the opposite direction for FF5C. Nevertheless, the results are overall much stronger in support of H3. Therefore, we conclude that the probability of a fund manager leaving a fund is inversely proportional to the degree of risk that they assume.

Additional robustness checks

We have seen that our main empirical findings are consistent across the different modelling assumptions we make about the risk factors. This section is about confirming that our inference is robust in the presence of heterogeneity and endogeneity. In both cases, the results are almost identical to our main results, establishing the validity of our inference.

Heterogeneity

A particularly interesting feature of our dataset is that it perfectly reflects the fact that the overwhelming majority of managers are male (about 90% in our sample) with at least an MSc/MBA degree (about 98% in our sample). This extraordinary degree of homogeneity is well documented in the literature (see among others Fang and Wang, 2015; Huang *et al.*, 2021). The very small fraction of managers with a PhD (about 10% in our sample) indicates that either experience in the field is more important than further studies or that the industry is not appealing to individuals with a PhD – or both.

Nevertheless, heterogeneity can stem from institutionalized fund practices. For example, the presence of impactful trailer fees may flatten the flow–performance relation – money comes in regardless of poor past performance (see, for example, Berkowitz and Kotowitz, 2000; and Cumming, Johan and Zhang, 2019). The resulting information asymmetry-based conflict of interest amongst investors, financial advisors and brokers can affect the way investors value their investments or their responsiveness on a fund manager's performance and in turn the latter's departure from the fund. In our setup, this could cause unobserved heterogeneity.

To make our results robust to the presence of unobserved heterogeneity, we turn to frailty models, the survival analysis counterpart of the random effects setup. Frailty models, first introduced by Vaupel, Manton and Stallard (1979) and used in their first incarnation by Lancaster (1979), are widely used to account for heterogeneous times-to-events. The most popular variants, which we also adopt here, assume that the frailty term follows an inverse Gaussian or gamma distribution.

Table 4 shows the relevant results. When compared with our main results (Table 3), for all model variants and frailty assumptions, our results in terms of our estimates and fit are almost identical. Consequently, our inference is robust even when we entertain the possibility of unobserved heterogeneity.

Endogeneity

Our monthly frequency counting process setup is mostly robust to the possibility of endogeneity. Indeed, our flow variable, risk factors and up/down dummy are explanatory variables that can hardly be considered stochastic at the time that the event of a managerial position change takes place, which suggests that they are strongly exogenous for the model parameters.[9] But even if they were assumed to be stochastic, it would be a stretch for them to be considered correlated contemporaneously with the dependent variable at monthly frequencies because the event of a managerial position change, although observed at a specific month, is based on firm or manager decisions that are not impulsive but established over time.

However, endogeneity may creep in through Jensen's alpha measure of performance. This is not because the correlation is contemporaneous, because there is no inherent simultaneity issue.[10] It is because the contractual obligations of the firm and manager may lead to deviations from this accurately ex-post measure. The counter-argument is that such deviations are idiosyncratic and therefore naturally captured in the error term. Still, they may reflect market norms and frictions of the Chinese labour market, in which case they would act as a measurement error that could induce endogeneity.

To address this issue, we adopt the two-stage residual inclusion (2SRI) procedure for unmeasured confounding, first introduced by Terza *et al.* (2008), which is the survival analysis counterpart to the instrumental variable (IV) approach for the standard regression analysis. The Martinez-Camblor *et al.* (2019) two-stage residual inclusion-frailty (2SRI-F) extension that we use here enables us to obtain unbiased estimates of the log-hazard ratio in the presence of unmeasured confounding and therefore can confirm the robustness of our analysis and inference.

Table 5 shows the results from following this approach. Even though the evidence for Hypothesis 3 is less prominent, our results are nearly identical to our main results. Therefore, our inference is robust even when we entertain the possibility of endogeneity.

Discussion

Overall, our results show that there are three distinct periods in the probability of a fund manager staying in post, namely the *settling-in*, *stirring* and *temperate* periods. The first and third periods are of relative stability in terms of the probability of

[9]Also, it is worth noting that the 'up'/'down' dummy may suffer from measurement errors because it is based on an underlying market benchmark index, which may not always capture the exact timing of changes in the market conditions. However, such errors cannot be justified as a source of endogeneity because they would be both infrequent, or the index would be modified accordingly and sufficiently idiosyncratic to not be considered random.

[10]Jensen's alpha characterizes the manager for the duration of the counting process, unlike the event of moving posts, which takes place only in the last period of them serving a fund.

Table 4. *Results based on frailty models*

Panel A1	Coefficient estimates (gamma frailty)					Panel B1	Coefficient estimates (inverse Gaussian frailty)			
	CAPM	FF3	FF3C	FF5	FF5C	CAPM	FF3	FF3C	FF5	FF5C
'Up'-market dummy	4.12***	4.24***	3.99***	4.23***	4.00***	4.11***	4.23***	3.99***	4.25***	4.00***
	[1.42]	[1.44]	[1.39]	[1.45]	[1.39]	[1.42]	[1.44]	[1.39]	[1.45]	[1.39]
	(0.32)	(0.33)	(0.34)	(0.34)	(0.34)	(0.32)	(0.33)	(0.34)	(0.34)	(0.34)
Flows	0.20**	0.23**	0.23**	0.27*	0.31	0.20**	0.23**	0.23**	0.27*	0.31
	[−1.59]	[−1.48]	[−1.49]	[−1.33]	[−1.16]	[−1.59]	[−1.48]	[−1.48]	[−1.33]	[−1.16]
	(0.65)	(0.72)	(0.73)	(0.77)	(0.81)	(0.65)	(0.72)	(0.73)	(0.77)	(0.81)
Alpha	0.97	0.67**	0.71*	0.74*	0.67**	0.97	0.67**	0.71**	0.74*	0.67**
	[−0.03]	[−0.41]	[−0.34]	[−0.29]	[−0.39]	[−0.03]	[−0.41]	[−0.34]	[−0.29]	[−0.39]
	(0.14)	(0.17)	(0.17)	(0.17)	(0.17)	(0.14)	(0.17)	(0.17)	(0.17)	(0.17)
Beta MRP	0.66	0.14***	0.15***	0.22**	0.18**	0.66	0.14***	0.15***	0.22**	0.18**
	[−0.42]	[−1.97]	[−1.90]	[−1.54]	[−1.71]	[−0.47]	[−1.97]	[−1.90]	[−1.54]	[−1.71]
	(0.75)	(0.74)	(0.73)	(0.75)	(0.76)	(0.75)	(0.74)	(0.73)	(0.75)	(0.76)
Beta SMB		0.39*	0.46	0.44*	0.26**		0.39*	0.46	0.44*	0.26**
		[−0.94]	[−0.78]	[−0.83]	[−1.36]		[−0.94]	[−0.78]	[−0.83]	[−1.36]
		(0.53)	(0.53)	(0.48)	(0.55)		(0.53)	(0.53)	(0.48)	(0.55)
Beta HML		1.03	1.11	1.17	1.27		1.03	1.11	1.17	1.27
		[0.03]	[0.10]	[0.15]	[0.24]		[0.03]	[0.10]	[0.15]	[0.24]
		(0.27)	(0.28)	(0.20)	(0.20)		(0.27)	(0.28)	(0.20)	(0.20)
Beta MOM			0.64		0.67			0.64		0.67
			[−0.45]		[−0.40]			[−0.45]		[−0.40]
			(0.50)		(0.45)			0.50		(0.45)
Beta RMW				1.36	1.68***				1.37	1.68***
				[0.31]	[0.52]				[0.31]	[0.52]
				(0.20)	(0.19)				(0.20)	(0.19)

Table 4. *(Continued)*

Panel A1	Coefficient estimates (gamma frailty)					Panel B1	Coefficient estimates (inverse Gaussian frailty)			
	CAPM	FF3	FF3C	FF5	FF5C	CAPM	FF3	FF3C	FF5	FF5C
Beta CMA				0.95 [−0.05] (0.15)	0.86 [−0.16] (0.15)				0.95 [−0.05] (0.15)	0.86 [−0.16] (0.15)
XP	0.99 [−0.02] (0.04)	0.97 [−0.03] (0.04)	0.97 [−0.03] (0.04)	0.99 [−0.01] (0.04)	0.98 [−0.02] (0.04)	0.99 [−0.02] (0.042)	0.97 [−0.03] (0.04)	0.97 [−0.03] (0.04)	0.99 [−0.01] (0.04)	0.98 [−0.02] (0.04)
BMXP	0.79 [−0.24] (0.29)	0.81 [−0.22] (0.29)	0.82 [−0.21] (0.29)	0.82 [−0.20] (0.29)	0.86 [−0.15] (0.29)	0.79 [−0.24] (0.29)	0.81 [−0.22] (0.29)	0.82 [−0.21] (0.29)	0.82 [−0.20] (0.29)	0.86 [−0.15] (0.29)
Frailty	<0.01	<0.01	<0.01	<0.01	<0.01	0.05	0.05	0.05	0.05	0.05
Panel A2						Panel B2				
Log-likelihood 1	–209.76	–209.76	–209.76	–209.76	–209.76	–209.76	–209.76	–209.76	–209.76	–209.76
Log-likelihood 2	194.68	–190.06	–190.71	–190.96	–188.27	–194.63	–190.01	–190.66	–190.91	–188.21
Concordance	0.63*** (0.06)	0.69*** (0.05)	0.699*** (0.05)	0.69*** (0.05)	0.71*** (0.05)	0.64*** (0.06)	0.70*** (0.05)	0.70*** (0.05)	0.70*** (0.05)	0.71*** (0.05)
Likelihood ratio test	30.16***	39.40***	38.1***	37.60***	42.99***	30.27***	39.51***	38.19***	37.71***	43.09***
Wald test	26.31***	36.36***	35.7***	35.92***	42.16***	26.29***	36.33***	35.68***	35.89***	42.13***
Score (log-rank) test	6.00***	8.00***	9.00***	10.00***	11.00***	6.06***	8.05***	9.05***	10.05***	11.05***

This table presents the results regarding heterogeneity for gamma frailty (Panels A1 and A2) and Gaussian frailty (Panel B1s and B2). The hazard ratios that have been derived from the coefficient estimates (in square brackets) as well as the respective standard errors (in brackets) for each of the five asset-pricing models, namely the CAPM, FF3 (Fama and French three-factor), FF3C (Carhart model), FF5 (Fama and French five-factor model), and FF5C (custom six-factor model) model. MRP, market factor; SMB, small minus big; HML, high minus low; MOM, momentum; CMA, investment; RMW, profitability; XP, industry experience; and BMXP, other relevant business experience. The likelihood ratio test statistic is given for the frailty term (in all cases statistically not significant). '*', '**' and '***' denote statistical significance at the 10%, 5% and 1% level, respectively. Goodness-of-fit statistics and, where appropriate, the respective test results are presented as well.

Table 5. Results based on the two-stage residual inclusion-frailty (2SRI-F) model

Panel A1	Coefficient estimates (gamma frailty)					Panel B1	Coefficient estimates (inverse Gaussian frailty)			
	CAPM	FF3	FF3C	FF5	FF5C	CAPM	FF3	FF3C	FF5	FF5C
‘Up’-market	4.41***	11.26***	10.13***	10.9***	24.06***	4.35***	11.24***	10.08***	10.98***	23.94***
dummy	[1.48]	[2.42]	[2.32]	[2.39]	[3.18]	[1.47]	[2.42]	[2.31]	[2.39]	[3.18]
	(0.48)	(0.55)	(0.59)	(0.66)	(0.86)	(0.48)	(0.55)	(0.59)	(0.66)	(0.86)
Flows	0.23*	1.28	0.98	1.17	4.41	0.23*	1.32	1.00	1.21	4.56
	[−1.48]	[0.25]	[−0.02]	[0.16]	[1.48]	[−1.49]	[0.27]	[0.00]	[0.19]	[1.52]
	(0.84)	(1.02)	(1.03)	(1.15)	(1.44)	(0.86)	(1.04)	(1.04)	(1.17)	(1.46)
Fund returns	0.97	0.57**	0.61**	0.61*	0.40**	0.97	0.57**	0.61**	0.60*	0.40**
	[−0.04]	[−0.57]	[−0.50]	[−0.50]	[−0.91]	[−0.03]	[−0.57]	[−0.50]	[−0.51]	[−0.92]
	(0.17)	(0.24)	(0.25)	(0.28)	(0.39)	(0.17)	(0.24)	(0.25)	(0.28)	(0.39)
Beta MRP	0.62	1.11	1.34	1.08	2.66**	0.63	1.13	1.34	1.09	2.63
	[−0.48]	[0.11]	[0.29]	[0.08]	[0.98]	[−0.46]	[0.12]	[0.29]	[0.09]	[0.97]
	(0.91)	(0.76)	(0.89)	(0.76)	(0.94)	(0.92)	(0.77)	(0.90)	(0.77)	(0.94)
Beta SMB		0.85	0.73	0.55	0.29		0.86	0.74	0.55	0.29**
		[−0.17]	[−0.32]	[−0.60]	[−1.24]		[−0.16]	[−0.30]	[−0.60]	[−1.24]
		(0.49)	(0.46)	(0.46)	(0.53)		(0.49)	(0.47)	(0.46)	(0.54)
Beta HML		0.57	0.65	0.76	0.68		0.56	0.64	0.75	0.68
		[−0.57]	[−0.44]	[−0.28]	[−0.39]		[−0.58]	[−0.44]	[−0.28]	[−0.39]
		(0.37)	(0.37)	(0.31)	(0.31)		(0.37)	(0.37)	(0.31)	(0.31)
Beta MOM			0.72		0.87			0.73		0.87
			[−0.32]		[−0.14]			[−0.32]		[−0.14]
			(0.49)		(0.45)			(0.49)		(0.45)
Beta RMW				1.01	1.18				1.00	1.18
				[0.01]	[0.16]				[0.01]	[0.16]
				(0.18)	(0.16)				(0.19)	(0.16)
Beta CMA				0.74	0.63**				0.74	0.63**
				[−0.30]	[−0.47]				[−0.31]	[−0.47]
				(0.19)	(0.20)				(0.19)	(0.20)

Table 5. (Continued)

Panel A1	Coefficient estimates (gamma frailty)					Panel B1	Coefficient estimates (inverse Gaussian frailty)			
	CAPM	FF3	FF3C	FF5	FF5C	CAPM	FF3	FF3C	FF5	FF5C
XP	0.99	1.01	1.01	1.01	1.03	0.99	1.01	1.01	1.01	1.03
	[−0.01]	[0.01]	[0.01]	[0.01]	[0.03]	[−0.02]	[0.01]	[0.01]	[0.01]	[0.03]
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
BMXP	0.80	1.17	1.11	1.18	1.53	0.79	1.17	1.10	1.18	1.53
	[−0.22]	[0.16]	[0.10]	[0.16]	[0.42]	[−0.22]	[0.15]	[0.09]	[0.16]	[0.42]
	(0.29)	(0.32)	(0.33)	(0.35)	(0.38)	(0.30)	(0.33)	(0.33)	(0.35)	(0.38)
Residuals	1.04[0.04]	1.78**	1.67**	1.67*	2.51**	1.03	1.78*	1.67**	1.67*	2.52**
	(0.17)	[0.58]	[0.51]	[0.51]	[0.92]	[0.03]	[0.58]	[0.51]	[0.51]	[0.92]
		(0.24)	(0.25)	(0.28)	(0.39)	(0.18)	(0.24)	(0.25)	(0.29)	(0.39)
Frailty	<0.01	<0.01	<0.01	<0.01	<0.01	9.91	9.29	10.67	8.36	11.56
Panel A2						Panel B2				
Log-likelihood 1	–209.76	–209.76	–209.76	–209.76	–209.76	–209.76	–209.76	–209.76	–209.76	–209.76
Log-likelihood 2	–194.67	–189.98	–190.62	–190.88	–188.22	–184.84	–180.77	–182.33	–180.31	–176.79
Concordance	0.63***	0.707***	0.70***	0.69***	0.71***	0.73***	0.75***	0.74***	0.75***	0.77***
	(0.06)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.04)	(0.05)	(0.04)	(0.04)
Likelihood ratio test	30.19***	39.56***	38.3***	37.77***	43.08***	49.84***	57.98***	54.87	58.89***	65.93***
Wald test	26.33***	36.54***	35.89***	36.07***	42.32***	25.79***	35.59***	35.01	34.76***	40.45***
Score (log-rank) test	7.00***	9.00***	10.0***	11.00***	12.00***	16.6***	17.96***	18.07	21.22***	23.01***

This table presents the 2SRI-F results regarding endogeneity for gamma frailty (Panels A1, A2) and Gaussian frailty (Panesl B1, B2). The hazard ratios that have been derived from the coefficient estimates (in square brackets) as well as the respective standard errors (in brackets) for each of the five asset-pricing models, namely the CAPM, FF3 (Fama and French three-factor), FF3C (Carhart model), FF5 (Fama and French five-factor model), and FF5C (custom six-factor model) model. MRP, market factor; SMB, small minus big; HML, high minus low; MOM, momentum; CMA, investment; RMW, profitability; XP, industry experience; and BMXP, other relevant business experience. R_1 signifies the transformed residuals from the first stage. The likelihood ratio test is given for the frailty term (in all cases statistically not significant). '*', '**' and '***' denote statistical significance at the 10%, 5% and 1% level, respectively. The goodness-of-fit statistics and, where appropriate, the respective test results are presented as well.

the fund manager departing from the fund; but even intuitively, this stability should be attributed to very different factors. The second period, which schematically lasts anything between 1 and 3 years, is substantially more uncertain; indeed, most of the fund manager changes take place here. Given how tightly interlinked are the characteristics of funds and of their managers, it seems that the stirring period for individual funds is the period of greatest uncertainty as to whether the fund will or will not retain its characteristics, including trading norms and behaviours, during normal and turbulent periods. This is particularly important for individual but also for institutional investors, because it indicates that their own behaviour needs to be adjusted accordingly – for example, to account for the increased chances of having to rebalance their portfolios to reflect their actual risk–return preferences.

When we also add to the mixture the distinction between ‘up’ and ‘down’ markets, we see that for Chinese funds, the stirring period is very acute for the ‘up’ markets while very mild for the ‘down’ markets. Given that personal, health, retirement or other idiosyncratic reasons account for a small portion of fund manager changes or, alternatively, by making the assumption that they are independent of market conditions, if equity funds are – as is naturally expected – sufficiently diversified, such a result implies that in China fund managers are more likely to leave their post in the pursuit of better career prospects than to be forced out from the company as a way to improve the performance or outlook of the fund. This suggests that the finding of Auerbach and Gorodnichenko (2012), namely that the business cycle determines the response of fund strategies, might actually be the result of fund manager changes. Indeed, in those cases, given how intertwined the strategies that a fund adopts and the characteristics of its manager are, the arrival of a new fund manager would inevitably alter the fund strategy and give the impression that funds respond to the business cycle, when, in reality, they reflect a fund manager change.

However, this effect is countered to some extent by what abnormal returns the managers delivered and/or how successful they have been in increasing fund flows. This suggests that equity fund managers in China are rewarded sufficiently well when they outperform the market and/or attract new customers to remain in their posts even if (see Bryant, 2012 and Deuskar *et al.*, 2011) they may do so by imposing higher management fees that reduce net returns to investors. Alternatively, their success could either make them more confident that their position is secure or raise their bargaining power with their company, so that they do not seek new opportunities. Following Kellard *et al.* (2017), because fund managers have evidently strong connections with one another as well as with brokers, their access to superior information about market opportunities, including job opportunities, suggests that this is the most likely scenario.

For exactly the opposite reasons, when they underperform the market and/or the fund flows shrink, there is a higher chance of their leaving the fund. This confirms the finding of Chevalier and Ellison (1999b) – fund managers are indeed more likely to be replaced if they underperform. Moreover, in this respect, the finding of Clare *et al.* (2014), the rise in the average post-manager-exit performance, is likely to be the effect of the departure of an underperforming manager who left the fund, rather than the arrival of an overperformer.

Finally, the exposure of the fund to market risk is also pointing in the same direction, namely that the more exposed to market risk the fund is, the higher the probability of its manager leaving. Together with what has been found about market conditions, this may well demonstrate that Chinese fund managers are able to successfully exploit the benefits from positive market movements and elude responsibility for negative market movements. A similar argument could be raised for the size factor, but its effect is largely countered by the momentum factor when it is present in the model and statistically significant. In this respect, Clare *et al.* (2014), who find a reduction in the market risk exposure when a manager is replaced, are essentially pointing to this phenomenon.

Conclusions

For the first time, we examine fund managers’ mobility across different funds and the factors associated with their moving to new posts using survival methods. Our analysis has built on the strong and theoretically well-documented connection between a fund manager’s decision to change jobs and a fund’s characteristics (performance, risk profile, customer base, reputation, survivability amongst others) and explored the factors that accelerate (or otherwise) the change of fund manager from their post in the booming market of China. Such very prominent events, the possibility and realization of which are closely monitored by the financial press, investors and policymakers alike, can have dramatic consequences for the characteristics of equity funds, given how closely linked these are to the characteristics of a fund manager (education, experience, trading norms and behaviours, reputation, personal links with small, large and institutional investors, amongst other factors) and how they will manage the fund they lead.

Our study makes valuable contributions to the finance microstructure literature. It introduces the application of survival analysis to this field by considering the time to departure of a fund manager as a time-to-event counting process. Our findings demonstrate that the manager's performance, fund exposure to market risk and 'up' markets are consistently important in determining when a fund manager will leave their post. The novelty of our approach also provides new intuition from a very different angle to the ongoing discussion about fund management. Most importantly, it provides an additional tool for investors to optimize their investment decisions and presents a challenge to regulators, who must ensure the timely disclosure of appropriate information to investors regarding fund manager changes.

Future research could explore the potential impact of other factors, such as financial regulation (Cumming *et al.*, 2012) and corporate governance (Haß, Johan and Schweizer, 2016), which have been shown to affect performance persistence in the context of the hedge fund industry. In the meantime, it should also consider whether similar phenomena are intrinsic to other funds in different jurisdictions, most notably in the United States and Europe, and if regulators provide information regarding fund manager behaviours to prospective investors. Finally, an interesting follow-up question to our work is whether or not a fund manager who moves into a new fund retains their performance and whether and, if so, to what extent they alter the fund characteristics that their predecessor has established. In conjunction with our findings, this would effectively provide insights into fundamental reasons why fund companies hire one manager over another which would in turn inform policy and practice.

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Michail Karoglou is a senior lecturer in Economics and Finance at Aston Business School. An economist and computer scientist by training, his research has been predominantly in the areas of applied macroeconometrics and financial econometrics. Nevertheless, his expertise in machine learning and experience with large datasets has allowed him to work on more cross-disciplinary topics that span the spectrum of quantitative research.

Jia Liu is a professor in Accounting and Finance at the University of Portsmouth Business School. Her research focuses on accounting, finance and business economics, which she integrates with business management disciplines, including law, business ethics, leadership, strategic management, entrepreneurship, R&D, strategic management, public administration and management, Fintech, Big Data, the Green Economy, social inclusion, diversity and wellbeing. She has published in the *Journal of Corporate Finance* and *British Journal of Management*, among others, and has written books on governance, sustainability and decision-making. Her research has featured in the media, including in *The Conversation*.

Dimitrios Stafylas is an assistant professor of Finance at the University of York, and he has industry experience. He has a PhD in Finance, an MBA and an MSc. His research interests lie in empirical finance and issues in corporate finance. He has published in journals such as *European Journal of Finance*, *International Review of Financial Analysis*, *British Accounting Review*, *Research in International Business and Finance*, and *Applied Economics*. His work has been presented at international academic conferences.