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Mesure de performance et liquidité dans l'industrie des hedge funds

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Mesure de performance et liquidité dans l'industrie des hedge
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Introduction

Depuis les années 1950 et l'apparition de la théorie de portefeuille moderne, initiée par Markowitz (1952), la mesure de la performance des gestionnaires d'actifs a été au centre de la finance académique, tant au niveau des études empiriques que du développement de la théorie financière.

En effet, la théorie de l'efficience informationnelle des marchés financiers, formalisée par Fama (1970), implique que les gestionnaires d'actifs ne peuvent pas durablement "battre" le marché, c'est-à-dire générer de la performance en excès de la rémunération pour le risque pris. Ce postulat théorique a engendré un champ de recherche actif sur la mesure de la performance des gérants de fonds avec le développement de nombreuses mesures de performance, ainsi que l'émergence de nouveaux produits tels que les fonds indiciels et ETFs (*Exchange Traded Funds*), ou encore l'apparition du "smart beta". L'existence même des *hedge funds*, avec leur volonté de générer de la performance absolue, semble donc être un défi lancé à la recherche académique pour expliquer cette surperformance.

La mesure de performance en finance traditionnelle

Traditionnellement, la mesure de la performance d'un investissement a suivi deux grands courants. Le premier, initié par Sharpe (1966) et son "ratio de Sharpe" analyse la performance globale d'un titre ou d'un fonds d'investissement :

$$S_i = \frac{E[R_i - r_f]}{\sigma_i} \quad (1)$$

avec S_i le ratio de Sharpe du titre i , R_i son rendement, σ_i la volatilité de ses rendements et r_f le rendement sans risque.

Cependant, cette approche s'intéresse uniquement au risque total d'un investissement et ne va ni distinguer les sources de ce risque, ni s'intéresser aux co-variations entre plusieurs titres. La seconde approche, dite de modèles à facteurs, permet de palier ces faiblesses. À l'origine, l'analyse est effectuée par rapport à un indice de référence, que l'on appelle le *benchmark*. Elle se fonde initialement sur la théorie du Modèle d'Évaluation des Actifs Financiers ("*Capital Asset Pricing Model*" ou CAPM) de Treynor (1961), qui stipule que la performance de tout investissement peut être décomposée de la manière suivante :

$$r_{i,t} = \alpha_i + \beta_i(R_{M,t} - r_{f,t}) + \epsilon_{i,t} \quad (2)$$

où $r_{i,t}$ est le rendement en t du titre i , $R_{M,t}$ le rendement du marché, $r_{f,t}$ le rendement sans risque, β_i la mesure du risque systématique du titre, $\epsilon_{i,t}$ le risque idiosyncratique et α_i la sur- ou sous-performance par

rapport au marché.

L'idée sous-jacente est qu'il existe un portefeuille de marché, généralement un indice de marché actions, et que l'on peut évaluer la performance α_i d'un portefeuille de titres ou d'un titre en mesurant la corrélation β_i de ce portefeuille ou titre avec les mouvements de marché. La performance, appelée "*alpha* de Jensen", est ainsi le rendement qui ne dépend pas des conditions de marché et qui est stable quels que soient les environnements économique et financier. On distingue cette mesure de performance du "*beta*", qui n'est autre que la corrélation entre les rendements du titre et ceux des rendements en excès du *benchmark*. En pratique, on utilise généralement un indice de marché actions afin d'approximer les rendements du marché.

Jensen (1968) a été le premier à analyser empiriquement la performance des fonds mutuels en calculant leur alpha au sein du modèle du CAPM. De nombreux articles ont ensuite appliqué une méthodologie similaire afin d'estimer la performance des fonds mutuels ou de portefeuilles d'actions. Un certain nombre d'"anomalies" ont cependant été découvertes par la suite, remettant en cause le pouvoir explicatif du CAPM tant sur la coupe longitudinale que transversale des rendements des titres financiers. Parmi elles, on trouve la surperformance des titres ayant un faible *beta* découverte par Black et al. (1972), la surperformance des titres ayant un ratio "*book-to-market*" élevé (Rosenberg et al., 1985) ou encore la surperformance des titres ayant une faible capitalisation boursière (Banz, 1981). Ces anomalies ont conduit à un débat divisant le monde académique quant à leur nature. Une première explication retenue est celle d'une mauvaise évaluation des prix des actifs financiers par les participants de marché (voir Lakonishok et al. (1994) ou La Porta et al. (1997)). La seconde explication, conforme à l'hypothèse d'efficience informationnelle des marchés financiers, suppose que ces anomalies reflètent une exposition à un ou plusieurs facteurs de risques non-diversifiables.

Cette remise en cause du CAPM en tant que modèle explicatif de la variation des rendements des actifs financiers s'est étendue à celle de l'utilisation de l'alpha, issu de ce modèle, en tant que mesure de performance pertinente. Si le modèle n'explique pas correctement la variation des rendements, alors la mesure de performance α ne va pas refléter une réelle sur- ou sous-performance indépendante du risque mais un ensemble de facteurs de risques systématiques omis.

Afin d'améliorer le pouvoir explicatif des modèles à facteurs, Ross (1976) propose un cadre théorique (l'*Asset Pricing Theory* ou APT) pour développer des modèles de risque intégrant des facteurs de risques systématiques multiples. Fama et French (1993) vont développer leur modèle à trois facteurs, ajoutant au portefeuille de marché un facteur de taille (différence de rendement entre les petites et les grosses capitalisations boursières) ainsi qu'un facteur "*book-to-market*" (différence de rendement entre les titres à fortes et faibles valeurs comptables relativement à leurs capitalisations boursières). Carhart (1997) a ajouté un facteur *momentum*, qui est la différence de rendement entre les titres ayant eu les plus hauts et les plus bas rendements sur l'année passée.

Carhart (1997), avec son modèle à quatre facteurs, montre que l'alpha moyen des fonds mutuels est négatif, mettant en doute la capacité de la gestion active à battre le marché. Ce point de vue est appuyé par Barras et al. (2010) qui montrent que lorsque l'on corrige de l'effet chance, la proportion de fonds affichant une surperformance est nulle en 2006. Ces résultats ont favorisé l'essor de la gestion passive et des ETFs au détriment des fonds mutuels actifs.

L'émergence de la gestion alternative et des hedge funds

Parallèlement à l'essor de la gestion passive, ces dernières décennies ont vu se développer l'univers de la gestion dite "alternative", et plus particulièrement des *hedge funds* qui sortent du cadre d'investissement dans les produits traditionnels (actions et obligations). Le terme provient du verbe *to hedge*, indiquant que ce type de fonds d'investissement a pour objectif ou tout du moins pour mode opératoire la couverture du risque ("*hedging*"). Il n'y a pas de définition unique pour le terme *hedge fund* car il englobe une grande diversité de fonds. Une définition ne peut donc pas faire la liste exhaustive de l'ensemble des caractéristiques que revêt un *hedge fund* en particulier mais donne celles qui unissent des fonds d'investissement si divers sous une même appellation.

L'*Alternative Investment Management Association* (AIMA) définit un *hedge fund* comme étant un véhicule d'investissement qui poursuit de manière explicite des rendements absolus dans ses investissements sous-jacents. Du fait de la faible précision de cette définition, nous allons retenir la définition suivante : un *hedge fund* est un fonds actif investissant sur les marchés financiers au moyen de stratégies alternatives via des instruments traditionnels (actions, obligations) ou exotiques (produits structurés, dérivés, matières premières) afin d'obtenir un profil de performance relativement peu corrélé de celui des marchés ou fonds d'investissement traditionnels.

Les *hedge funds*, d'après Lhabitant (2009), ont un ensemble de caractéristiques communes : une organisation légale sous forme de partenariat privé, une structure de frais complexe avec un mélange de frais de gestion et de performance, une liberté dans le choix de la stratégie (les allocations peuvent être dynamiques, le fonds peut utiliser l'effet de levier, vendre à découvert ou encore investir dans des produits dérivés) et enfin un accès et une liquidité limités pour les investisseurs.

Ces caractéristiques communes se doublent d'une philosophie d'investissement différente de celle de la gestion active traditionnelle : alors que les fonds mutuels cherchent à surperformer un *benchmark* pré-déterminé (généralement un indice ciblant une classe d'actifs particulière), les *hedge funds* visent spécifiquement à générer des rendements "absolus", c'est-à-dire indépendamment des conditions de marché.

Les *hedge funds* sont généralement divisés en sous-groupes selon la stratégie employée. On compte parmi eux la stratégie *Equity-Hedge/Long-Short Equity*, la plus répandue, composée de fonds prenant des positions à la fois courtes et longues sur les marchés actions, avec un biais long (leur *beta* est positif). Les fonds *Global Macro* s'intéressent principalement aux évolutions des variables macroéconomiques pour investir sur différents marchés financiers. Il s'agit plus d'une approche que d'une stratégie, avec une grande flexibilité dans le choix des instruments et marchés investis. La catégorie *Event-Driven* comprend l'ensemble des stratégies se concentrant sur les événements spéciaux affectant les entreprises (fusions-acquisitions, scissions, défauts, problèmes avec les régulateurs, etc.). Pour la stratégie *Dedicated-Short*, il s'agit, comme les fonds *Equity Hedge*, de fonds prenant des positions longues et courtes sur les marchés actions mais avec un biais court. De même, les fonds *Equity Market-Neutral* prennent des positions longues similaires mais de manière à avoir un *beta* nul. La stratégie *Convertible Arbitrage* regroupe les fonds investissant dans des obligations convertibles et les actions des entreprises concernées. Les fonds *Emerging Markets* sont spécialisés sur les marchés financiers des pays émergents. Les *hedge funds Fixed-Income* se concentrent sur des stratégies d'arbitrage sur les marchés obligataires. La stratégie *Options* se spécialise dans l'usage des options et produits dérivés. Les *Funds of Hedge Funds* sont des fonds investissant dans d'autres *hedge funds* afin de diversifier le portefeuille de gérants et/ou de stratégies. Enfin, la stratégie *Multi-Strategies* regroupe les fonds poursuivant plusieurs stratégies.

Les facteurs de risque expliquant les rendements des hedge funds : un ensemble incomplet en expansion

La grande diversité des entités retenues sous le vocable de *hedge fund* complique la mesure et la comparaison appropriée de leur performance. En effet, il est très difficile de développer un cadre uniforme permettant d'expliquer la variation tant en coupe transversale que longitudinale de leurs rendements. Le succès des méthodes de mesure de performance traditionnelles tient en partie au fait qu'elles ont été appliquées à des titres ou fonds d'investissement relativement similaires, ayant des rendements tendant à être fortement corrélés entre eux, ce qui facilite leur explication et leur comparaison.

Fung et Hsieh (1997) explorent la structure des rendements des *hedge funds* individuels en supposant qu'ils ont une structure par facteurs similaire à celle de l'APT de Ross (1976), c'est-à-dire une exposition à plusieurs facteurs de risques macroéconomiques. Si l'APT explique plus de 75% des rendements des fonds mutuels, ce taux passe à moins de 25% pour les *hedge funds*. Cette chute montre que les facteurs de risques utilisés traditionnellement pour la mesure de performance ne fonctionnent pas avec les *hedge funds*. De plus, les cinq premières composantes principales n'expliquent que 43% de la variance en coupe transversale des rendements, ce qui souligne la diversité des profils de rendements et risques au sein de l'industrie des *hedge funds*. Ce point est souligné par Fung et Hsieh (1999) qui trouvent des profils statistiques très différents entre les différents styles de *hedge funds*.

Cette hétérogénéité des profils de risque et ces différences affichées avec les fonds mutuels ont conduit la recherche académique à chercher de nouveaux facteurs de risques systématiques pour expliquer tant les séries temporelles des rendements que leur coupe transversale. Fung et Hsieh (2001) montrent que les *hedge funds* sont exposés à des facteurs de risques de tendances. Fung et Hsieh (2002) proposent des facteurs obligataires pour expliquer les rendements des fonds *Fixed Income*. En 2004, Agarwal et Naik avancent que les rendements des *hedge funds* sont asymétriques, avec de petits gains fréquents et de larges pertes occasionnelles, et qu'un tel profil de risque peut être obtenu avec des facteurs issus d'options sur différents sous-jacents.

Cette même année, le modèle à facteurs de référence est développé par Fung et Hsieh, comprenant sept facteurs de risques : trois facteurs de tendances, deux facteurs actions et deux facteurs de crédit. Ces sept facteurs expliquent une grande partie de la variation des séries temporelles des rendements des indices *hedge funds* et vont être retenus comme étant le modèle de référence pour l'étude de leurs performances.

Les études académiques ont montré que les *hedge funds* génèrent de l'*alpha* lorsqu'ils étaient évalués avec ces sept facteurs de risques. Kosowski et al. (2007), après usage de techniques *bootstrap* et bayésiennes, montrent que les meilleurs *hedge funds* produisent de l'*alpha* qui n'est pas lié à la chance. Avramov et al. (2011) montrent qu'après avoir incorporé de la prédictabilité issue de variables macroéconomiques, il est possible de sélectionner *ex-ante* un portefeuille de *hedge funds* générant un alpha annualisé de 17% par rapport aux sept facteurs de Fung et Hsieh (2004).

Cette surperformance entre directement en contradiction avec l'hypothèse d'efficience informationnelle des marchés financiers et les résultats empiriques observés sur les autres classes d'actifs. Jurek et Stafford (2015) expliquent que cette surperformance peut provenir de l'exposition à un ou plusieurs facteurs de risques omis et montrent que les *hedge funds* sont exposés de manière significative à un risque de crash. Ce point est approfondi par Titman et Tiu (2011) qui montrent que les *hedge funds* ayant les rendements les moins bien expliqués par les facteurs de risques de Fung et Hsieh (2004) surperforment ceux dont les rendements sont les mieux expliqués,

soulignant notre compréhension partielle de la source des rendements des *hedge funds*. De même, Sun et al. (2011) démontrent que les fonds les moins corrélés avec les autres fonds de leur style stratégique surperforment les fonds les plus corrélés, en cohérence avec l'omission de facteurs de risques. Bollen (2013) va encore plus loin et avance que jusqu'à un tiers des *hedge funds* individuels sont virtuellement ni expliqués par le modèle à facteurs de Fung et Hsieh ni par celui d'Agarwal et Naik (2004). Cependant, ces fonds ont un risque de faillite plus élevé et ont des rendements corrélés entre eux, appuyant l'hypothèse que l'univers des facteurs expliquant les rendements des *hedge funds* est trop réduit pour correctement analyser leur performance.

Les facteurs actuels ne reflètent ni expliquent correctement la grande diversité des stratégies suivies par les *hedge funds*. Cela a été à l'origine de la course aux facteurs de risques systématiques propres aux *hedge funds* avec comme objectif d'analyser la performance de ces derniers à la lumière de ces nouveaux facteurs.

Ce champ de recherche s'est avéré très productif, avec la proposition d'un facteur de risque de liquidité par Sadka (2010), d'une mesure globale de risque systématique (Bali et al. (2012)), d'un facteur de risque de corrélation (Burashi et al. (2014)), d'un indicateur de risque macroéconomique (Bali et al. (2014)), d'un facteur de risque de sentiment de marché (Chen et al. (2016)) ou encore de la volatilité de la volatilité agrégée (Agarwal et al. (2017)). Tous ces facteurs ont en commun d'expliquer la coupe transversale des rendements ou d'avoir un pouvoir prédictif sur les rendements futurs des *hedge funds*. Brandon et Wang (2013) montrent que le facteur de risque de liquidité diminue fortement la proportion de fonds considérés auparavant comme générant de la surperformance, mettant ainsi en lumière un déterminant de la performance mesurée des *hedge funds*.

Si le nombre de facteurs explicatifs des rendements des *hedge funds* ne cesse de croître, il reste mesuré comparativement à celui du rendement des actions. En effet, Harvey et al. (2016) en recensent trois cent quatorze. Serions-nous arrivés, comme le dit Cochrane (2005) pour les actions, à un "zoo de facteurs" pour les *hedge funds*? La multiplication des "découvertes" de facteurs engendre un risque de "fausses découvertes", c'est-à-dire de facteurs de risques liés aux variations des rendements de manière statistiquement significative par pure chance. Novy-Marx (2014) précise ainsi qu'il est possible d'"expliquer" les rendements des actions US par les changements météorologiques, le parti politique du président des États-Unis ou encore la conjonction des planètes, mettant ainsi en garde contre les facteurs de risques obtenus de manière purement statistique, sans interprétation économique.

Afin de se prémunir autant que possible de ce risque de "fausses découvertes", Bali et al. (2011) préconisent de mesurer le pouvoir prédictif d'un facteur de risque *hedge fund* avec une fenêtre glissante, introduisant ainsi une analyse "hors-échantillon" et en validation croisée. De même, tout au long de ce travail de thèse, toute relation est systématiquement testée à la fois de manière paramétrique et non paramétrique ainsi que selon les modalités de Bali et al. (2011) dans le but de présenter des résultats statistiquement robustes.

Les particularités des hedge funds posent des problématiques spécifiques de mesure de performance

Le choix des facteurs de risques appropriés n'est pas la seule difficulté liée à la mesure de performance au sein de l'industrie des *hedge funds*. En effet, il n'existe pas de base de données *hedge fund* qui recense l'ensemble des performances effectives ou réelles de tous les *hedge funds*. La raison de ce manque tient à la réglementation qui n'impose pas aux *hedge funds* de rendre publique cette information. Les conséquences sont multiples, avec en premier lieu la répartition des données disponibles entre une multitude de bases de données, souvent commerciales, ce qui engendre des problèmes de représentativité et d'agrégation. De plus, les données disponibles peuvent avoir été retouchées, dans le but par exemple de lisser les rendements. Joenväärä et al. (2016) agrègent l'ensemble des bases de données utilisées par la recherche académique et procèdent à une comparaison systématique des bases entre elles. Ils arrivent à la conclusion que les bases ne diffèrent pas qualitativement entre elles une fois que les effets de taille des fonds sont pris en compte.

En parallèle de la disponibilité des données, il est important de bien choisir celles qui sont retenues afin de ne pas créer un problème de variable tronquée ou de biais du survivant. Celui-ci se manifeste par le fait que les fonds encore en activité ont tendance à avoir de meilleurs rendements moyens et une volatilité plus faible que les fonds ayant cessé leur activité, générant un biais dans les inférences issues d'études effectuées uniquement sur des bases de données de fonds "vivants". Liang (2000) chiffre ce biais potentiel à une différence de rendement moyen de 2% par an. Ce biais n'est cependant plus prégnant au sens où aujourd'hui l'immense majorité des études est effectuée sur des bases de données incluant des fonds "vivants" et "morts".

Le lissage des variations des rendements est potentiellement problématique pour les investisseurs au sens où l'autocorrélation a tendance à affecter les moments de leur distribution statistique. Par exemple, Geltner (1993) montre que des portefeuilles autocorrélés vont avoir une volatilité et une corrélation avec d'autres classes d'actifs plus faibles tandis que Loudon et al. (2006) documentent un gros effet réducteur sur la *Value-at-Risk*. De même, Lo (2002) démontre que l'autocorrélation dans les rendements des *hedge funds* conduit à fortement surestimer leur ratio de Sharpe.

On sait depuis Asness et al. (2001) et Brooks et Kat (2002) que les rendements des *hedge funds* sont autocorrélés, ce qui signifie que les rendements du mois t dépendent des rendements des mois passés. Getmansky et al. (2004) expliquent que ce phénomène est pervasive au sein de l'industrie des *hedge funds* et que l'on observe des niveaux élevés d'autocorrélation jusqu'au second ordre pour l'ensemble des stratégies de *hedge funds*. On a cependant une grande variabilité dans le niveau d'autocorrélation d'un fonds à l'autre, y compris au sein d'une même stratégie. De tels niveaux d'autocorrélation contrastent avec le reste de l'industrie de la gestion d'actifs et semblent contredire l'hypothèse d'efficience informationnelle des marchés financiers. Getmansky et al. (2004) montrent cependant qu'il n'y a pas de contradiction avec des marchés efficients : l'autocorrélation proviendrait de l'illiquidité des actifs du portefeuille et/ou d'un phénomène de lissage des rendements de la part du gérant du fonds.

Une conséquence de ces études est que l'on ne sait toujours pas séparer l'autocorrélation provenant de l'illiquidité de celle résultant d'un lissage artificiel des rendements par le gérant. Une partie de l'objet de mon travail de thèse est de quantifier ces deux sources de l'autocorrélation des rendements des *hedge funds* afin d'identifier dans quelle mesure ces derniers sont exposés à un risque de liquidité ou à des conflits d'agences et du risque opérationnel.

L'autocorrélation peut également directement influencer la mesure de performance extraite des modèles à facteurs. En effet, Scholes et Williams (1977) ou encore Dimson (1979) montrent dans le cas des actions que l'autocorrélation biaise à la hausse l'estimateur de l' α et à la baisse celui du β . Cohen et al. (1983) expliquent que l'ampleur de ces biais va dépendre de celle de l'autocorrélation. C'est le niveau d'autocorrélation, bien supérieur pour les *hedge funds* que pour les autres classes d'actifs, qui rend le biais potentiellement très important.

Dans ce contexte de remise en cause des indicateurs de performance traditionnels pour l'industrie des *hedge funds*, mes travaux de thèse cherchent à approfondir notre connaissance des limites des mesures employées jusqu'à présent et proposent un cadre nouveau pour déterminer la part de rendement "absolu" dans les rendements des *hedge funds*. En effet, dans le sillage du développement des indices intelligents dits de "*smart beta*" et de l'apparition des stratégies de gestion d'actifs visant spécifiquement à capturer des primes de risque, des auteurs tels qu'Hasanhodzic et Lo (2007) ont proposé de répliquer les rendements des *hedge funds* de manière transparente via l'utilisation de modèles à facteurs. Bien que jusqu'à présent les produits de réplcation des *hedge funds* n'aient pas généré la performance attendue, les progrès de la compréhension des rendements de cette classe d'actifs laissent présager de son développement futur. Une telle évolution irait dans le sens des marchés efficients, avec la réplcation de stratégies *hedge fund* associée à des frais de gestion bien inférieurs aux fameux "*2 and 20*" (2% de frais de gestion des actifs et 20% de frais de performance). En effet, l'industrie des *hedge funds* est accusée dans sa majorité de collecter des frais de gestion en promettant des rendements absolus qui se révèlent *ex-post* être des expositions passives à des facteurs de risques investissables.

Présentation des travaux de recherche structurés en trois chapitres complémentaires

Le premier chapitre s'intéresse à l'impact de l'autocorrélation des rendements des *hedge funds* sur la mesure de performance obtenue à partir des modèles à facteurs. Si la littérature a montré qu'elle augmente de manière artificielle les mesures de performance similaires au ratio de Sharpe en diminuant fortement la variance des rendements, aucune étude approfondie n'a, à ma connaissance, été menée sur le lien entre α et autocorrélation dans l'industrie des *hedge funds*. Ce chapitre montre au moyen de méthodes paramétriques et non-paramétriques que les *hedge funds* les plus autocorrélés surperforment les *hedge funds* les moins autocorrélés. Alors que l'effet de l'autocorrélation est marginal sur les fonds mutuels ou les actions, dans le cas des *hedge funds* les résultats empiriques montrent qu'il est substantiel. Deux explications sont possibles : cela pourrait provenir de l'omission d'un facteur de risque (faisant l'objet du deuxième chapitre) ou de l'existence d'un fort biais dans les estimateurs de mesure de performance et de risque. Afin de tester cette dernière hypothèse, la relation entre l'autocorrélation et chaque facteur de risque est analysée dans la coupe transversale des *hedge funds*. Conformément à l'hypothèse retenue, les fonds les plus autocorrélés sont également moins exposés à chacun des sept facteurs de risques proposés par Fung et Hsieh (2004). En déliissant les rendements, la proportion de fonds ayant une surperformance statistiquement significative diminue de manière consistante et le nombre de "fausses découvertes", c'est-à-dire de fonds surperforants par chance, augmente fortement. Ce chapitre a des implications pratiques pour les investisseurs en *hedge funds* en mettant en exergue l'importance de prendre en compte l'autocorrélation lors de la mesure de performance.

Faisant suite à l'étude des biais engendrés par l'autocorrélation des rendements des *hedge funds*, le deuxième chapitre étudie l'hypothèse d'un facteur de risque omis expliquant l'autocorrélation, et la "surperformance" qui lui est associée. Inspiré par Getmansky et al. (2004), ce chapitre teste le lien potentiel entre autocorrélation et risque de liquidité. L'idée est que si l'autocorrélation est le résultat de l'illiquidité du portefeuille sous-jacent, les fonds les plus autocorrélés devraient être les plus exposés au risque de liquidité. Dans ce cas, le risque de

liquidité étant associé à une prime de risque, comme montré par Sadka (2010), les *hedge funds* devraient être rémunérés pour cette exposition au risque. Ceci donne deux manières de tester empiriquement cette hypothèse. La première consiste à tester directement le lien entre autocorrélation et *betas* de risque de liquidité. La seconde est indirecte et s'attache à vérifier l'existence d'une éventuelle prime de risque associée à l'autocorrélation. Les résultats contrastés obtenus montrent que les fonds les plus et les moins autocorrélés sont les plus et les moins exposés au risque de liquidité. Cependant, cette relation n'est pas linéaire et ne donne pas lieu à une compensation sous forme de prime de risque systématique. Nos résultats montrent que l'effet du lissage des rendements par les gérants prédomine la liquidité pour expliquer l'autocorrélation des rendements des *hedge funds*. L'autocorrélation des rendements *hedge funds* provient donc majoritairement d'un conflit d'agence entre gérants et investisseurs.

Dans la continuité des deux premiers chapitres sur la mesure de performance des *hedge funds*, le troisième chapitre cherche à savoir s'il existe une prime de risque dans l'utilisation par les *hedge funds* de services fournis par des tierces parties telles que des *prime brokers*. Les *hedge funds*, de par leur utilisation de stratégies sophistiquées impliquant l'usage du levier et des produits dérivés et/ou négociés de gré-à-gré, sont exposés au risque de capital de leurs contreparties. Le chapitre trois va montrer que les *hedge funds* sont exposés au risque de capital des *primary dealers*, les banques contreparties de la *New York Fed*. La variation dans le degré d'exposition à ce risque est un bon prédicteur de rendement espéré. Une partie significative de la variation du rendement en excès des *hedge funds* provient également de l'hétérogénéité dans l'exposition à ce risque, montrant qu'il complète l'univers des facteurs actuels. Les résultats sont robustes à l'utilisation d'un grand nombre de méthodes empiriques et à l'usage de facteurs additionnels comme la liquidité ou le risque des pays émergents.

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Chapitre 1

Is your hedge fund manager really skilled ?
Serially correlated returns and
risk-adjusted returns

Les analyses au moyen de modèles à facteurs de risques multiples montrent que les *hedge funds* génèrent des rendements ajustés du risque positifs et statistiquement significatifs. Ce constat contraste fortement avec les résultats obtenus sur des véhicules d'investissements traditionnels comme les fonds mutuels et a longtemps été présenté comme un "puzzle" pour la théorie financière, du fait de son opposition avec la théorie de l'efficience informationnelle des marchés financiers. Un second fait stylisé des rendements des *hedge funds* est leur fort niveau affiché d'autocorrélation. Un tel degré de prédictibilité contraste également avec les autres classes d'actifs.

Dans ce chapitre, nous analysons conjointement ces deux faits stylisés. Nous démontrons l'existence d'une relation forte dans la coupe longitudinale des *hedge funds* entre les rendements ajustés du risque et le niveau d'autocorrélation. En classant les fonds individuels en des portefeuilles déciles en fonction du niveau de corrélation observé dans leurs rendements, nous montrons que les fonds les plus autocorrélés surperforment les fonds les moins autocorrélés avec comme mesure de performance l'*alpha* du modèle à facteurs de Fung et Hsieh (2004). De plus, une régression en deux étapes Fama et McBeth démontre une relation linéaire positive et statistiquement significative entre le degré d'autocorrélation et le rendement ajusté du risque. Ces résultats sont robustes à une validation croisée au moyen d'une fenêtre glissante de trente-six mois, permettant ainsi de prendre en compte des expositions aux risques potentiellement dynamiques.

Nous faisons l'hypothèse que deux mécanismes complémentaires peuvent expliquer nos résultats. Le premier est que l'autocorrélation lisse les variations dans les rendements, diminuant ainsi les *betas* et accroissant artificiellement l'*alpha*. La seconde explication est l'existence d'un facteur de risque de liquidité omis qui expliquerait la présence d'autocorrélation dans les rendements et compenserait son exposition par une prime de risque.

Nous explorons la première option dans ce chapitre et laissons la seconde pour le chapitre suivant. Afin de tester l'hypothèse d'un biais dans les mesures de performance, nous partons du fait que l'autocorrélation devrait également biaiser les estimateurs des mesures de risque *betas*. En classant les *hedge funds* individuels en portefeuilles déciles selon leur niveau d'autocorrélation, nous trouvons que la différence d'exposition moyenne pour chaque facteur de risque en valeur absolue est négative et statistiquement significative entre les fonds les plus et les moins autocorrélés. De même, une régression Fama et McBeth en coupe transversale montre une relation négative statistiquement significative entre autocorrélation des rendements et mesures de risque en valeurs absolues. Ces deux résultats confirment l'explication que les fonds les plus autocorrélés ont des rendements ajustés du risque supérieurs aux fonds les moins autocorrélés du fait de biais statistiques dans les mesures des modèles à facteurs. Ce constat corrobore celui de Dimson (1979) pour les actions, mais à un degré de magnitude bien supérieur. Les résultats sont robustes à une procédure de validation croisée utilisant une fenêtre glissante de trente-six mois.

Si l'autocorrélation lisse les variations des rendements et ainsi accroît le montant d'*alpha* mesuré par les modèles à facteurs, nous pouvons dès lors nous demander si cet effet est économiquement important. Pour évaluer la magnitude de l'impact de l'autocorrélation sur les rendements ajustés du risque au sein de l'industrie *hedge fund*, nous explorons le lien entre la proportion de gérants de fonds pouvant être considérés comme "talentueux", c'est-à-dire générant de la surperformance corrigée de l'effet chance. Nous employons une méthodologie de "fausses découvertes" similaire à celle de Barras et al. (2010). L'idée initiale est de calculer la proportion attendue de fonds ayant des *alphas* positifs et statistiquement significatifs par chance et de soustraire celle-ci de la proportion observée de fonds ayant des rendements ajustés du risque positifs et statistiquement significatifs. De cette manière, nous obtenons la "vraie" proportion de gérants de fonds "talentueux". Nous calculons cette proportion sans tenir compte de l'autocorrélation, en la prenant en compte de manière indirecte au moyen d'estimateurs statistiques robustes et enfin directement en déliissant les rendements au moyen de la procédure de Getmansky et al. (2004).

Nous trouvons que l'autocorrélation dans les rendements des *hedge funds* accroît substantiellement la proportion de gérants de fonds considérés comme étant "talentueux" par le biais de deux mécanismes : une augmentation de la proportion de fonds ayant un *alpha* positif et statistiquement significatif et une diminution de la part attendue des gérants "chanceux", c'est-à-dire surperformant par chance.

Ce chapitre souligne l'importance de la prise en compte de l'autocorrélation afin d'expliquer le "puzzle" de la surperformance affichée des *hedge funds* : le niveau de cette surperformance est considérablement plus faible une fois les rendements déliés, diminuant ainsi l'anomalie vis-à-vis de la théorie des marchés efficients. Deuxièmement, du point de vue d'un investisseur, ce chapitre met en exergue le côté amplificateur de l'autocorrélation sur la performance attendue *ex-ante* des *hedge funds*, conduisant à des regrets *ex-post* pour les investisseurs peu sophistiqués. Finalement, ce chapitre indique que la réplication passive des *hedge funds* peut être appliquée de manière plus aisée que précédemment envisagé du fait des expositions aux facteurs de risques plus importantes et des rendements ajustés du risques plus faibles que ceux considérés auparavant.

**Is your hedge fund manager really skilled? Serially correlated returns
and risk-adjusted returns**

This paper demonstrates that serial correlation is an important determinant in the cross-section of risk-adjusted hedge-fund returns. Our results show that funds having highly serially correlated returns outperform lowly serially-correlated funds by an average monthly risk-adjusted return of 0.39% . Consistent with the interpretation that serial-correlation biases alpha estimates upward, we find that serial-correlation is also associated with lower exposures to systematic risk factors. The proportion of managers considered as skilled in the cross-section of individual hedge funds decreases after having controlled for serial-correlation.

Key-words : hedge funds, serial correlation, performance, measurement bias, factor model

1.1 Introduction

Traditional linear factor regressions analysis have long indicated that hedge funds earn statistically significant positive risk-adjusted returns, as documented by Fung and Hsieh (2004) for example. This stylized fact contrasts with other parts of the asset management industry such as mutual funds, for which Fama and French (2010) show that really few exhibit superior performance, and has long puzzled industry observers. The supposed outperformance of hedge funds has led to a strong growth in the industry assets under management, which amounted to 3.2 trillion dollar in 2017 according to Hedge Fund Research. Hedge funds have become an asset class in itself sought after by large institutional investors such as pension funds and universities' endowments.

However, this strand of performance measurement does not take into account another well-known stylized fact about hedge fund returns : the fact that they present strong serial correlation (see Brooks and Kat (2002), Getmansky et al. (2004)). Indeed, Lo (2002) demonstrates that serial correlation in hedge fund returns can strongly bias downward the measured variance, giving rise to inflated Sharpe ratios up to 70%. Correcting the reported Sharpe ratios for serial correlation gives radically different funds' rankings. While the impact of hedge fund serial correlation on their Sharpe ratios is well documented, most of the empirical studies assessing hedge fund performance rely on linear factors models. Such methodologies can also be biased by autocorrelation in returns. For example, Asness et al. (2001) show cases of hedge funds marketed as market neutral, i.e. funds with a zero market beta, having lagged positive and statistically significant exposure to the equity market due to serial correlation in their returns. Patton (2009) filters for serial correlation before testing for various concepts of "market neutrality" on a subset of market-neutral hedge funds, highlighting the potential influence of returns' autocorrelation.

To the best of our knowledge, this paper is the first to thoroughly document the empirical relation between serial correlation in hedge fund returns and measured risk-adjusted returns. Our major finding is the strong relation we demonstrate between the degree of serial correlation in a fund's reported return and its risk-adjusted return, as measured by the alpha with respect to the Fung and Hsieh seven factors. This relation is robust using both parametric and non-parametric methodologies and controlling for time-varying risk-exposures. Such a relationship between serial-correlation and outperformance can arise due to two main reasons : serially-correlated funds are in fact exposed to an omitted systematic risk-factor and earn a risk premium for bearing undiversifiable risk ; or serial-correlation biases the estimates and artificially increases the risk-adjusted returns of the most serially correlated funds. We explore this second explanation, focusing on the link between risk exposures and serial correlation conjointly with risk-adjusted returns. Indeed, Scholes and Williams (1977) and Dimson (1979) show in the case of stocks that serial correlation biases alpha estimates upward and beta estimates downward. Lo and MacKinlay (1990) develop a framework to test the effect of trading asynchronicity (which generates serial-correlation) in stock returns and demonstrate that it decreases returns' variances and correlations and increases serial-correlation estimates. Furthermore, Cohen et al. (1983) show that the bias in beta depends on the relative magnitude of the serial correlation in returns. Because hedge fund returns are far more serially correlated than those of stocks, we expect the biases to be more pronounced.

Consistent with the bias in estimates explanation, we find that funds having more serially correlated returns are less exposed to systematic risk factors. This relation, combined with the positive relation between risk-adjusted returns and serial-correlation, is coherent with biased performance estimates for the most serially correlated funds. We then show, using a false discoveries rate methodology similar to Barras et al. (2010), that the effect of serial correlation is non-trivial in contrasting the proportion of measured skilled funds in the hedge fund industry with and without correcting for serial correlation.

Our paper is linked with the literature on serial correlation in asset pricing and investments. Fisher (1966) was the first to identify autocorrelation in returns as having a potential impact on performance measurement. Atchison et al. (1987) and Kadlec and Patterson (1999) later developed models linking non-synchronous trading to serial correlation. Scholes and Williams (1977), Dimson (1979) and Cohen et al. (1983) examine the impact of infrequent trading, and hence serial correlation, on risk estimates and find that autocorrelation in returns biases alphas upward and betas downward. While infrequent prices and serial correlation were initially studied for stocks and equity indices, where serial correlation is relatively low, the academic literature broadened its scope : see Geltner (1991) for real-estate, Hendricks et al. (1993) for mutual funds, Emery (2003) for private-equity and Getmansky et al. (2004) for hedge funds.

This study also complements the strand of literature on hedge fund performance. Fung et al. (2008) document that risk adjusted returns determines future hedge funds' inflows, highlighting the importance of this particular metric among investors in this industry. Numerous papers have demonstrated that individual funds' performance is related to their characteristics. Sun et al. (2011) show that the funds pursuing the most unique strategies, i.e. strategies that are the most different in terms of correlation with other funds' returns, outperform the most generic hedge funds. Similarly, Titman and Tiu (2011) present evidence that funds having lower R-squared in linear factors-model regressions outperform funds having higher R-squared. Bollen (2013) find that about a third of individual hedge funds have R-squared statistically insignificantly different from zero and that these funds outperform other hedge funds.

Finally, this paper adds to the literature on hedge funds' risks. Agarwal and Naik (2004) find that hedge funds returns present similarities with a short position in a put option on the equity market, leading to significant left-tail risk. Bali et al. (2012) show that a measure of systematic risk explains significantly the cross-section of individual hedge fund returns. Similarly, Buraschi et al. (2014) show that hedge funds are exposed to correlation risk, the risk of an unexpected change in the correlation of the returns between different asset classes. Bollen and Whaley (2009) find that hedge fund change their exposure to risk over time. Sadka (2010) demonstrates that liquidity risk is priced in the cross-section of hedge fund returns while Agarwal et al (2017) show that hedge fund returns are exposed to the volatility of volatility and Bali et al (2014) that their returns are correlated to the macroeconomic uncertainty. Our paper complements this literature in showing that risk estimates are artificially lowered by serial correlation in the returns.

The rest of this paper is organized as follows. Section 2 describes the data used for this study and presents evidence of positive risk-adjusted returns among hedge funds. Section 3 investigates empirically the impact of serial correlation in hedge fund factors models' estimates. Section 4 looks how filtering for serial correlation in hedge fund returns change the estimated proportion of skilled funds' managers. Section 5 concludes.

1.2 Data and stylized facts on risk-adjusted returns

1.2.1 Data

Monthly individual hedge fund returns come from the Lipper TASS database, with both live and dead funds to avoid survivorship biases. We select funds having at least 36 observations over the sample period January 1994 - February 2015, reporting their returns at a monthly frequency and net of fees in US dollars. We exclude Funds of Hedge Funds to avoid double counting, i.e. a Fund of Hedge Fund having invested in an individual hedge fund already included in the database. Table 1.1 reports averages of summary statistics for the whole database as for

individual hedge funds grouped according to 10 investment styles : Convertible-Arbitrage, Dedicated Short Bias, Emerging Markets, Equity Market Neutral, Event Driven, Fixed-Income Arbitrage, Global Macro, Long/Short Equity, Multi-Strategies and Options. Our sample contains 4,864 individual hedge funds, having an average return of 0.74% and an average volatility of 4.34%. We find that, on average, individual hedge funds report returns that are negatively skewed, with a coefficient of -0.23, and have a kurtosis of 7.81, in excess to a gaussian distribution. This means that, on average, hedge fund returns are frequently small and positive and occasionally negative and very large. All investment style exhibit average kurtosis in excess to the gaussian distribution and only three strategil.

TABLE 1.1 – **Basic statistics of individual hedge funds**

This table provides averages of summary statistics for each hedge fund strategy in the Lipper TASS database for the period January 1994 - February 2015. This includes the mean (μ), standard deviation (σ), kurtosis, skewness, the Sharpe ratio (SR) and θ_0 the weight of the current "true" return in reported returns of Getmansky et al (2004). The full sample contains 4,864 funds with both live funds and dead funds to avoid survivorship bias.

	μ	σ	skewness	kurtosis	SR	numObs
All	0.74	4.34	-0.23	7.81	0.27	4,864
Convertible-Arbitrage	0.51	2.56	-0.93	11.33	0.4	195
Dedicated-Short	0.2	6.12	0.34	5.56	0.05	41
Emerging-Markets	0.68	5.72	-0.38	8.06	0.18	640
Macro	0.63	4.21	0.29	6.38	0.18	325
Equity Market-Neutra	0.8	4.88	-0.27	8.18	0.27	309
Event-Driven	0.8	2.96	-0.47	8.14	0.42	554
Fixed-Income	0.57	2.45	-1.31	16.17	0.67	209
Long-Short Equity	0.84	4.83	0.03	6.35	0.21	2,073
Multi-Strategies	0.57	3.25	-0.45	8.94	0.32	492
Options	0.87	3.33	-0.97	13.38	0.29	26

The most important statistic in our case is the amount of serial correlation, proxied here by θ_0 the weight of the current "true" return in reported returns : a value of one indicates no serial correlation in reported returns while the closer to zero, the more serially correlated the reported returns. To model and measure serial-correlation in hedge funds' reported returns, we rely on the methodology developed by Getmansky et al. (2004). We denote R_t the "true" economic return of a hedge fund at date t , i.e. its returns absent of artificial smoothing or frictions in marking-to-market due to illiquidity. R_t follows linear single factor model :

$$R_t = \mu + \beta\Lambda_t + \epsilon_t, \quad E[\Lambda_t] = E[\epsilon_t] = 0, \quad \epsilon_t, \Lambda_t \sim IID \quad (1.1)$$

$$Var(R_t) = \sigma^2$$

These true returns represent the returns updated with the contemporaneous flow of information in a frictionless market, determining the equilibrium value of the fund's underlying assets. However, investors only observe the smoothed returns R_t^0 which are weighted averages of the true returns over the most recent $k + 1$ and current periods :

$$R_t^0 = \theta_0 R_t + \theta_1 R_{t-1} + \dots + \theta_k R_{t-k} \quad (1.2)$$

$$\theta_j \in [0, 1], j = 0, \dots, k$$

$$1 = \theta_0 + \theta_1 + \dots + \theta_k$$

Furthermore, we define ξ the Herfindahl index of the smoothing weights in reported returns, a measure of the concentration of the smoothing process :

$$\xi = \sum_j^k \theta_j^2 \quad (1.3)$$

A lower value of ξ implies a more marked smoothing process, while a greater value indicates a low serial correlation in reported returns.

To estimate the smoothing coefficients, we follow Getmansky et al. (2004) that have used a moving average procedure. We define the de-meaned observed returns process X_t with the following properties :

$$\begin{aligned} X_t &= R_t^0 - \mu \\ X_t &= \theta_0 \eta_t + \theta_1 \eta_{t-1} + \dots + \theta_k \eta_{t-k} \\ \eta &\sim N(0, \sigma_\eta^2) \end{aligned} \quad (1.4)$$

The parameters are obtained through maximum likelihood optimization. Once the weights are estimated, we can recover unsmoothed returns with the following identification :

$$R_t = \frac{R_t^0 - \hat{\theta}_1 R_{t-1}^0 - \dots - \hat{\theta}_k R_{t-k}^0}{\hat{\theta}_0} \quad (1.5)$$

In practice, we follow Getmansky et al. (2004) and fix $k = 2$, meaning that we stop after a lag at the order two. Table 1.2 presents the average empirical results for the whole sample of individual funds as for the different trading styles samples.

Our results are consistent with Asness et al. (2001) and indicate that hedge funds' reported returns exhibit serial correlation, with an average weight on the one month lagged return $\hat{\theta}_1$ of 14%. We further notice that average serial correlations vary greatly across different hedge fund strategies. For example, the average weight on the current "true" return $\hat{\theta}_0$, which can be taken as a proxy for the amount of serial correlation, goes from 64% for Convertible Arbitrage to 98% to Dedicated Short. This difference in serial correlation among strategies may indicate that different trading styles involving different underlying assets and markets induce different levels of serial correlation.

This variability in the amount of serial correlation is nonetheless important across but also within strategies : funds within a given style can report widely different serial correlation estimates, with cross-sectional standard-deviation of the contemporaneous return's weight parameter θ_0 going from 15% for Convertible Arbitrage to 58% for Multi Strategy, indicating that averaging results at the strategy level does not enable to fully assess the impact of serial correlation in the performance measurement process.

Most of the serial-correlation is present at the order one, with low coefficients at order two. Estimates for lag two goes from -5% for Dedicated Short to 15% for Convertible Arbitrage. The Herfindahl index ξ indicates that on average hedge fund reported returns are serially correlated and show a great variability, with an average of 0.73 for a standard-deviation 0.37. Hedge funds report, on average, serially correlated returns but this amount

TABLE 1.2 – Means and standard deviations of the smoothing estimates

This table presents the average (Mean) and the standard deviation (SD) of the MA(2) smoothing process $R_t^0 = \theta_0 R_t + \theta_1 R_{t-1} + \theta_2 R_{t-2}$ and $\xi = \theta_0^2 + \theta_1^2 + \theta_2^2$ is the index of smoothing (the smaller ξ , the greater the smoothing). The sample period is from January 1994 to February 2015.

Serial correlation statistics										
Category	N	$\hat{\theta}_0$		$\hat{\theta}_1$		$\hat{\theta}_2$		ξ		
		Mean	SD	Mean	SD	Mean	SD	Mean	SD	
All	4,864	0.8	0.33	0.14	0.2	0.06	0.2	0.73	0.37	
Convertible Arbitrage	195	0.64	0.15	0.21	0.22	0.15	0.16	0.57	0.27	
Dedicated Short	41	0.98	0.24	0.07	0.17	-0.05	0.17	1.08	0.6	
Emerging Markets	640	0.79	0.16	0.16	0.11	0.05	0.14	0.7	0.3	
Equity Market Neutral	325	0.84	0.24	0.11	0.17	0.05	0.16	0.83	0.57	
Event Driven	554	0.71	0.2	0.19	0.13	0.1	0.12	0.62	0.59	
Fixed Income	209	0.71	0.22	0.19	0.16	0.1	0.13	0.64	0.42	
Long-Short Equity	2,073	0.83	0.34	0.12	0.2	0.05	0.19	0.79	0.55	
Macro	309	0.93	0.29	0.05	0.2	0.02	0.21	1.04	1.05	
Multi Strategy	492	0.79	0.58	0.15	0.29	0.06	0.33	0.68	0.32	
Options	26	0.82	0.17	0.13	0.15	0.05	0.13	0.76	0.28	

of serial correlation is far from uniform. This variation enables us to test for the influence of serial correlation in the performance measures in cross-sectionally linking serial correlation with risk-adjusted returns and systematic risk measures.

To measure risk-adjusted returns and exposures to systematic risk, we use the seven factors shown by Fung and Hsieh (2004) to be of importance to explain the variation of hedge fund returns. These factors are the three trend-following factors of Fung and Hsieh (2001), namely PTFSBD for bonds, PTFSX for currencies and PTFSCOM for commodities¹, two equity factors, the returns of the S&P 500 and the difference of returns between the Russell 2000 and the S&P 500, and two bond oriented-factors, the change in the 10 year Treasury yield and the change in the Moody’s Baa yield minus the 10 year Treasury yield. Taken together, these factors form the Fung and Hsieh seven factor model, which is the standard benchmark for hedge fund performance measurement.

Table 1.3 presents the summary statistics for our risk factors over the sample period January 1994 - February 2015. The hedge fund risk factors present widely different risk/return profiles, with factors having positive and negative returns and diverse volatility profiles. They all exhibit excess kurtosis but only the S&P 500 has negative skewness, which is surprising as on average hedge funds report returns with negative skewness. The three trend-following factors and the bond factor all have negative average returns, which can be explained by a negative correlation with the broad market return. Interestingly, their serial correlation, as measured with an AR(1) process, goes from -3.7% for the trend-following factor on commodities to 31.8% for the credit-spread factor.

1. The trend-following factors are freely available at <http://faculty.fuqua.duke.edu/dah7/DataLibrary/TF-FAC.xls>

TABLE 1.3 – Summary statistics of the risk factors

This table provides summary statistics for each hedge fund risk factor for the period January 1994 - February 2015. This includes the mean (μ), standard deviation (σ), kurtosis, skewness, the Sharpe Ratio (SR) and the serial correlation measured by an AR(1).

	μ	σ	kurtosis	skewness	SR	AR(1)
PTFSBD	-1.36	15.35	5.38	1.34	-0.089	11.91
PTFSFX	-0.62	19.59	4.63	1.09	-0.0318	5.66
PTFSCOM	-0.27	14.36	4.0877	1.6304	-0.0189	-3.7
S&P 500	0.66	4.28	4.182	-0.6954	0.1554	8.03
Size	0.08	3.28	7.89	0.03	0.0268	5.67
Bond	-0.12	7.3	-0.03	5.86	-0.018	8.43
Credit Spread	0.33	20.97	12.81	1.19	0.02	31.8

1.2.2 Risk-adjusted returns in the hedge fund industry

We now question the existence of "skill" among hedge fund managers and investigate its relationship with serial correlation. We proxy skill as positive and statistically significant risk adjusted returns with respect to common risk factors, i.e. the portion of expected returns that is not captured by traditional Fung and Hsieh risk factors. This is a traditional measure of skill in the hedge fund performance measurement literature, used by Fung and Hsieh (2004), Titman and Tiu (2011) and Sun et al (2012), among others.

We hypothesize that the degree of serial correlation in hedge fund returns might affect the magnitude of measured "skill". Indeed, Scholes and Williams (1977) show that serial-correlation induced by infrequent trading, i.e. the fact that some securities exhibit stall prices, bias the statistical properties of least-squares estimators. Dimson (1979) finds that serial-correlation decreases the beta estimates and henceforth artificially increase the measured alpha. Therefore, serially correlated hedge fund reported returns may artificially indicate managers' "skill" and skew our perception of hedge funds' risks.

We first show evidence of "skill" in the hedge fund industry, as measured by the alpha with respect to the Fung and Hsieh seven factors of hedge fund indices. Then, using a bootstrap framework, we show that the observed proportion of funds exhibiting skill cannot be considered the product of luck alone.

Skill at the hedge fund index level

In this section, we empirically examine the presence of skill in hedge fund indices' returns, when we do not control for serial correlation. Because investment strategies are vastly different among the hedge fund industry, we expect that they are exposed to different risk factors and exhibit varying degrees of measured skill.

TABLE 1.4 – Factors’ exposure at the index level

	α	PTFSBD	PTFSFX	PTFSCOM	S&P 500	Size	Bond	Credit Spread	R-squared
Convertible Arbitrage	0.42 (2.66)***	-0.84 (-1.09)	-0.87 (-1.07)	-1.08 (-1.19)	18.7 (4.48)***	4.92 (1.48)	-1.18 (-3.48)***	-3.43 (-7.02)***	39.48
Dedicated Short	0.62 (2.84)***	0.31 (0.18)	-0.31 (-0.31)	-0.03 (-0.02)	-65.7 (-9.89)***	0.17 (0.05)	-0.04 (-0.6)	-0.22 (-0.2)	48.33
Emerging Markets	0.53 (1.9)*	-2.64 (-1.12)	0.45 (0.42)	-0.94 (-0.7)	54.57 (12.91)***	0.87 (0.24)	-0.09 (-0.01)	-2.68 (-2.55)***	40.17
Equity Market-Neutral	0.97 (4.63)***	-2.87 (-1.28)	2.89 (1.36)	0.34 (0.36)	-5.01 (-0.51)	-5.55 (-1.56)	1.55 (1.3)	3.07 (1.13)	8.8
Event-Driven	0.62 (7.15)***	-1.47 (-2.44)***	0.21 (0.54)	-1.18 (-2.12)**	23.36 (12.61)***	0.63 (0.39)	-0.43 (-1.51)	-2.36 (-7.57)***	59.65
Fixed-Income	0.59 (7.12)***	-0.85 (-1.42)	-0.9 (-1.68)*	-0.05 (-0.1)	6.77 (2.85)***	0.67 (0.51)	-0.59 (-1.87)*	-2.26 (-5.27)***	30.33
Long/Short Equity	0.72 (5.77)***	-0.7 (-1)	0.99 (1.9)*	-0.64 (-0.85)	45.37 (17.09)***	-0.67 (-0.37)	-0.15 (-0.34)	-1.36 (-2.08)**	59.17
Macro	0.64 (6.73)***	-0.84 (-1.1)	3.33 (4.92)***	1.02 (1.31)	16.62 (6.43)***	0.32 (0.18)	0.06 (0.13)	-0.44 (-0.59)	27.74
Multi-Strategies	0.65 (7.07)***	-0.37 (-0.84)	0.23 (0.67)	-0.27 (-0.52)	20.27 (12.24)***	0.98 (0.61)	-0.45 (-1.79)*	-1.56 (-5.56)***	49.21
Options	0.7 (7.96)***	-0.06 (-0.08)	0.05 (0.09)	-0.71 (-1.43)	9.54 (4.49)***	1.78 (1.07)	0.31 (0.6)	0.5 (0.75)	12.14
All	0.65 (6.4)***	-1.18 (-1.88)*	0.85 (2.05)**	-0.52 (-0.88)	32.34 (16.69)***	-0.07 (-0.05)	-0.16 (-0.43)	-1.44 (-2.77)***	57.74

This table shows the results of regression of hedge funds indices built in averaging our individual hedge fund returns on the Fung & Hsieh seven risk factors. The R-squared column presents adjusted R-squared. Results are for the sample January 1994 - February 2015. The results statistically significant at the 10% risk level are indicated by a *, 5% by ** and 1% ***

We construct the hedge fund indices from the data on individual hedge fund returns. Each month, we take the return of an index as the fund-weighted average of its constituent individual hedge fund returns. Table 1.4 reports the results of the time-series regressions of hedge fund indices' returns on Fung and Hsieh seven factors. Results show that all but the Emerging Markets index have positive and statistically significant risk-adjusted returns at the 5% risk level, showing that at the index level hedge funds are for almost all strategies perceived as "skilled". The most "skilled" strategy is Equity Market-Neutral, with a monthly alpha of 0.97% but no significant exposure to any systematic risk factor. The adjusted R-squared goes from 8.8% for the strategy Equity Market Neutral to 59.65% for the Event Driven index, showing that on average the strategy equity-market neutral is not well explained by the standard hedge fund risk factors : only the constant is statistically significant.

Consistent with past academic research on hedge fund investment such as Hasanhodzic and Lo (2007) or Agarwal and Naik (2004), our results indicate that globally, hedge funds deliver statistically significant risk-adjusted returns. Here we confirm that hedge fund present evidence of positive risk-adjusted returns when we do not control for serial correlation.

Are individual hedge funds skilled? A bootstrap approach

We have seen previously that hedge fund have positive risk-adjusted returns at the index level. However, individual hedge funds exhibit high degrees of heterogeneity, even within a given strategy, as shown by Brown and Goetzman (2003). A way of taking into account this heterogeneity is to directly study the presence or not of outperformance at the individual hedge fund level. To do so, we now investigate the proportion of individual funds exhibiting "skill", as measured by a positive and statistically significant alpha in a Fung and Hsieh seven factors regression.

Table 1.5 reports the cross-sectional distribution of t-statistics for the regressions' alphas across individual funds. It shows the percentage of observed alphas' t-statistics exceeding indicated cutoff values. For example, 49.26% of the individual funds have t-statistics greater than 1.645, and hence have alphas statistically significant at the 10% risk level. Our results show that, for the overall sample of individual funds, there is a far thicker right tail of the cross-sectional distribution of the risk-adjusted returns' t-statistics than the left tail. Indeed, 42.33% and 35.79% have t-statistics exceeding 1.96 and 2.326 respectively, while only 1.54% of the funds have t-statistics smaller than -2.326 and -1.96. This result is consistent with positive skill with respect to the Fung and Hsieh seven factors.

When we break down the cross-sectional distribution of alphas' t-statistics by trading style, our results are qualitatively similar. Each hedge fund strategy have right tails of their t-statistics' distribution far thicker than the left tails. The strategy Emerging Markets has the thinnest right tail with 26.09% and 19.69% of the funds having t-statistics exceeding 1.96 and 2.326, while having only 3.59% and 2.5% of t-statistics inferior to -1.96 and -2.326 respectively. Overall, a large part of the individual hedge funds exhibit skill, and only a small subset of funds have negative skill. Consistent with past studies, more than half the funds have no statistically significant alpha, indicating that their returns could be replicated passively.

The empirical cross-sectional distribution of individual funds risk-adjusted returns t-statistics, both at the global sample and strategies samples' levels, suggests that a large portion of individual hedge funds presents "skill" as measured with respect to a common set of risk benchmarks.

TABLE 1.5 – Percentage of funds significantly skilled and unskilled

Cross-sectional distribution of t-statistics for the seven factors' alpha coefficients across individual hedge funds. This table reports the number of funds having t-statistics for different cut-offs values. For each fund having at least 36 monthly return observations, we estimate the Fung and Hsieh seven factors' model $r_{p,t} = \alpha_p + \sum_{j=1}^J \beta_{i,j} f_{j,t} + \epsilon_{p,t}$ where $r_{p,t}$ is the return on each individual fund in month t . The explanatory variables are $\sum_{j=1}^J f_j$ the Fung and Hsieh seven factors. The coefficient α_p measures the risk-adjusted returns and proxy for manager's skill. The results are for the sample January 1994 - February 2015. The significance thresholds are 1%, 5% 10% ad 20% for absolute values of 2.326, 1.96, 1.645 and 1.282 respectively.

	percentage of the funds							
	t<-2.326	t<-1.96	t<-1.645	t<-1.282	t>1.282	t>1.645	t>1.96	t>2.326
Convertible-Arbitrage	1.54	1.54	2.05	3.08	64.1	58.97	52.31	49.74
Dedicated Short	0	2.44	7.32	7.32	43.9	36.58	31.71	19.51
Emerging Markets	2.5	3.59	4.22	5.94	42.03	32.5	26.09	19.69
Equity Market-Neutral	0	0.32	0.32	0.65	63.75	52.75	44.34	40.78
Event-Driven	0	0.18	0.72	1.62	75.99	70.22	65.34	58.12
Fixed-Income	0.96	1.43	1.43	1.43	70.33	64.11	59.33	55.5
Longshort Equity	0.29	0.77	1.35	2.03	55.82	46.55	38.64	31.26
Macro	1.54	1.54	3.38	5.85	49.85	43.38	35.38	27.08
Multi-Strategies	0.2	1.63	2.03	4.27	56.5	50.61	45.53	40.24
Options	0	0	0	0	80.77	65.38	53.85	46.15
All	0.68	1.25	1.87	2.93	57.24	49.26	42.33	35.79

To further assess the statistical significance of the risk-adjusted returns for individual hedge funds, we then follow a bootstrap procedure. Indeed, when we infer the cross-sectional of outperformance in individual hedge fund returns, standard parametric inferences may not apply due to potential cross-sectional outperformance correlation within funds in a similar strategy or to the non-normality of hedge fund returns. The bootstrap procedure will enable us to overcome this potential bias in our inference. The objective is to challenge our results and to see if the high proportion of "skilled" hedge funds can be due to luck only. For each cross-sectional statistic of the t-statistic of the hedge funds alpha, we compare the empirical estimate with the corresponding distribution of cross-section t-statistic estimates based on bootstrapped pseudo-funds, i.e. individual hedge funds without the alpha coefficient. This procedure gives the likelihood to obtain the same cross-sectional estimates due to luck only, i.e. that all funds are in reality unskilled and hence have true alpha of zero.

Our methodology is similar to that of Cao et al. (2013) and Kosowski et al. (2006), and reframes the initial method developed by Efron (1979). The idea here is to randomly resample data, i.e. regression residuals, to generate funds returns that have the same factor loadings as the actual funds returns except that they have no risk-adjusted returns. Then we evaluate if the t-statistics of the alpha coefficients obtained from the bootstrapped distribution, that assumes no risk-adjusted returns, are different from the real hedge fund returns.

Our bootstrap procedure follows five steps :

1. we estimate the Fung and Hsieh seven factors model for fund p :

$$r_{p,t} = \alpha_p + \sum_{j=1}^J \beta_j f_{j,t} + \epsilon_{p,t} \tag{1.6}$$

where α_p is the intercept of the regression, J is the number of risk factors, $\sum_{j=1}^J \beta_j f_{j,t}$ is the part of the returns captured by the Fung and Hsieh seven factors' exposures and $\epsilon_{p,t}$ is the vector of the residuals.

We store the estimated coefficients $(\hat{\alpha}_p, \hat{\beta}_1, \dots)$ as well as the time series of residuals $(\hat{\epsilon}_{p,t}, t = 1, \dots, T_p)$ where T_p is the number of monthly observations for fund p ;

2. we resample the residuals with replacement in order to obtain a randomly resampled residual time series $\hat{\epsilon}_{p,t}^b$, where b is the index of the bootstrap iteration ($b = 1, 2, \dots, B$). We generate monthly returns for a fund that has no excess return by construction, i.e. $\alpha_p = 0$;

$$\tilde{r}_{p,t} = \sum_{j=1}^J \hat{\beta}_j f_{j,t} + \hat{\epsilon}_{p,t}^b \quad (1.7)$$

3. we estimate the seven factors' model Eq (1.6) using the bootstrapped returns obtained from Step 2, and we store the estimate of the alpha and its t-statistic. Because we build bootstrapped returns with a true $\alpha_p = 0$, any nonzero t-statistic and coefficient for excess return comes from sampling variation;
4. we complete steps 1-3 across all the funds so that we can observe the cross-sectional statistics of the estimates and their t-statistics for risk-adjusted returns.
5. we repeat steps 1-4 for B iterations to generate the empirical distributions for the cross-sectional statistics. We set $B = 10,000$ in our analysis. For a given cross-sectional statistic, we calculate its empirical p-value as the frequency that the values of the bootstrapped cross-sectional statistic for the bootstrapped funds from B simulations exceed the observed value of the cross-sectional statistic for the real funds.

This bootstrap procedure enables us to assess the likelihood that a positive or negative test outcome for risk-adjusted returns is the consequence of pure noise. For each cross-sectional statistic of the t-statistic of the intercept coefficient, we compare the estimate from the real hedge fund sample to the distribution for the bootstrapped funds.

Table 1.6 reports the empirical p-values corresponding to the t-statistics of risk-adjusted at extreme percentiles from the bootstrap analysis. For all percentiles considered, from 1% to 10%, top alpha funds, as measured by their associated alpha t-statistic, have a very low likelihood of being "skilled" by pure luck. More specifically, for the global sample of our 4,864 individual hedge funds, the t-statistics for the risk-adjusted return for the top 1%, 3%, 5% and 10% funds are 11.66, 7.41, 6.01 and 4.6 respectively with empirical p-values very close to zero.

We also investigate the bootstrap analysis for funds in each strategy category. We find low empirical p-values for the top-ranked t-statistics for every strategy, confirming the idea that most hedge funds are not skilled by chance. Furthermore, the negative risk-adjusted returns cannot be attributed to a lack of luck for individual funds. Indeed, the bottom 1% t-statistics have empirical p-values of 1 for all the strategies, Options excepted, which has a p-value of 0.28. These low p-values demonstrates that a sub-sample of hedge funds outperform the markets without this fact being the result of luck. Some hedge fund managers can then be considered as "skilled"

Figure 1.1 shows the kernel density distributions of bootstrapped 10th percentile t-statistics in grey areas and the actual t-statistics of the estimated alpha for the 10th percentile as a vertical line. First, these graphs show that the distributions of the bootstrapped t-statistics are non-normal. Second, we notice that, for the global sample and for most strategies as well, the top 10% cross-sectional t-statistics are really far away to the right from the tail of the bootstrapped distributions, making really unlikely that those statistics are obtained by luck only. From these distributions, we can confidently say that a sample of individual hedge funds earn positive risk-adjusted returns for other reasons than luck.

Category	Number of funds		Bottom t-statistics for α				Top t-statistics for α			
			1%	3%	5%	10%	10%	5%	3%	1%
All funds		t-statistic	-2.04	-1.24	-0.84	-0.31	4.6	6.01	7.41	11.66
		p-value	1	1	1	0	0	0	0	0
Convertible arbitrage		t-statistic	-2.39	-1.05	-0.86	-0.6	6.63	8.25	9.86	43.74
		p-value	1	0.99	0.99	0.99	0	0	0	0
Dedicated Short		t-statistic	-1.9	-1.73	-1.65	-0.63	3.82	4.14	4.15	4.3
		p-value	1	1	1	0.99	0	0	0	0
Emerging Markets		t-statistic	-3.56	-2.04	-1.52	-0.93	3.27	4.13	5.72	8.28
		p-value	1	1	1	1	0	0	0	0
Equity Market Neutral		t-statistic	-1.15	-0.74	-0.44	-0.02	4.7	6.12	7.07	11.25
		p-value	0.8	0.37	0	0	0	0	0	0
Event Driven		t-statistic	-1.54	-0.81	-0.5	0.14	6.64	9.39	10.21	15.74
		p-value	1	0.9	0.01	0	0	0	0	0
Fixed Income		t-statistic	-2.17	-0.71	-0.41	0.15	8.14	12.51	29.35	61.91
		p-value	1	0.22	0	0	0	0	0	0
Long-Short Equity		t-statistic	-1.83	-0.94	-0.63	-0.13	3.78	4.54	5.19	6.47
		p-value	1	1	0.95	0	0	0	0	0
Global Macro		t-statistic	-2.68	-1.76	-1.34	-0.39	3.53	4.19	4.78	5.54
		p-value	1	1	1	0.03	0	0	0	0
Multi-Strategy		t-statistic	-1.99	-1.52	-0.96	-0.6	5.71	7.92	9.19	13
		p-value	1	1	1	1	0	0	0	0
Options		t-statistic	-0.7	-0.56	-0.16	0.89	3.36	4.11	4.44	4.59
		p-value	0.28	0.21	0	0	0	0	0	0

TABLE 1.6 – Bootstrap analysis of risk-adjusted returns

This table represents the results of the bootstrap analysis of risk-adjusted returns. For each fund having at least 36 monthly return observations, we estimate the model $r_{p,t} = \alpha_p + \sum_{j=1}^J \beta_{i,j} f_{j,t} + \epsilon_{p,t}$ where $r_{p,t}$ is the return on each individual fund in month t . The explanatory variables are $\sum_{j=1}^J f_j$ the Fung and Hsieh seven factors. In the table, the first row reports the sorted t-statistics of risk-adjusted returns across individual funds, and the second row is the empirical p-values from bootstrap simulations. The number of resampling iterations is 10,000.

1.3 Asset pricing implications of serial-correlation in hedge fund returns

We show that there is strong evidence of perceived "skill" in the cross-section of individual hedge fund returns. We now want to investigate what is the impact of serial correlation in reported returns on these measures of hedge fund managers' skill. We first look at the relationship between hedge funds' serial correlation and risk-adjusted returns. Then, we check if serial-correlation in hedge fund returns are linked with the amount of measured systematic risk.

1.3.1 Serial correlation and risk-adjusted returns

Scholes and Williams (1977) demonstrate that infrequently traded financial instruments will exhibit serially correlated returns, biasing estimates. More specifically, the estimated risk adjusted returns will be biased upward and the market beta will be biased downward, giving a false impression of outperformance.

Given the amount of serial correlation found in hedge fund reported returns and its huge variability, we want to formally test its impact on risk-adjusted returns. Specifically, do more serially correlated funds have higher risk adjusted returns? We want to know if serial-correlation is a driver of individual hedge funds' cross-sectional differences in risk adjusted returns, as measured by the Fung and Hsieh seven-factors' alpha.

To answer this question, we first follow a simple non-parametric approach and sort individual hedge fund returns into decile portfolios, sorted with respect to their serial correlation. We measure the amount of serial correlation as the weight $\hat{\theta}_0$ on the current contemporaneous "true" return in reported returns. The higher this weight, the lower the serial correlation in a given funds' returns. So our deciles are ranked from the most serially correlated (low $\hat{\theta}_0$) to the least (high $\hat{\theta}_0$).

Table 1.7 reports the results for our decile portfolios. The global sample portfolios θ_0 goes from 0.49 for the first decile to 1.26 for decile 10. We find that, as the current weight on the contemporaneous "true" return θ_0 increases from the bottom to the top decile, the measured risk-adjusted return is globally decreasing. There seems that a relationship exists between the amount of serial correlation and the magnitude of risk-adjusted returns. The first decile has a monthly risk-adjusted return of 0.69% while the last decile has an alpha of 0.3%, giving a economically and statistically significant difference in measured monthly risk-adjusted performance of -0.39%.

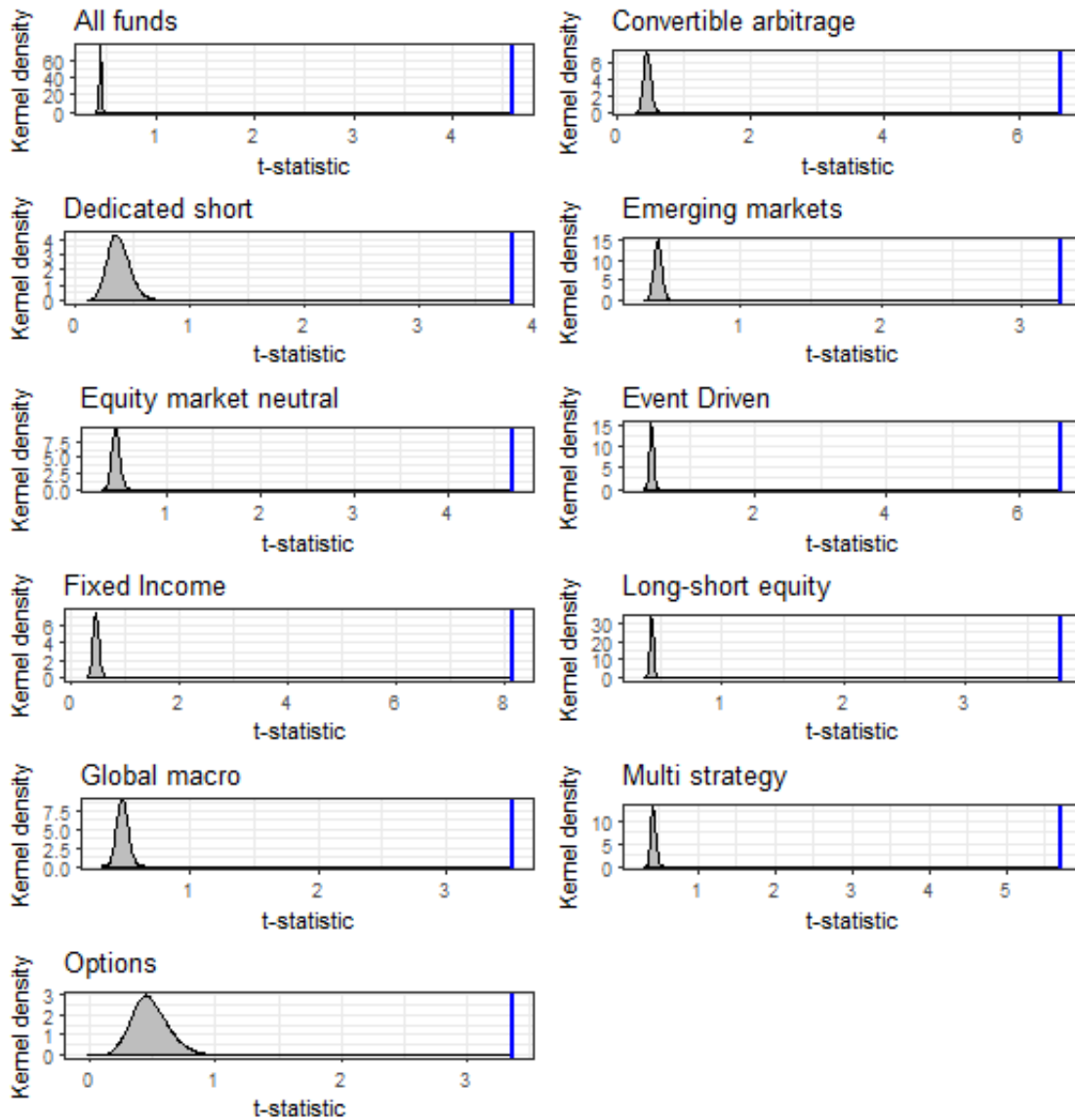
We further investigate this relationship for the different strategies' subsamples. All but the strategies Dedicated Short and Macro exhibit a negative statistically significant high-minus-low risk-adjusted return. The other two strategies have positive but non statistically significant high-minus-low alphas. These results mean that for almost every strategy subsample as for the global sample of individual funds, the most serially correlated hedge funds seem to outperform the lowest serially correlated funds. Hence, funds selected as being "skilled" can in fact only be the most serially correlated funds.

To further analyze the relation between serial-correlation in hedge funds' reported returns and measured risk-adjusted returns in using a parametric regression framework. More specifically, we conduct Fama and McBeth (1973) two-stage regressions of individual funds' risk-adjusted returns on their weight on current "true" return θ_0 . For each individual hedge fund i , we estimate risk-adjusted returns from the Fung and Hsieh seven factor model :

$$R_t^i = \alpha^i + \sum_{k=1}^7 \beta_{FH,k}^i R_t^k + \epsilon_t^i \quad (1.8)$$

FIGURE 1.1 – T-statistics of the risk-adjusted returns for the top 10th percentile : actual versus bootstrapped funds

The grey area represents the density distribution of t-statistics of the coefficient alpha for 10,000 bootstrapped funds that appear at the top 10th percentile in each of 10,000 bootstrap simulations for the cross-section of sample funds. The vertical line corresponds to the actual t-statistics for the risk-adjusted returns' coefficient for the actual fund at the top 10th percentile for each fund strategy category. The sample period is from January 1994 to February 2015.



	Low	2	3	4	5	6	7	8	9	High	High-Low
All	θ_0	0.49	0.62	0.68	0.72	0.76	0.83	0.89	0.97	1.26	0.76
	α	0.69	0.63	0.65	0.71	0.62	0.51	0.51	0.59	0.3	-0.39
		(17.56)***	(14.74)***	(16.27)***	(22.49)***	(21.31)***	(13.48)***	(17.42)***	(6.07)***	(7.38)***	(-7.01)***
Convertible-Arbitrage	θ_0	0.41	0.5	0.53	0.56	0.59	0.67	0.72	0.81	0.92	0.51
	α	0.58	0.57	0.43	0.76	0.61	0.58	0.41	0.02	-0.18	-0.75
		(5.02)***	(6.59)***	(3.99)***	(6.18)**	(7.34)***	(3.32)**	(4.52)***	(0.29)	(-1.37)	(-4.38)***
Dedicated-Short	θ_0	0.71	0.75	0.83	0.87	0.9	0.98	1.04	1.19	1.43	0.73
	α	0.57	0.8	0.47	0.76	0.3	0.68	1.32	1.33	1.15	0.58
		(2.07)**	(1.03)	(3.19)***	(0.21)	(0.9)	(3.06)***	(2.53)***	(3.03)***	(1.54)	(0.86)
Emerging-Markets	θ_0	0.54	0.65	0.69	0.72	0.75	0.81	0.85	0.93	1.12	0.58
	α	0.72	-0.06	0.66	0.57	0.52	0.32	0.29	0.4	-0.06	-0.78
		(4.8)***	(-0.33)	(5.47)***	(6.06)**	(6.22)***	(4.57)***	(3.18)***	(3.05)***	(-0.39)	(-3.76)***
Equity Market-Neutral	θ_0	0.53	0.64	0.7	0.74	0.78	0.86	0.93	1.02	1.32	0.79
	α	0.87	0.52	0.51	0.52	0.61	0.4	0.5	1.9	0.26	-0.61
		(5.76)***	(8.22)***	(6.14)***	(7.19)***	(5.9)***	(4.79)***	(7.38)***	(1.37)	(3.5)***	(-3.79)***
Event-Driven	θ_0	0.49	0.57	0.6	0.63	0.66	0.73	0.78	0.84	1.05	0.56
	α	0.77	0.83	0.69	0.77	0.77	0.69	0.57	0.54	0.39	-0.37
		(7.33)***	(7.64)***	(12.29)***	(9.53)***	(4.23)**	(9.65)***	(5.44)***	(6.9)***	(3.69)***	(-2.36)***
Fixed-Income	θ_0	0.39	0.51	0.58	0.63	0.67	0.75	0.8	0.88	1.09	0.7
	α	0.85	0.84	0.62	0.71	0.61	0.55	0.23	0.22	0.28	-0.57
		(7.62)***	(4.26)***	(6.55)***	(6.71)***	(5.49)***	(5.98)***	(1.37)	(1.58)	(2.05)**	(-2.72)***
Long-Short Equity	θ_0	0.54	0.68	0.72	0.76	0.79	0.86	0.91	0.98	1.23	0.69
	α	0.77	0.81	0.81	0.73	0.59	0.59	0.58	0.59	0.36	-0.41
		(12.23)***	(14.64)***	(15.74)***	(16.94)***	(12.64)***	(13.44)***	(14)***	(6.22)***	(6.83)***	(-5.19)***
Macro	θ_0	0.61	0.71	0.77	0.81	0.86	0.95	1.01	1.13	1.51	0.9
	α	0.27	0.66	0.55	0.57	0.74	0.65	0.4	0.21	0.43	0.16
		(0.74)	(4.67)***	(4.15)***	(3.99)**	(4.86)***	(7.89)***	(5.08)***	(1.39)	(1.46)	(0.35)
Multi-Strategies	θ_0	0.47	0.57	0.62	0.66	0.7	0.81	0.86	0.95	1.33	0.86
	α	0.64	0.68	0.44	0.41	0.62	0.46	0.47	0.41	0.13	-0.51
		(5.86)***	(10.29)***	(3.25)***	(4.99)**	(7.27)***	(4.93)***	(1.91)*	(4.29)***	(1.39)	(-3.67)***
Options	θ_0	0.58	0.62	0.65	0.69	0.8	0.88	0.92	0.93	1.05	0.47
	α	1.02	0.98	1.13	1.03	0.6	1.31	1.41	0.58	0.82	-0.2
		(38.13)***	(16.47)***	(3.96)***	(61.89)***	(4.33)***	(8.94)***	(1.46)	(2.17)**	(21.64)***	(-4.98)***

TABLE 1.7 – Decile portfolios of hedge funds sorted by serial correlation

This table reports properties of equal-weighted decile portfolios of individual hedge funds. For each fund having at least 36 monthly return observations, we estimate the Fung & Hsieh model $r_{p,t} = \alpha_p + \sum_{j=1}^J \beta_{i,j} f_{j,t} + \epsilon_{p,t}$ where $r_{p,t}$ is the return on each individual fund in month t . The explanatory variables are $\sum_{j=1}^J f_j$ the Fung and Hsieh seven factors. Simultaneously, we estimate an MA(2) model on $r_{p,t}$. Portfolios are formed in ranking each fund according to its weight of the current return on its reported returns θ_0 , so the portfolio Low is the portfolio with the lowest θ_0 . The sample period is January 1994 - February 2015. For each decile portfolio, we report the average serial correlation parameter θ_0 , the average risk-adjusted return α and its t-statistic.

To further analyze the relation between serial-correlation in hedge funds' reported returns and measured risk-adjusted returns in using a parametric regression framework. More specifically, we conduct Fama and McBeth (1973) two-stage regressions of individual funds' risk-adjusted returns on their weight on current "true" return θ_0 . For each individual hedge fund i , we estimate risk-adjusted returns from the Fung and Hsieh seven factor model :

$$R_t^i = \alpha^i + \sum_{k=1}^7 \beta_{FH,k}^i R_t^k + \epsilon_t^i \quad (1.9)$$

where R_t^i is the return of fund i in month t , α^i is the risk-adjusted return, $\beta_{FH,k}^i$ is the exposure of fund i to the risk factor k and ϵ_t^i is the the residual of fund i in month t . We then estimate the serial correlation parameters with a moving average process of order two as in Eq (1.4) and run a cross-sectional regression of individual funds' risk-adjusted returns on the weight on current "true" returns :

$$\hat{\alpha}^i = \gamma + \lambda_{\theta_0} \hat{\theta}_0^i + \nu^i \quad (1.10)$$

where $\hat{\alpha}^i$ is the measured Fung and Hsieh seven factors' alpha of fund i , γ is the intercept, λ_{θ_0} is the slope coefficient and ν^i is the residual for fund i .

Table 1.8 presents the estimates for the cross-sectional regressions for the global sample of individual hedge funds and for the subsamples of hedge funds by trading styles. We find that, for the whole sample of individual funds, we have a negative slope of -0.2% statistically significant at the 5% risk level with both Newey-West's (1987) estimators corrected for serial-correlation and heteroskedasticity (using the automatic lag selection of Newey and West (1994)), with a t-statistic of -2.2529, and Hansen's (1982) generalized methods of moments, with a t-statistic of -2.2613. This implies that there is a negative relationship between the weight on contemporaneous "true" return in reported returns and the measured amount of risk-adjusted returns. At the individual level, the more a fund has serially correlated reported returns, the higher is its measured risk-adjusted returns. Hence, the subsample of "skilled" funds managers obtained in the previous section has higher serial correlation on average than the rest of funds, indicating that they have biased risk-adjusted returns estimates.

When we look at the different strategies' subsamples, we notice that half of the strategies have negative and statistically significant slopes at the 10% level, confirming the result obtained with the global sample. Strategies Equity Market Neutral and Long/Short Equity have a negative but statistically non-significant slopes. Only one strategy, Dedicated Short, exhibits a positive and statistically significant slope, meaning that less serially correlated funds have higher risk-adjusted returns. These results show that, even with smaller cross-sectional subsamples, the relationship holds in the majority of the cases.

To further investigate the relation between risk adjusted returns and serial correlation for individual hedge funds, we use a rolling-window framework. The idea is to repeat our asset pricing tests over time-rolling subsamples in order to get a cross-validation of our previous results and allow for time-variation in serial-correlation and risk exposures. Indeed, Bollen and Whaley (2009) show that time-variation in risk exposures can bias performance measurement. We also expect that changes in serial-correlation may have the same effect and hence want to control it. We first use a non-parametric portfolio approach. Specifically, we form both quintile and decile portfolios of hedge funds every month using three-year weights on current "true" returns in reported returns, estimated with a MA(2) process as in Getmansly et al. (2004). Funds are kept in the portfolios for one month.

At any given month, we exclude funds having missing observations. A period of thirty-six months ensure the accuracy of our serial correlation estimates while allowing for flexibility in the time variation. The portfolio formation begins in January 1997 and ends February 2015, giving 219 monthly observations. Once funds are sorted into the portfolios, we estimate the average portfolio risk-adjusted return as the average of the individual Fung and Hsieh seven factors' alphas of funds in each portfolio.

FIGURE 1.2 – Risk-adjusted returns for decile portfolio sorted according to serial correlation

Each month hedge funds are sorted into 10 equally weighted portfolios according to their serial correlation coefficient θ_0 . θ_0 is defined as the current true return's weight on reported returns. For each fund having at least 36 monthly return observations, we estimate the Fung and Hsieh model $r_{p,t} = \alpha_p + \sum_{j=1}^J \beta_{i,j} f_{j,t} + \epsilon_{p,t}$ where $r_{p,t}$ is the return on each individual fund p in month t .

The explanatory variables are $\sum_{j=1}^J f_j$ the Fung and Hsieh seven factors. Portfolios' risk-adjusted returns are the average of individual funds' alphas in the portfolio. The sample period covers the period January 1997 to February 2015. The figure also displays the high-minus low portfolio.

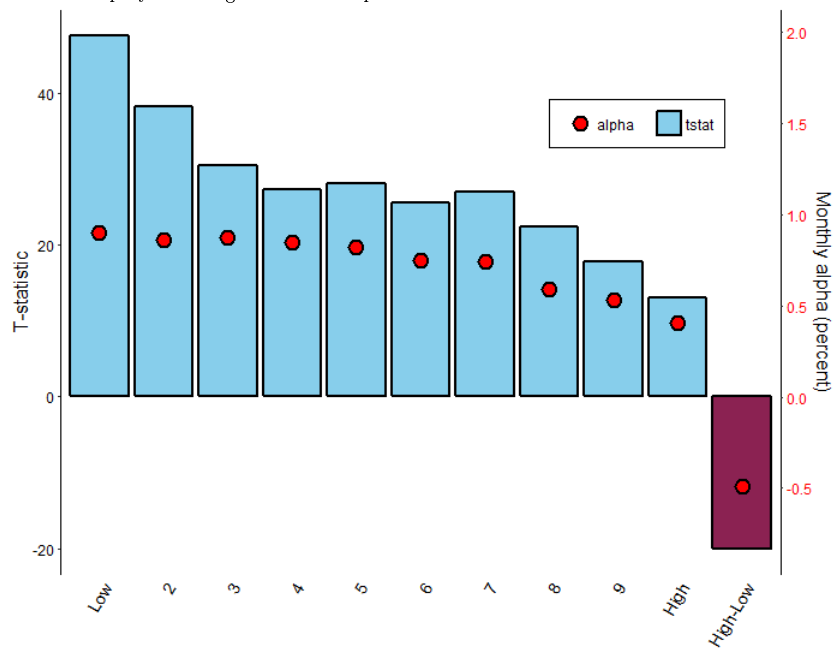


Figure 1.2 shows the time-series average risk-adjusted returns (points) of each decile portfolio sorted with respect to serial correlation, measured as the weight on the current "true" return θ_0^i , along with their respective time-series t-statistics (bars). The figure shows that the portfolio 1, the most serially correlated portfolio, has the highest risk-adjusted return of 0.9% while the portfolio 10, the least serially-correlated, has the lowest risk-adjusted return of 0.4%. There is a globally decreasing relationship between risk-adjusted returns and the current weight on the "true" return parameter θ_0 . The high-minus-low decile θ_0 portfolio has a monthly risk-adjusted return of -0.5%, highly statistically significant with a t-statistic of -20. This result strongly suggests that the measured alpha of serially correlated hedge funds is far higher than those of non-serially correlated funds, giving a gap in measured performance.

	All	Convertible-Arbitrage	Dedicated Short	Emerging	Equity MN	Macro	Event-Driven	Fixed-Income	LS Equity	Multi-Strat	Options
Intercept	0.73	1.27	-0.93	1.2	0.71	0.93	1.08	1.04	0.77	0.57	1.84
t_{NW}	(10.4539)***	(6.7544)***	(-1.3608)	(3.356)***	(2.824)***	(3.93)***	(8.9981)***	(4.7829)***	(6.649)***	(8.9777)***	(5.4412)***
t_{GMM}	(10.506)***	(6.5543)***	(-1.4957)	(3.2834)***	(2.808)***	(3.9373)***	(8.991)***	(4.6538)***	(6.6521)***	(8.284)***	(6.1704)***
λ_{θ_0}	-0.2	-1.33	1.68	-1.03	-0.07	-0.46	-0.58	-0.69	-0.15	-0.12	-1.29
t_{NW}	(-2.2529)**	(-4.6357)***	(2.3932)**	(-2.3647)**	(-0.1542)	(-1.84)*	(-3.8398)***	(-2.2119)**	(-1.0742)	(-1.8902)*	(-2.6983)***
t_{GMM}	(-2.2613)**	(-4.5284)***	(2.5017)**	(-2.2612)**	(-0.1536)	(-1.8477)*	(-3.8022)***	(-2.1579)**	(-1.0753)	(-1.8835)*	(-3.2113)***
R^2	0.38	14.11	16.21	2.53	0	1.39	2.12	5.74	0.32	0.56	12.82
nb funds	4,864	195	41	640	325	309	554	209	2,073	492	26

TABLE 1.8 – Risk-adjusted returns’ Fama-McBeth on θ_0 for individual hedge funds

Risk price estimates for the weight of current returns in reported returns θ_0 . Risk prices are the mean slopes of monthly cross-sectional regressions of individual hedge funds’ risk-adjusted returns on exposures to θ_0 . These exposures are estimated in a first-stage time-series regression as in Eq (8). The monthly sample is 01/1994-02/2015. R^2 is the adjusted coefficient of determination in percentage. Generalized methods-of-moments t_{GMM} and Newey-West t_{NW} t-statistics in parentheses adjust for cross-asset correlation in the residuals and for estimation error of the time-series betas.

We report the results for the quintile portfolios in Table 1.9 panel (b). Over the period January 1997 - February 2015, there is a monthly alpha spread of -0.81% for the high-minus-low portfolio, highly statistically significant with a t-statistic of -20.0046, confirming the link between serial correlation and risk-adjusted returns. Table 1.9 panel (b) also reports the risk-adjusted returns for the quintile portfolios of each strategy. Results show that the strategies Convertible arbitrage, Emerging Markets, Event-Driven, Fixed Income Long/Short Equity, Global Macro and Multi Strategy all have negative high-minus-low risk-adjusted returns highly statistically significant. The Equity Market Neutral strategy exhibit a negative but statistically non significant high-minus-low portfolio, while the Dedicated Short high-minus-low portfolio has a positive and statistically significant at the 5% level alpha. Once again, this positive relationship can come from data-snooping due to small sample issues. Another explanation could be the omission of a risk factor in our measurement of alpha. This risk factor should be highly correlated with the degree of serial correlation in hedge fund returns. In this paper, we focus on the first explanation and let the second one for future research.

To assess the pricing impact of the weight on current "true" return θ_0 on the risk-adjusted returns of individual funds, we also use rolling two-stage parametric tests. In the first stage, starting from January 1997, we estimate time-series of serial correlation parameters $\theta_{0,t}^i$ with a MA(2) process over a three-year period, similar to Getmansky et al. (2004). Simultaneously, we estimate time-series of risk-adjusted returns over the same 36-month period with a Fung and Hsieh seven factors model :

$$R_t^i = \alpha_t^i + \sum_{k=1}^7 \beta_{k,t}^i F_t^k + \epsilon_t^i \quad (1.11)$$

where R_t^i is the return on fund i in month t , $\sum_{k=1}^7 \beta_{k,t}^i F_t^k$ is the part of returns explained by Fung and Hsieh risk factors, α_t^i is the risk-adjusted return for fund i in date t .

In the second stage, we use Fama and McBeth cross-sectional regressions of individual hedge fund alphas on the weights on current "true" return in reported returns :

$$\hat{\alpha}_t^i = \omega_t + \lambda_t \cdot \hat{\theta}_{0,t}^i + \epsilon_{cross,t}^i \quad (1.12)$$

where $\hat{\alpha}_t^i$ is the Fung and Hsieh seven factor alpha of fund i in month t , ω_t and λ_t are the intercept of the regression and the slope for month t and $\hat{\theta}_{0,t}^i$ is the weight on contemporary "true" return in reported returns for fund i in month t .

Table 1.9 panel (a) shows the time-series average intercept and slope coefficients from Eq (1.11) over the sample period January 1997 - February 2015. The corresponding t-statistics are in parentheses. Results for the global sample of individual funds show a negative cross-sectional slope of -0.15% highly statistically significant with a t-statistic of -9.6533, indicating a global negative relation between the weight on current "true" equilibrium return in reported returns and risk-adjusted returns. This confirms our intuition that the most serially correlated funds have the highest amount of measured alpha. When we look at the strategies' subsamples, we notice that all but the strategy Equity Market Neutral exhibit strongly statistically significant negative slopes for the coefficient θ_0 . The subsample Equity Market Neutral has a surprising positive and statistically significant slope, which is counter-intuitive.

To summarize our results, serially-correlated hedge funds present higher risk-adjusted returns. This result holds for the global sample of individual funds as for the great majorities of individual strategies and using parametric and non-parametric methodologies, both for the global time-series sample and in a cross-validation fashion. Time variation in serial correlation or risk exposures do not drive our results. We can then confidently conclude that serial correlation is linked to measured risk-adjusted returns : it is then possible than when selecting the subset of "skilled" individual hedge funds, we in fact select the subset of the most serially correlated hedge funds.

1.3.2 Serial correlation and risk exposures

The previous subsection investigates the relationship between the Fung and Hsieh seven factor alpha of individual hedge funds and the amount of serial-correlation present in their reported return. We find that serial correlation is positively correlated with the measured risk-adjusted return. This result is consistent with two non-mutually exclusive interpretations. First, serially correlated hedge funds are exposed to an unknown risk factor, causing probably this serial correlation in their reported returns. The most serially correlated hedge funds are then the most exposed to this specific hidden risk factor who earn a compensation for this systematic non-diversifiable risk loading, which is reflected in measured risk-adjusted returns. The second interpretation states that, consistent with Dimson (1979) and Scholes and Williams (1977), serial-correlation bias regression estimates and so serially-correlated hedge fund exhibit higher risk-adjusted returns due to distortions in their risk measurement.

In this section, we explore this second explanation. Getmansky et al (2004) show that serially-correlated funds have significant exposures to past market returns, inducing artificially lower measured market betas. If the amount of serial-correlation is sufficient to significantly bias upward measured risk-adjusted returns, we should also observe a significant downward bias in measured hedge fund risk betas. We want to test if more serially correlated hedge funds, i.e. funds having lower coefficients θ_0 , have lower risk exposures than less serially correlated funds.

To investigate this relationship, we begin with a simple non-parametric approach. We sort individual hedge funds into decile portfolio sorted with respect to their parameter θ_0^i , i.e. the weight on the contemporaneous "true" return in their observed returns. Once individual funds are sorted, we regress their observed returns on the Fung and Hsieh risk factors. We then compute the average absolute exposure to each risk factor for each decile in order to see if more serially correlated reported returns is associated with lower absolute risk exposures, consistent with a bias in performance measures.

TABLE 1.9 – Rolling-window relation between risk-adjusted returns and serial-correlation

	All	Convertible-Arbitrage	Dedicated Short	Emerging	Equity MN	Event-Driven	Fixed-Income	LS Equity	Macro	Multi-Strat
Intercept	0.85 (31.0937)***	1.22 (32.7198)***	0.67 (6.5813)***	1.15 (14.2171)***	0.42 (5.1242)***	1.08 (30.0094)***	1.38 (37.8534)***	1.03 (25.1571)***	0.91 (27.882)***	1.2 (25.6038)***
λ_{θ_0}	-0.15 (-9.6533)***	-0.88 (-15.4121)***	-0.24 (-2.4084)***	-0.5 (-9.1181)***	0.47 (3.3668)***	-0.58 (-16.0854)***	-0.96 (-18.9142)***	-0.29 (-10.3528)***	-0.26 (-7.5932)***	-0.73 (-12.6236)***

(a) Rolling-window Fama-McBeth cross-sectional regressions of individual hedge fund Fung and Hsieh 7 factors alphas on θ_0

	All	Convertible-Arbitrage	Dedicated Short	Emerging	Equity MN	Event Driven	Fixed-Income	LS Equity	Macro	Multi-Strat
Low θ_0	0.88 (44.62)***	0.83 (39.9292)***	0.45 (7.4651)***	0.93 (16.0748)***	0.81 (15.487)***	0.86 (41.4878)***	0.96 (50.0453)***	1.01 (25.8919)***	0.73 (28.1508)***	0.88 (49.0053)***
2	0.86 (23.64)***	0.72 (29.6433)***	0.44 (6.4725)***	0.84 (13.0779)***	0.76 (31.1171)***	0.77 (38.1895)***	0.82 (49.5127)***	0.92 (23.5445)***	0.78 (31.5403)***	0.77 (35.7954)***
3	0.79 (27.44)***	0.69 (26.099)***	0.46 (7.2905)***	0.84 (12.1545)***	0.71 (15.965)***	0.71 (36.0478)***	0.78 (34.0888)***	0.83 (23.3284)***	0.77 (29.0994)***	0.79 (30.8744)***
4	0.67 (25.41)***	0.64 (20.4755)***	0.54 (8.7545)***	0.79 (12.9696)***	0.65 (9.2978)***	0.63 (28.5934)***	0.69 (22.458)***	0.7 (24.6747)***	0.64 (21.2212)***	0.73 (23.9262)***
High θ_0	0.47 (16.98)***	0.55 (17.63)***	0.61 (8.7364)***	0.42 (7.6103)***	0.67 (4.0313)***	0.48 (16.608)***	0.36 (14.8687)***	0.49 (17.0348)***	0.41 (14.9575)***	0.43 (20.8372)***
High θ_0 - Low θ_0	-0.81 (-20.0046)***	-0.28 (-12.3857)***	0.17 (2.3125)**	-0.51 (-11.9116)***	-0.14 (-0.7973)	-0.38 (-14.3325)***	-0.6 (-20.8399)***	-0.52 (-15.772)***	-0.32 (-8.6125)***	-0.45 (-21.6778)***

(b) Rolling-window quintile portfolios of hedge funds Fung and Hsieh's 7-factors alphas sorted by θ_0

Panel (a) presents cross-sectional estimates of hedge fund Fung and Hsieh 7 factors' alpha regressed on the serial-correlation coefficient θ_0 . θ_0 is defined as the current return's weight on contemporary return. It is estimated through a moving average-process. λ_{θ_0} is the mean slope of monthly cross-sectional regression of hedge fund indices' returns on θ_0 . The exposures are estimated in a first-stage time-series regression (a regression with the Fung and Hsieh 7 factors for the alpha and separately a MA(2) for the serial correlation parameter θ_0). The monthly sample is 01/1994-02/2015.

Panel (b) presents quintile portfolios formed every month by sorting individual hedge funds on their past 24-month financial intermediaries' risk exposure. The sample goes from 01/1996 to 01/2015. Quintile 1 is the portfolio of hedge funds with the lowest θ_0 and quintile 5 is the portfolio of hedge funds with the highest θ_0 . For each quintile portfolio, we report the average 36-month Fung and Hsieh 7 factors' alpha.

Table 1.10 shows the results for each Fung and Hsieh risk factor in the whole sample of individual hedge funds sum of absolute betas. There is a positive and statistically significant spread in average absolute beta for each risk factor, indicating that funds having the lowest θ_0^i , hence reporting more serially correlated returns, are less exposed to systematic risk factors than funds reporting the highest θ_0^i . This result is consistent with the second interpretation of more serially-correlated funds having higher risk-adjusted returns at least partly due to bias in estimators, which reflects itself in the lower exposures to systematic risk.

Next we extend our analysis of the impact of serial correlation on the amount of measured systematic risk exposures with parametric tests. To do so, we use two-stage cross-sectional regressions of individual sum of absolute exposure to standardized risk factors on the weight on current "true" return in reported returns θ_0^i . For each individual hedge fund i we estimate the risk exposures :

$$r_{i,t} = \alpha_i + \sum_{j=1}^J \beta_{i,j} F_{j,t} + \epsilon_{i,t} \quad (1.13)$$

where $r_{i,t}$ is the return of fund i in month t , α_i is the regression intercept, $\beta_{i,j}$ is the exposure of fund i to the risk factor j , $F_{j,t}$ is the return of the Fung and Hsieh factor j in month t and $\epsilon_{i,t}$ is the residual of fund i in month t . We define $\hat{\beta}_{i,j}$ as fund's i absolute estimated beta :

$$\hat{\beta}_i = |\beta_{i,j}| \quad (1.14)$$

Simultaneously, we estimate the serial correlation parameters with a moving average at the order two as in Eq (1.4) to get θ_0^i the weight on the current "true" return in reported returns. Then, for each Fung and Hsieh seven risk factor F_j , we the run cross-sectional regression of absolute estimated betas $\hat{\beta}_{i,j}$ on θ_0^i :

$$\hat{\beta}_{i,j} = \gamma_j + \lambda_{\beta_j} \hat{\theta}_0^i + \nu_{i,j} \quad (1.15)$$

where $\hat{\beta}_{i,j}$ is the measured absolute beta of fund i for factor j , γ_j is the intercept for the cross-sectional regression on factor j , λ_{β_j} is the slope coefficient and $\nu_{i,j}$ is the residual for fund i .

Table 1.11 presents the results for the cross-sectional regressions on each risk factor for the whole sample of individual hedge funds. We find that, for each risk factor, there is a positive slope statistically significant at the 5% level with both Newey-West (1987) and Hansen's (1982) generalized-method-of-moments t-statistics. For example, for the equity market return, there is a positive slope of 13.54% with associated t-statistics of 2.27. This implies a positive linear relationship between θ_0^i and the measured absolute exposure to a risk factor $\hat{\beta}_{i,j}$: the less serially correlated the returns are, i.e. the higher the coefficient θ_0^i is, then the higher the estimated exposures to systematic risk factors are.

	Low	2	3	4	5	6	7	8	9	High	High-Low
θ_0	0.49	0.62	0.68	0.72	0.76	0.8	0.83	0.89	0.97	1.26	0.76
PTFSBD	$ \beta $	2.19	2.3	2.91	2.69	2.84	2.82	3.01	3.38	4.84	2.65 (7.95)***
PTFSFX	$ \beta $	1.49	1.52	1.74	1.91	1.98	2.12	2.09	2.33	4.76	3.25 (8.43)***
PTFSCOM	$ \beta $	1.64	1.92	2.4	2.19	2.44	2.84	2.75	3.17	4.54	4.11 (9.88)***
SP500	$ \beta $	21.32	25.77	34.36	37.96	41.67	42.23	42.71	41.98	52.48	46.51 (9.65)***
Size	$ \beta $	5.52	5.14	6.16	5.03	5.83	5.28	5.78	6.26	8.71	9.28 (6.59)***
Bond	$ \beta $	1.51	1.49	1.56	1.56	1.5	1.68	1.74	1.61	2.61	2.32 (4.61)***
Credit	$ \beta $	3.53	3.56	3.54	3.04	3.35	2.83	3.2	3.09	4.55	4.33 (2.07)**

TABLE 1.10 – Decile portfolios of hedge funds sorted by serial correlation

This table reports properties of equal-weighted decile portfolios of individual hedge funds. For each fund having at least 36 monthly return observations, we estimate the Fung and Hsieh model $r_{p,t} = \alpha_p + \sum_{j=1}^J \beta_{i,j} F_{j,t} + \epsilon_{p,t}$ where $r_{p,t}$ is the return on each individual fund in month t . The explanatory variables are $\sum_{j=1}^J F_{j,t}$ the Fung and Hsieh seven factors. Simultaneously, we estimate an MA(2) model on $r_{p,t}$. Portfolios are formed in ranking each fund according to its weight of the current return on its reported returns θ_0^i . The sample period is January 1994 - February 2015. For each decile portfolio, we report the average serial correlation parameter θ_0^i , the average of absolute betas $|\beta|$ and its high-minus-low t-statistic.

	PTFSBD	PTFSFX	PTFSCOM	SP500	Bond	Size	Credit
Intercept	1.69	1.25	1.64	27.82	1.69	4.38	1.31
t_{NW}	(2.91)***	(2.71)**	(2.86)***	(6.15)***	(2.91)***	(4.71)***	(6.92)***
t_{GMM}	(2.9)***	(2.7)**	(2.88)***	(6.15)***	(2.9)***	(4.73)***	(6.84)***
λ_{β_i}	2.08	1.33	1.45	13.54	2.08	2.39	0.56
t_{NW}	(2.36)**	(1.99)**	(1.99)**	(2.27)**	(2.36)**	(2)**	(2.03)**
t_{GMM}	(2.35)**	(1.98)**	(2)**	(2.27)**	(2.35)**	(2.01)**	(2.02)**
R^2	0.1	2.49	3.75	0.25	0.1	0.22	0.07

TABLE 1.11 – **Absolute betas Fama-McBeth on θ_0 for individual hedge funds**

Estimates for cross-sectional regressions on the weight of current "true" returns in reported returns θ_0 . λ_{β_i} are the slopes of monthly cross-sectional regressions of individual hedge funds' absolute betas on θ_0 . These exposures are estimated in a first-stage time-series regression as in Eq (20). The monthly sample is 01/1994-02/2015. R^2 is the adjusted coefficient of determination in percentage. Generalized methods-of-moments t_{GMM} and Newey-West t_{NW} t-statistics in parentheses adjust for cross-asset correlation in the residuals and for estimation error of the time-series betas.

To sum up, there is strong evidence that funds having a higher degree of serial correlation in their reported returns are less exposed to systematic risk, as measured with their absolute standardized risk factor betas. Taken jointly with the fact, found in the last section, that more serially correlated funds have higher risk-adjusted returns, this indicates that serial correlation in hedge fund returns biases estimates of risk factors' models.

We now deploy a rolling-window framework to dig more deeply into the relationship between serial correlation and exposure to systematic risk. With this procedure, we control for potential time-varying risk exposures in hedge fund returns, as found in hedge fund returns by Patton and Ramadorai (2013) or Bollen and Whaley (2009). We begin with a non-parametric portfolio methodology. We form five and ten portfolios of hedge funds every months, with an equal number of individual funds in each portfolio, sorting them with respect to their three year rolling weights on the current "true" returns in reported returns θ_0 . Portfolios are re-balanced each month. In any given month, we only include funds without missing observations over the three year period. Our portfolios period begins January 1997 and ends February 2015. Once the portfolios are formed, we estimate their average absolute risk exposures, as in Eq (1.13).

Table 1.12 panel (b) shows the quintile portfolio results for the global sample of individual hedge funds for each risk factor. It reports the portfolios' averages of the absolute risk exposures. The results shows that for each Fung and Hsieh risk factor there is a positive and highly statistically significant high-minus-low risk exposure, confirming the strong positive link between measured betas and serial correlation among individual hedge funds.

To further explicit the relation between θ_0 and the absolute betas, we conduct two-stage parametric tests. In the first stage, beginning in January 1997, we estimate $\theta_{0,t}^i$ the month t weight on current "true" returns in fund's i reported returns with a MA(2) process. We simultaneously regress hedge fund returns on the Fung and Hsieh risk factors to get the absolute risk exposures.

In the second stage, we conduct Fama and McBeth cross-sectional regressions of individual hedge fund absolute betas $|\hat{\beta}_t^{i,j}|$ on the weights on current "true" return in reported returns :

$$|\hat{\beta}_t^{i,j}| = \omega_{t,j} + \lambda_{t,j} \cdot \hat{\theta}_{0,t}^i + \epsilon_{cross,t}^{i,j} \tag{1.16}$$

where $|\hat{\beta}_t^{i,j}|$ is the absolute exposure to the Fung and Hsieh factor j of fund i in month t , $\omega_{t,j}$ and $\lambda_{t,j}$ are the intercept of the cross-sectional regression and the slope for factor j in month t and $\theta_{0,t}^i$ is the weight on contemporary "true" return in reported returns for fund i in month t .

TABLE 1.12 – Rolling-window relation between sum of absolute betas and serial-correlation

	PTFSBD	PTFSCOM	PTFSFX	SP500	Bond	Size	Credit
Intercept	3.47 (28.41)***	2.63 (24.67)***	3.18 (26.06)***	34.72 (39.23)***	6.63 (28)***	2.04 (30.61)***	4.2 (20.27)***
λ_{β_i}	1.31 (11.08)***	0.96 (10.51)***	1.36 (9.57)***	10.34 (8.97)***	2.95 (9.39)***	0.78 (8.715)***	2.11 (5.81)***
(a) Rolling-window Fama-McBeth cross-sectional regressions of individual hedge fund Fung and Hsieh 7 factors absolute betas on θ_0							
	PTFSBD	PTFSCOM	PTFSFX	SP500	Bond	Size	Credit
Low θ_0	2.66	2.01	2.39	23.55	5.69	1.72	3.88
2	3.62	2.73	3.41	36.14	7.34	2.19	5.07
3	4.35	3.26	4.35	46.75	8.68	2.65	5.88
4	4.84	3.74	4.99	52.3	10.1	2.94	6.31
High θ_0	6.88	5.05	6.02	54.99	12.62	3.66	7.87
High θ_0 - Low θ_0	4.22 (20.76)***	3.04 (20.59)***	3.63 (17.82)***	31.44 (16.96)***	6.93 (20.12)***	1.94 (17.61)***	3.99 (18.34)***

(b) Rolling-window quintile portfolios of hedge funds Fung and Hsieh's 7-factors absolute betas sorted by θ_0

Panel (a) presents cross-sectional estimates of hedge fund Fung and Hsieh 7 factors' sum of absolute exposures regressed on the serial-correlation coefficient θ_0 . θ_0 is defined as the current return's weight on contemporary return. It is estimated through a moving average-process. λ_{θ_0} is the mean slope of monthly cross-sectional regression of hedge fund absolute exposures to risk factors on θ_0 . The exposures are estimated in a first-stage time-series regression (a regression with the Fung and Hsieh 7 factors for the absolute risk exposures and separately a MA(2) for the serial correlation parameter θ_0). The monthly sample is 01/1997-02/2015.

Panel (b) presents quintile portfolios formed every month by sorting individual hedge funds on their past 36-month financial intermediaries' risk exposure. The sample goes from 01/1997 to 01/2015. Quintile 1 is the portfolio of hedge funds with the lowest θ_0 and quintile 5 is the portfolio of hedge funds with the highest θ_0 . For each quintile portfolio, we report the average 36-month Fung and Hsieh 7 risk factors' absolute betas.

Table 1.12 panel (a) presents the time series average coefficients of the cross-sectional regressions and their associated t-statistics in parentheses. There are positive and highly statistically significant slopes for the global sample of individual hedge funds for each Fung and Hsieh seven risk factors. These findings strongly confirm our intuition of an empirical relation between the amount of serial correlation in individual hedge funds' reported returns and their global exposures to systematic risk and that serial-correlation in hedge fund reported returns is sufficiently strong to bias performance measures in an economically significant manner.

The fact that more serially correlated hedge funds are less exposed to systematic risks than funds reporting less serially correlated returns is consistent with the bias interpretation of serial correlation. Serially correlated returns bias conventional econometric estimators, leading to overestimate risk-adjusted returns and underestimate betas. Fund managers that are perceived as skilled within a regression framework may be considered so due to a high level of serial correlation in their reported returns.

1.4 Serial correlation and false discoveries in the hedge fund industry

Serial correlation in hedge fund returns is linked to higher risk-adjusted returns and lower risk estimates. Does this really influence our perceptions about the distribution of skill in the industry? Stated differently, does filtering for serial correlation in hedge fund returns change the percentage of funds that are considered as truly skilled? In this section, we investigate this question using a False Discoveries approach, as in Barras et al. (2010). This methodology controls for the prior proportion of "lucky" funds, i.e funds that can be considered as measured with a positive and statistically significant alpha by luck alone. This approach is closely linked with the bootstrap as it uses it to determine the distribution of risk-adjusted returns under the null hypothesis, i.e. when we are sure that the funds are zero-alpha.

1.4.1 Serial correlation and the proportion of skilled managers

Linear factor regressions, for example the popular Fung and Hsieh's (2004) seven factor model, indicate that hedge funds deliver statistically significant positive risk-adjusted returns, at the index level and for a substantial subset of individual funds. Given the cross-sectional volatility in observed hedge fund returns, a part of this "skilled" managers may exhibit statistically significant positive risk adjusted returns by luck alone. We have seen previously, with a bootstrap method, that such variability alone cannot account for the vast majority of "skilled" funds.

However, linear regressions are biased due to the presence of strongly serially correlated reported returns. More serially correlated hedge fund returns have higher measured risk-adjusted returns and lower measured risk exposures. Does the serial correlation in hedge fund returns increases the frequency of false discoveries in the right tail of the cross-sectional alpha t-distribution? Stated differently, how much serial correlation increases the probability that a positive alpha fund is statistically significant by luck only, rather than being truly skilled?

To answer this question, we will first look at the proportion of individual hedge funds having statistically significant risk adjusted returns with Newey and West (1987) estimators. These estimators reduce the influence of heteroskedasticity and, specifically interesting in our case, serial-correlation for time-series data. We use the automatic lag selection version of Newey and West (1994).

Table 1.13 reports the cross-sectional distribution of Newey-West's t-statistics associated with risk-adjusted returns across individual funds, showing the percentage of t-statistics exceeding indicated threshold values. Our

results show that, for the overall sample of the individual hedge funds, there has been a slight reduction in the number of funds having positive and statistically significant alphas. For example, with Newey West coefficients, 34.27% and 41.26% of the funds have t-statistics greater than 2.326 and 1.96 respectively, while without the Newey-West correction, these numbers go to 35.79% and 42.33%, as we can see in Table 5. For the strategies subsamples, all but Dedicated Short see their proportion of funds having t-statistics exceeding the threshold shrinking. The right tails of the cross-sectional distribution of the t-statistics are far thicker than the left tail of the cross-sectional distribution, indicating that there is still measured "skill" in the cross-section of hedge fund managers.

The case of the Dedicated Short strategy is interesting, because it is the only strategy which sees its percentage of funds exceeding the cutoff values to increase using the Newey-West correction. This rise in measured "skilled" funds is substantial, with 26.83% of the funds having t-statistics exceeding 2.326 while this proportion is only 19.51% without the correction. Why did the proportion of "skilled funds" increase for Dedicated Short while it decreased for other funds? First and foremost, Dedicated Short is the least serially correlated of the hedge fund strategies of our sample, with the highest average weight on the current "true" return in reported returns θ_0 of 0.98 (really close to unity) and the highest Herfindahl's index of 1.08. This indicates that the correction for serial correlation is supposed to be really low, so another factor should have been at play. Indeed, Newey and West (1994) explain that their automatic lag selection is unbiased asymptotically but induce greater size, i.e. a greater probability of falsely rejecting the null hypothesis, for small samples. As individual hedge funds have relatively small monthly time-series, this bias can be quite large and eventually overcome the correlation for serial-correlation, as for Dedicated Short hedge funds.

TABLE 1.13 – Percentage of funds significantly skilled - Newey-West coefficients

Cross-sectional distribution of t-statistics for the seven factors' alpha coefficients across individual hedge funds. This table reports the number of funds having t-statistics for different cut-offs values. For each fund having at least 36 monthly return observations, we estimate the Fung and Hsieh seven factors' model $r_{p,t} = \alpha_p + \sum_{j=1}^J \beta_{i,j} f_{j,t} + \epsilon_{p,t}$ where $r_{p,t}$ is the return on each individual fund in month t. The explanatory variables are $\sum_{j=1}^J f_j$ the Fung and Hsieh seven factors. The coefficient α_p measures the risk-adjusted returns and proxy for manager's skill. The results are for the sample January 1994 - February 2015.

	percentage of the funds							
	t<-2.326	t<-1.96	t<-1.645	t<-1.282	t>1.282	t>1.645	t>1.96	t>2.326
Convertible-Arbitrage	0.51	1.54	2.05	2.05	61.02	54.87	51.79	44.1
Dedicated Short	0	2.44	7.32	7.32	43.9	36.58	31.71	26.83
Emerging Markets	2.19	3.12	4.06	6.72	38.44	29.37	23.59	18.75
Equity Market-Neutral	0	0	0.32	0.32	64.08	52.43	45.63	38.19
Event-Driven	0	0	0.72	1.62	75.63	69.85	63.54	57.4
Fixed-Income	0.48	0.96	1.43	1.44	68.89	63.64	58.37	51.67
Longshort Equity	0.38	0.67	1.16	2.03	54.65	45.29	37.58	29.67
Macro	1.54	2.77	4	5.85	49.85	43.08	34.46	27.08
Multi-Strategies	0.41	1.42	2.44	3.66	56.3	49.59	46.34	39.23
Options	0	0	0	0	73.08	65.38	50	38.46
All	0.64	1.15	1.85	2.92	56.23	47.94	41.36	34.27

Because of this small sample bias, we need another procedure to discard the effect of serial correlation in the measured proportion of "skilled" hedge funds. To do so, we use the procedure of Getmansky et al. (2004) and recover the "true" non-serially correlated hedge fund returns as in Eq (1.4). Once we recover the time-series of non-serially correlated hedge fund returns, we re-estimate the the Fung and Hsieh seven factors model :

$$R_{i,t}^{unsmoothed} = \alpha_i^{unsmoothed} + \sum_{j=1}^J \beta_{i,j}^{unsmoothed} F_{j,t} + \epsilon_{i,t}^{unsmoothed} \quad (1.17)$$

where $R_{i,t}^{unsmoothed}$ is the non-serially correlated return of individual fund i in month t , $\beta_{i,j}^{unsmoothed}$ is the exposure of fund i to factor j with non-serially correlated returns, $\alpha_i^{unsmoothed}$ is the risk-adjusted return of fund i with non serially correlated returns and $\epsilon_{i,t}^{unsmoothed}$ is the residual of fund's i non-serially correlated returns in month t .

TABLE 1.14 – **Percentage of funds significantly skilled - unsmoothed returns**

Cross-sectional distribution of t-statistics for the seven factors' alpha coefficients across individual hedge funds. This table reports the number of funds having t-statistics for different cut-offs values. For each fund having at least 36 monthly return observations, we estimate the Fung and Hsieh seven factors' model $r_{p,t} = \alpha_p + \sum_{j=1}^J \beta_{i,j} f_{j,t} + \epsilon_{p,t}$ where $r_{p,t}$ is the return on each individual fund in month t . The explanatory variables are $\sum_{j=1}^J f_j$ the Fung and Hsieh seven factors. The coefficient α_p measures the risk-adjusted returns and proxy for manager's skill. The results are for the sample January 1994 - February 2015.

	percentage of the funds							
	t<-2.326	t<-1.96	t<-1.645	t<-1.282	t>1.282	t>1.645	t>1.96	t>2.326
Convertible-Arbitrage	0.51	3.08	3.59	4.61	50.26	42.05	36.41	29.23
Dedicated Short	0	0	0	4.88	41.46	31.71	24.39	17.07
Emerging Markets	2.03	2.81	3.59	5.94	28.75	21.25	15.62	9.69
Equity Market-Neutral	0	0.32	0.32	0.32	55.34	45.95	39.16	29.13
Event-Driven	0	0	0.54	1.08	65.7	56.68	48.37	38.99
Fixed-Income	0	0.96	0.96	0.96	60.29	54.54	49.28	44.98
Longshort Equity	0.43	0.63	1.16	1.93	46.41	36.03	27.16	18.04
Macro	1.54	1.85	2.77	5.54	44.61	36	28.61	21.85
Multi-Strategies	0.2	1.02	1.83	3.66	50.81	43.9	35.77	28.66
Options	0	0	0	0	61.53	46.15	34.61	19.23
All	0.6	1.05	1.6	2.75	47.96	38.92	31.13	22.96

Table 1.14 shows the cross-sectional distribution of t-statistics for the regressions' alphas across individual hedge funds' returns, filtered for serial-correlation through the Getmansky et al. (2004) procedure. There is a drastic reduction in the percentage of funds exhibiting positive and statistically significant risk-adjusted returns. For the global sample of individual funds, the percentage of funds having t-statistics associated with their risk-adjusted returns greater than 1.96 and 2.326 is now 31.13% and 22.96% respectively (while it was 42.33% and 35.79% respectively for serially correlated returns). We observe a general decrease in the number of measured "skilled" funds for each strategy, with the amount of funds having t-statistics superior to 2.326 going from 9.69% for Emerging Markets to 44.98% for Fixed Income funds.

To summarize our results, serial correlation strongly biases risk-adjusted returns upward, increasing the number of managers appearing to be skilled, as measured with the statistical significance of their risk adjusted returns. Using Newey-West (1987) robust estimators is not sufficient to deal with the amount of serial correlation present in hedge fund data.

1.4.2 False discoveries and serial correlation

Does serial correlation change the expected proportion of funds having statistically significant risk-adjusted returns by luck? The question is to know if, in addition to increase the proportion of measured statistically si-

gnificant alphas, serial correlation in reported hedge fund returns also decreases the proportion of "lucky funds", i.e. zero-alpha funds having positive and statistically significant t-statistics for their risk-adjusted returns. Such a phenomenon may arise if serial correlation changes the expected proportion of zero-alpha funds in the population of interest.

To answer this question, we will rely on the false discoveries methodology developed by Barras et al. (2010) for mutual funds, and latter applied by Criton and Scaillet (2014) in the context of hedge funds. This methodology is based on the False Discovery Rate (FDR), initially developed by Storey (2002).

The basic principle of this approach is to compute the expected proportion of individual hedge funds getting positive and statistically significant risk-adjusted returns by luck only. By developing a statistical procedure that control for the amount of lucky funds among the perceived "skilled" managers, we can estimate the true proportion of skilled funds, i.e. the proportion truly generating positive risk-adjusted returns.

Traditionally, we estimate the proportion of "skilled" funds as the proportion having positive alphas statistically significant at a given level. However, this procedure does not account for luck in the sample : for example, with the usual statistical significance threshold of 5%, it is expected that 5% of the zero-alpha funds (the having having true risk-adjusted returns equal to zero) will have positive and statistically significant alphas. These funds are called the "lucky funds". To control for this phenomenon in assessing the proportion of skilled managers, we determine the frequency of false discoveries in estimating the proportion of zero-alphas funds π_0 in the population in using alpha p-values.

The proportions of skilled, zero-alpha and unskilled individual funds in the population are respectively π_A^+ , π_0 and π_A^- . The basic principle of the FDR approach is to conduct multiple significance tests simultaneously :

$$\begin{aligned} H_{0,1} : \alpha = 0, H_{A,1} : \alpha \neq 0 \\ \dots \\ H_{0,M} : \alpha = 0, H_{A,M} : \alpha \neq 0 \end{aligned} \tag{1.18}$$

with M the number of funds in the data sample. We divide funds in three categories : unskilled funds ($\alpha < 0$), zero-alpha funds ($\alpha = 0$) and skilled funds ($\alpha > 0$). Because the true alphas are unobservable, we use the t-statistics $\hat{t}_i = \frac{\hat{\alpha}_i}{\hat{\sigma}_{\hat{\alpha}_i}}$ as performance measures, where $\hat{\alpha}_i$ is the estimated alpha for fund i and $\hat{\sigma}_i$ is its estimated standard deviation. After choosing a significance level γ , it is possible to observe the \hat{t}_i that are outside the thresholds implied by γ (denoted by t_γ^- and t_γ^+). The individual fund t-statistic distributions are supposed normal. The observer expects to find a proportion $E[S_\gamma^+]$ of positive-alpha funds in the data : this proportion contains the skilled funds and lucky zero-alpha funds. The probability that a skilled fund is very unlucky and has a negative and significant alpha is considered negligible.

At a given significance level γ , the probability that a zero-alpha fund exhibits luck equals $\frac{\gamma}{2}$. If the proportion of zero-alpha funds in the population is π_0 , the expected proportion of lucky funds is :

$$E[F_\gamma^+] = \pi_0 \cdot \frac{\gamma}{2} \tag{1.19}$$

We define the proportion of truly skilled funds as the observed proportion of positive and statistically significant alpha funds minus the expected proportion of lucky funds :

$$E[T_\gamma^+] = E[S_\gamma^+] - E[F_\gamma^+] = E[S_\gamma^+] - \pi_0 \cdot \frac{\gamma}{2} \quad (1.20)$$

The chosen significance level determines the segment of the tail examined for lucky versus truly skilled funds : as γ increases, $E[T_\gamma^+]$ converges to π_A^+ the true proportion of skilled funds, thus minimizing type 2 error.

To estimate π_0 the proportion of zero-alpha fund in the whole population of individual hedge funds, we use the "False Discovery Rate" (FDR) estimation approach used by Barras et al. (2010). By definition, zero-alpha funds satisfy the null hypothesis and have p-values that are uniformly distributed over the interval $[0;1]$. P-values of skilled funds tend to be very small because their estimated t-statistic tends to be far from zero. It is possible to exploit this information to estimate π_0 without knowing the exact distribution of the p-values of the skilled funds. The FDR approach uses information from the center of the cross-sectional t-distribution to correct for luck in the right tail.

Given the sampled p-values, we estimate π_0 in knowing that the majority of p-values larger than a sufficiently high threshold λ^* are zero-alpha funds. After choosing the threshold, we measure the proportion of funds $\frac{\hat{W}(\lambda^*)}{M}$ (with $\hat{W}(\lambda^*)$ the number of funds with p-values exceeding λ^* and M the total number of funds) above the threshold. In extrapolating this number over the region between zero and one, there is :

$$\hat{\pi}_0(\lambda^*) = \frac{\hat{W}(\lambda^*)}{M} \frac{1}{1 - \lambda^*} \quad (1.21)$$

To select λ^* , we use the bootstrap procedure introduced by Storey (2002). We proxy $E[S_\gamma^+]$ by the observed proportion of significant funds in the right tail. This enables us to estimate $E[T_\gamma^+]$. The estimated proportions of skilled funds is then equal to :

$$\hat{T}_\gamma^+ = \hat{S}_\gamma^+ - \hat{F}_\gamma^+ = \hat{S}_\gamma^+ - \hat{\pi}_0 \frac{\gamma}{2} \quad (1.22)$$

Finally, we estimate the proportion of skilled funds in the entire population as :

$$\hat{\pi}_A^+ = \hat{T}_{\gamma^*}^+ \quad (1.23)$$

Because $\hat{\pi}_0$ is a proportion estimator which depends on the proportion of p-values higher than λ^* , the law of large numbers leads it to converge towards its true value when the sample is sufficiently large.

To determine the value of λ^* from the data, we use a resampling approach which chooses λ from the data such that the MSE of $\hat{\pi}_0(\lambda)$ (defined as $E[\hat{\pi}_0(\lambda) - \pi_0]$) is minimized. First $\hat{\pi}_0$ is computed across a wide range of λ values ($\lambda = 0.01, \dots, \lambda = 0.99$). Then, for each possible value of λ , we form 1,000 bootstrap replications of $\hat{\pi}_0(\lambda)$, noted $\hat{\pi}_0^b(\lambda)$ for $b=1, \dots, 1000$. Third, we compute the estimated MSE for each value of λ :

$$\widehat{MSE}(\lambda) = \frac{1}{1000} \sum_{b=1}^{1000} [\hat{\pi}_0^b(\lambda) - \min_{\lambda} \hat{\pi}_0(\lambda)]^2 \quad (1.24)$$

Then, λ^* is chosen such that $\lambda^* = \operatorname{argmin}_{\lambda} \widehat{MSE}(\lambda)$.

TABLE 1.15 – Proportion of "truly" skilled funds

	Global sample						Unsmoothed													
	Standard $\hat{\pi}_0 = 37.96$			Newey West $\hat{\pi}_0 = 38.55$			1%			5%			10%			20%				
significance level γ	1%	5%	10%	20%	1%	5%	10%	20%	1%	5%	10%	20%	1%	5%	10%	20%	1%	5%	10%	20%
lucky funds $E[F_\gamma]$	0.19	0.95	1.9	3.79	0.19	0.96	1.93	3.85	0.22	1.11	2.21	4.42	0.22	1.11	2.21	4.42	0.22	1.11	2.21	4.42
significant funds $E[S_\gamma^+]$	30.59	41.71	48.78	56.97	28.1	40.6	47.53	55.88	17.06	30.3	38.4	47.61	17.06	30.3	38.4	47.61	16.84	29.19	36.19	43.19
skilled funds $E[T_\gamma^+]$	30.4	40.76	46.88	53.18	27.91	39.64	45.6	52.03	16.84	29.19	36.19	43.19	16.84	29.19	36.19	43.19	16.84	29.19	36.19	43.19
fdr_γ^+	0.62	2.28	3.89	6.65	0.68	2.36	4.06	6.89	1.29	3.66	5.75	9.28	1.29	3.66	5.75	9.28	1.29	3.66	5.75	9.28
Convertible Arbitrage																				
	Standard						Unsmoothed													
	Standard $\hat{\pi}_0 = 28.34$			Newey West $\hat{\pi}_0 = 20.51$			1%			5%			10%			20%				
significance level γ	1%	5%	10%	20%	1%	5%	10%	20%	1%	5%	10%	20%	1%	5%	10%	20%	1%	5%	10%	20%
lucky funds $E[F_\gamma]$	0.14	0.71	1.42	2.83	0.1	0.51	1.03	2.05	0.08	0.43	0.85	1.71	0.08	0.43	0.85	1.71	0.08	0.43	0.85	1.71
significant funds $E[S_\gamma^+]$	44.61	52.31	57.95	63.59	35.9	50.26	54.87	61.02	23.08	35.38	42.05	50.26	23.08	35.38	42.05	50.26	23	34.95	41.2	48.55
skilled funds $E[T_\gamma^+]$	44.47	51.6	56.53	60.76	35.8	49.75	53.84	58.97	23	34.95	41.2	48.55	23	34.95	41.2	48.55	23	34.95	41.2	48.55
fdr_γ^+	0.31	1.36	2.45	4.45	0.28	1.01	1.88	3.36	0.35	1.21	2.02	3.4	0.35	1.21	2.02	3.4	0.35	1.21	2.02	3.4
Dedicated Short																				
	Standard						Unsmoothed													
	Standard $\hat{\pi}_0 = 17.42$			Newey West $\hat{\pi}_0 = 18.76$			1%			5%			10%			20%				
significance level γ	1%	5%	10%	20%	1%	5%	10%	20%	1%	5%	10%	20%	1%	5%	10%	20%	1%	5%	10%	20%
lucky funds $E[F_\gamma]$	0.09	0.43	0.87	1.74	0.09	0.47	0.94	1.88	0.13	0.68	1.35	2.71	0.13	0.68	1.35	2.71	0.13	0.68	1.35	2.71
significant funds $E[S_\gamma^+]$	19.51	29.27	36.58	43.9	19.51	31.71	36.58	43.9	14.63	21.95	29.27	41.46	14.63	21.95	29.27	41.46	14.5	21.27	27.92	38.75
skilled funds $E[T_\gamma^+]$	19.42	28.84	35.71	42.16	19.42	31.24	35.64	42.02	14.5	21.27	27.92	38.75	14.5	21.27	27.92	38.75	14.5	21.27	27.92	38.75
fdr_γ^+	0.46	1.47	2.38	3.96	0.46	1.48	2.57	4.28	0.89	3.1	4.61	6.54	0.89	3.1	4.61	6.54	0.89	3.1	4.61	6.54

This table provides the results of the FDR approach for the alphas for different econometric specification. $\hat{\pi}_0(\lambda^*)$ is the estimated proportion of zero-alpha funds, $E[S_\gamma^+]$ is the proportion of funds having a positive and significant alpha, $E[F_\gamma]$ is the proportion of funds having a positive/negative and significant alpha by luck, $E[T_\gamma^+]$ is the true proportion of skilled funds. Risk-adjusted returns are estimated with respect to the seven factors of Fung & Hsieh. The sample period goes from January 1994 to February 2015.

In our case, the alphas are estimated with the seven factors model of Fung and Hsieh for each fund. We chose values of 1.282, 1.645, 1.96 and 2.326 for the significance threshold γ . Note that it is possible to give a bayesian interpretation to the false discovery rate. Let G_i be a random variable that take the value of -1 if fund i is unskilled, 0 if it has zero alpha and 1 if it is skilled. The three possible values are given by the prior proportions of each skill group. Using Bayes's theorem, the false discovery rate is :

$$fdr_{\gamma}^{+} = \frac{prob(T_i^{+} \in \tau^{+}(\gamma)|G_i = 0)prob(G_i = 0)}{prob(T_i \in \tau^{+}(\gamma))} = \frac{\frac{\gamma}{2}\pi_0}{E[S_{\gamma}^{+}]} \quad (1.25)$$

where $\tau^{+}(\gamma) = (t_{\gamma}^{+}, \infty)$ the region of the t-statistics above the required threshold to be considered as potentially skilled. fdr_{γ}^{+} is a measure of how the investor changes his prior probability that fund i has no skill after observing that its t-statistic exceeds the threshold given by the significance level.

Tables 1.15-1.18 present the results for the global sample of individual hedge funds as for the hedge fund trading styles subsamples over the period January 1994 to February 2015. Individual risk-adjusted returns are estimated with respect to the Fung and Hsieh seven-factors model. Three empirical specifications are presented : one ("Standard") showing the results for ordinary least-squares p-values and t-statistics, the second the results with Newey and West (1987) coefficients and the third ordinary least-squares coefficients for the regressions applied on hedge fund returns filtered for serial correlation (as in Eq 1.4). Results show, for each sample, the estimated proportion $\hat{\pi}_0$ of zero-alpha funds in the population. We see a general pattern of an increase in the proportion of zero-alpha funds in the population when we take into account the serial-correlation in hedge fund returns, indirectly with Newey-West estimators or directly in unsmoothing them. For example, for the global sample of individual hedge funds Table 1.15, we see that $\hat{\pi}_0$ goes from 37.96% of the funds with standard coefficients, to 38.55% with Newey and West coefficients to finally 44.2% of the population when we filter for serial correlation. This is roughly an increase of 16% in the estimated proportion of funds having no risk-adjusted returns.

This increase in $\hat{\pi}_0$ is not monotonic for every hedge fund strategy. For example, the strategy Equity Market Neutral has a lower measured proportion fo zero-alpha funds with Newey and West coefficients with respect to standard ordinary least squares. However, all strategies except Convertible Arbitrage have a higher $\hat{\pi}_0$ with unsmoothed returns with respect to the ordinary least squares coefficients on serially-correlated returns. This indicates that the estimated proportion of skilled funds is dependent on the amount of serial correlation in the reported returns and that returns filtered for serial correlation will give lower statistical significance for risk-adjusted returns, confirming our previous results.

This general increase in the number of zero-alpha funds when we filter hedge fund returns for serial correlation goes conjointly with a decrease in the proportion of funds having measured positive and significant risk-adjusted returns, as documented in the previous subsection. This leads to an increase in the proportion of "lucky funds", i.e. funds having positive and statistically significant alphas by luck only and a decrease in the proportion of measured "truly" skilled funds, i.e. funds that are not statistically significant by luck alone. At the global sample level, there is a reduction in the proportion of estimated "truly skilled" funds at the 1% statistical significance level by almost half, going from 30.04% to 16.84%. The false discovery rate has more than doubled, going from 0.62% to 1.29%.

TABLE 1.16 – Proportion of "truly" skilled funds

	Emerging Markets						Unsmoothed																	
	Standard $\hat{\pi}_0 = 56.2$			Newey West $\hat{\pi}_0 = 59.17$			1%			5%			10%			20%								
significance level γ	1%	5%	10%	20%	1%	5%	10%	20%	1%	5%	10%	20%	1%	5%	10%	20%	1%	5%	10%	20%				
lucky funds $E[F_\gamma]$	0.28	1.4	2.81	5.62	0.29	1.48	2.96	5.92	0.33	1.67	3.35	6.7	0.33	1.67	3.35	6.7	0.33	1.67	3.35	6.7				
significant funds $E[S_\gamma^+]$	16.87	25.78	32.19	41.25	14.84	23.12	29.22	37.66	7.03	15.16	20.78	28.44	7.03	15.16	20.78	28.44	7.03	15.16	20.78	28.44				
skilled funds $E[T_\gamma^+]$	16.59	24.38	29.38	35.63	14.55	21.64	26.26	31.74	6.7	13.49	17.43	21.74	6.7	13.49	17.43	21.74	6.7	13.49	17.43	21.74				
fdr_γ^+	1.66	5.43	8.73	13.62	1.95	6.4	10.13	15.72	4.69	11.01	16.12	23.56	4.69	11.01	16.12	23.56	4.69	11.01	16.12	23.56				
Equity Market Neutral																								
	Standard $\hat{\pi}_0 = 21.57$						Newey West $\hat{\pi}_0 = 16.18$						Unsmoothed $\hat{\pi}_0 = 44.32$											
	1%			5%			10%			20%			1%			5%			10%			20%		
significance level γ	1%	5%	10%	20%	1%	5%	10%	20%	1%	5%	10%	20%	1%	5%	10%	20%	1%	5%	10%	20%	1%	5%	10%	20%
lucky funds $E[F_\gamma]$	0.11	0.54	1.08	2.16	0.08	0.4	0.81	1.62	0.22	1.11	2.22	4.43	0.22	1.11	2.22	4.43	0.22	1.11	2.22	4.43	0.22	1.11	2.22	4.43
significant funds $E[S_\gamma^+]$	34.3	53.39	66.99	87.05	28.48	44.98	51.78	63.75	22.33	38.18	45.95	54.69	22.33	38.18	45.95	54.69	22.33	38.18	45.95	54.69	22.33	38.18	45.95	54.69
skilled funds $E[T_\gamma^+]$	34.19	52.85	65.91	84.89	28.4	44.58	50.97	62.13	22.11	37.07	43.73	50.26	22.11	37.07	43.73	50.26	22.11	37.07	43.73	50.26	22.11	37.07	43.73	50.26
fdr_γ^+	0.32	1.01	1.61	2.48	0.28	0.89	1.56	2.54	0.98	2.91	4.83	8.1	0.98	2.91	4.83	8.1	0.98	2.91	4.83	8.1	0.98	2.91	4.83	8.1
Event Driven																								
	Standard $\hat{\pi}_0 = 9.02$						Newey West $\hat{\pi}_0 = 19.95$						Unsmoothed $\hat{\pi}_0 = 9.03$											
	1%			5%			10%			20%			1%			5%			10%			20%		
significance level γ	1%	5%	10%	20%	1%	5%	10%	20%	1%	5%	10%	20%	1%	5%	10%	20%	1%	5%	10%	20%	1%	5%	10%	20%
lucky funds $E[F_\gamma]$	0.04	0.22	0.45	0.9	0.1	0.5	1	2	0.04	0.22	0.45	0.9	0.04	0.22	0.45	0.9	0.04	0.22	0.45	0.9	0.04	0.22	0.45	0.9
significant funds $E[S_\gamma^+]$	20.76	31.77	39.53	50.9	50.36	62.45	69.31	75.63	30.87	46.9	56.68	65.52	30.87	46.9	56.68	65.52	30.87	46.9	56.68	65.52	30.87	46.9	56.68	65.52
skilled funds $E[T_\gamma^+]$	20.72	31.55	39.08	50	50.26	61.95	68.31	73.63	30.83	46.68	56.23	64.62	30.83	46.68	56.23	64.62	30.83	46.68	56.23	64.62	30.83	46.68	56.23	64.62
fdr_γ^+	0.19	0.69	1.14	1.77	0.2	0.8	1.44	2.64	0.13	0.47	0.79	1.37	0.13	0.47	0.79	1.37	0.13	0.47	0.79	1.37	0.13	0.47	0.79	1.37

This table provides the results of the FDR approach for the alphas for different econometric specification. $\hat{\pi}_0$ is the estimated proportion of zero-alpha funds, $E[S_\gamma^+]$ is the proportion of funds having a positive and significant alpha, $E[F_\gamma]$ is the proportion of funds having a positive/negative and significant alpha by luck, $E[T_\gamma^+]$ is the true proportion of skilled funds. Risk-adjusted returns are estimated with respect to the seven factors of Fung & Hsieh. The sample period goes from January 1994 to February 2015.

TABLE 1.17 – Proportion of "truly" skilled funds

	Standard $\hat{\pi}_0 = 13.05$						Fixed Income Newey West $\hat{\pi}_0 = 7.97$						Unsmoothed $\hat{\pi}_0 = 40.04$					
	1%	5%	10%	20%	1%	5%	10%	20%	1%	5%	10%	20%	1%	5%	10%	20%		
significance level γ	0.06	0.33	0.65	1.3	0.04	0.2	0.4	0.8	0.2	1.01	2.02	4.04	0.2	1.01	2.02	4.04		
lucky funds $E[F_\gamma]$	52.15	58.37	63.64	69.85	50.24	55.98	63.64	67.94	38.28	49.28	54.07	60.29	38.28	49.28	54.07	60.29		
significant funds $E[S_\gamma^+]$	52.09	58.04	62.99	68.55	50.2	55.6	63.24	67.14	38.08	48.27	52.05	56.25	38.08	48.27	52.05	56.25		
skilled funds $E[T_\gamma^+]$	0.11	0.56	1.02	1.86	0.08	0.36	0.63	1.18	0.52	2.05	3.74	6.7	0.52	2.05	3.74	6.7		
fdr_γ^+																		
	Long/Short Equity																	
	Standard $\hat{\pi}_0 = 39.32$						Newey West $\hat{\pi}_0 = 37.59$						Unsmoothed $\hat{\pi}_0 = 45.02$					
	1%	5%	10%	20%	1%	5%	10%	20%	1%	5%	10%	20%	1%	5%	10%	20%		
significance level γ	0.2	0.98	1.97	3.93	0.19	0.94	1.88	3.76	0.22	1.12	2.25	4.5	0.22	1.12	2.25	4.5		
lucky funds $E[F_\gamma]$	25.18	37.92	46.07	55.19	23.15	37	44.77	54.32	13.02	26.29	35.5	45.97	13.02	26.29	35.5	45.97		
significant funds $E[S_\gamma^+]$	24.98	36.94	44.1	51.26	22.96	36.06	42.89	50.56	12.8	25.17	33.25	41.47	12.8	25.17	33.25	41.47		
skilled funds $E[T_\gamma^+]$	0.79	2.58	4.28	7.12	0.82	2.54	4.2	6.92	1.69	4.26	6.34	9.79	1.69	4.26	6.34	9.79		
fdr_γ^+																		
	Global Macro																	
	Standard $\hat{\pi}_0 = 18.46$						Newey West $\hat{\pi}_0 = 21.98$						Unsmoothed $\hat{\pi}_0 = 36.92$					
	1%	5%	10%	20%	1%	5%	10%	20%	1%	5%	10%	20%	1%	5%	10%	20%		
significance level γ	0.09	0.46	0.92	1.85	0.11	0.55	1.1	2.2	0.18	0.92	1.85	3.69	0.18	0.92	1.85	3.69		
lucky funds $E[F_\gamma]$	22.77	34.15	42.77	49.85	21.85	33.85	42.46	49.54	14.15	28.3	36	44	14.15	28.3	36	44		
significant funds $E[S_\gamma^+]$	22.68	33.69	41.85	48	21.74	33.3	41.36	47.34	13.97	27.38	34.15	40.31	13.97	27.38	34.15	40.31		
skilled funds $E[T_\gamma^+]$	0.39	1.35	2.15	3.71	0.5	1.62	2.59	4.44	1.27	3.25	5.14	8.33	1.27	3.25	5.14	8.33		
fdr_γ^+																		

This table provides the results of the FDR approach for the alphas for different econometric specification. $\hat{\pi}_0$ is the estimated proportion of zero-alpha funds, $E[S_\gamma^+]$ is the proportion of funds having a positive and significant alpha, $E[F_\gamma]$ is the proportion of funds having a positive/negative and significant alpha by luck, $E[T_\gamma^+]$ is the true proportion of skilled funds. Risk-adjusted returns are estimated with respect to the seven factors of Fung and Hsieh. The sample period goes from January 1994 to February 2015.

TABLE 1.18 – Proportion of "truly" skilled funds

significance level γ	Multi Strategies						Options									
	Standard			Newey West			Standard			Newey West						
	$\hat{\pi}_0 = 10.16$			$\hat{\pi}_0 = 20.32$			$\hat{\pi}_0 = 6.99$			$\hat{\pi}_0 = 10.12$						
	1%	5%	10%	20%	1%	5%	10%	20%	1%	5%	10%	20%	1%	5%	10%	20%
lucky funds $E[F_\gamma]$	0.05	0.25	0.51	1.02	0.1	0.51	1.02	2.03	0.07	0.36	0.71	1.42	0.07	0.36	0.71	1.42
significant funds $E[S_\gamma^+]$	35.98	45.12	50.41	56.3	33.13	45.52	49.39	56.1	30.77	50	65.38	73.08	7.69	30.77	42.3	61.54
skilled funds $E[T_\gamma^+]$	35.93	44.87	49.9	55.28	33.03	45.01	48.37	54.07	30.72	49.75	64.87	72.07	7.62	30.41	41.59	60.12
fdr_γ^+	0.13	0.55	1.01	1.81	0.3	1.12	2.06	3.62	0.16	0.5	0.78	1.38	0.91	1.17	1.68	2.31

This table provides the results of the FDR approach for the alphas for different econometric specification. $\hat{\pi}_0$ is the estimated proportion of zero-alpha funds, $E[S_\gamma^+]$ is the proportion of funds having a positive and significant alpha, $E[F_\gamma]$ is the proportion of funds having a positive/negative and significant alpha by luck, $E[T_\gamma^+]$ is the true proportion of skilled funds. Risk-adjusted returns are estimated with respect to the seven factors of Fung & Hsieh. The sample period goes from January 1994 to February 2015.

These results highlight the importance of serial correlation in the fund selection process. While hedge funds exhibit positive and statistically significant risk adjusted returns, this feature can be the byproduct of reported serial correlation. Indeed, we have showed that there is a positive correlation between serial correlation and risk-adjusted returns. This effect is economically important, as serial correlation inflates the measured proportion of "skilled" funds by almost two in the global sample of individual funds.

1.5 Conclusion

This paper provides empirical evidence for the importance of serial correlation in hedge funds' performance measurement. Funds reporting more serially correlated returns have higher measured risk-adjusted betas over the period January 1994 - February 2015. A decile high-minus-low portfolio of individual funds sorted on serial correlation will earn a monthly risk-adjusted return of 0.81%, highly statistically significant. This result is corroborated by a Fama and McBeth cross sectional regression, which gives a slope of 0.88% per month in risk adjusted returns for serial correlation.

We show that this risk-adjusted return spread is accompanied by a spread in the absolute risk exposures. The decile of the least serially correlated hedge funds is more exposed to common Fung and Hsieh seven factors than the most serially correlated funds. These findings are of high importance because they show that the most serially correlated funds outperform and are less risky according to traditional performance measurement.

We hypothesize that this effect of serial correlation on performance and risk of hedge funds may come from two channels. The first potential channel is through risk factors that are out of the scope of the traditional Fung and Hsieh seven factors model : the most serially correlated funds are exposed to unknown systematic risk factors, earning risk premia for their exposures, while being not exposed to the traditional hedge fund risk factors, and hence have positive risk-adjusted returns and weak betas. In this paper, we do not consider this first explanation and let it for future research.

The second potential channel is that serial correlation is sufficiently important among the most serially correlated hedge funds to strongly bias risk factors estimates, leading to risk-adjusted returns being biased upward and risk exposures being biased downward. Consistent with this explanation, we find that the proportion of funds having highly statistically significant positive risk-adjusted returns strongly decreases when we take into account serial correlation, both indirectly with robust estimators and directly in "un-smoothing" the reported returns.

Our results highlight the importance of taking into account serial correlation in reported returns when analyzing hedge fund investments. First and foremost, they show that the most serially correlated hedge fund managers may artificially be considered as "skilled" and not risky due to the biases in estimates. Second, from an asset pricing point of view, the most serially correlated hedge funds might be exposed to unknown risk factors, which leaves their identification for future work. Third, hedge funds serial correlation can artificially lower their risk exposures, giving a false impression that this type of investment cannot be passively replicated, as proposed by Hasahodzic and Lo (2007). Finally, our results show that the number of hedge fund exhibiting positive alphas is lower than previously thought.

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1.6 Appendix : robustness checks with Funds of Hedge Funds

Previously, we excluded funds of hedge funds in our data sample of individual hedge funds in order to avoid statistical issues with potential double counting of a particular hedge fund investment : our dataset may contain the returns for a fund of hedge funds and the returns of its hedge funds' investments. In this section, we test our previous results on the link between serial correlation and risk-adjusted returns on funds of hedge funds only, as a robustness check.

Our sample consists of 2,243 individual funds of hedge funds having at least 36 monthly observations over the period January 1994 - February 2015. The average monthly return is 0.38% for an average volatility of 2.54%, which gives an average Sharpe ratio of 0.31. Consistent with the statistical profile of hedge funds, funds of hedge funds returns exhibit an average negative skewness of -0.77 and an average kurtosis of 7.83, showing a strong departure from normality. Using an autoregressive process at the order one, we estimate that the average serial correlation in funds of hedge funds' returns is 22.83%, superior to the average of 16.29% found in individual hedge funds. There is a cross-sectional standard deviation of 19.19% in serial-correlation estimates, showing a large dispersion in amounts of serial correlation, which is convenient to test its potential effects.

First and foremost, we sort individual funds of hedge funds over the period January 1994 - February 2015 into decile portfolios according to their weight θ_0^i of current "true" returns in their reported returns. This is a measure of the amount of serial correlation present in their reported returns : the lower the coefficient θ_0^i , the higher is the serial correlation. We want to see if a higher level of serial correlation, i.e. a lower estimated coefficient θ_0^i , is associated with higher risk-adjusted returns α_i and lower systematic risk exposures $|\beta_j^i|$, as for individual hedge funds.

Table 1.19 shows the results for our decile portfolios of individual funds of hedge funds risk-adjusted returns. The decile coefficient θ_0 goes from 0.53 for the lowest decile to 1.19 for decile 10, indicating a large variability in serial-correlation among funds of hedge funds. We find that, as the coefficient θ_0 increases from the bottom to the top decile, the risk-adjusted return α is globally decreasing consistent with our previous results on individual hedge funds. There is a negative High-minus-Low spread of -0.32, statistically significant with an associated t-statistic of -6.16. Table 1.19 also presents the results for the systematic risk factor exposures. There is a positive and statistically significant an the 1% risk level beta spread for every risk factor with the exception of Credit, which has a negative but statistically insignificant spread. These two results combined confirm our intuition of biasing effect of serial correlation on hedge fund performance measurement.

To further investigate the relationships between serial correlation and risk-adjusted returns and risk exposures, we estimate univariate cross-sectional Fama and McBeth regressions of risk-adjusted returns α_i on the weight $\theta_{0,i}$. We then cross-sectionally regress the absolute beta for each risk factor $|\beta_{i,j}|$ on $\theta_{0,i}$ to test the existence of a linear relation between the amount of serial correlation in funds of hedge funds and their measured exposures to risk factors. Table 1.20 presents the estimates for both types of cross-sectional regressions. For the risk-adjusted returns regression, there is a negative slope for θ_0 of -0.45%, highly statistically significant with t-statistics of -6.08 for Newey & West coefficients and -6.38 with a generalized-method-of-moments : the more a fund of hedge fund is serially correlated, the higher its risk-adjusted return. It is interesting to note that every risk factor presents a positive and strongly statistically significant θ_0 slope, indication that the higher the weight on current return θ_0 is, i.e. the lower the serial-correlation is, the higher the measured risk exposure is. These strong results are consistent with our intuition about the biasing effect of serial correlation in the cross-section of hedge fund returns.

	Low	2	3	4	5	6	7	8	9	High	High-Low
θ_0	0.53	0.61	0.65	0.68	0.71	0.74	0.78	0.82	0.9	1.19	0.66
α	0.38 (10.23)***	0.33 (12.23)***	0.33 (10.01)***	0.34 (14.61)***	0.27 (11.64)***	0.28 (9.25)***	0.25 (9.81)***	0.26 (8.37)***	0.18 (4.64)***	0.06 (1.78)*	-0.32 (-6.16)***
PTFSBD	$ \beta $	1.53	1.69	1.5	1.51	1.53	1.61	1.85	3.07	3.89	2.36 (7.47)***
PTFSFX	$ \beta $	0.84	1.05	0.95	0.98	1.16	1.22	1.7	2.38	2.88	2.04 (9.21)***
PTFSCOM	$ \beta $	0.93	1.1	1.22	1.36	1.61	1.32	2.12	3.13	3.62	2.69 (9.74)***
SP500	$ \beta $	16.84	19.5	21.59	23.28	24.15	23.04	29.08	24.9	22.74	5.9 (3.04)***
Size	$ \beta $	3.62	3.16	3.02	2.87	2.81	2.8	3.81	4.54	5.81	2.19 (3.79)***
Bond	$ \beta $	0.96	0.96	0.87	0.83	0.86	0.98	0.92	1.25	1.3	0.34 (3.69)***
Credit	$ \beta $	2.98	2.59	2.51	2.38	2.47	2.27	2.12	2.6	2.55	-0.43 (-1.54)

TABLE 1.19 – Decile portfolios of funds of hedge funds sorted by serial correlation

This table reports estimates for equal-weighted decile portfolios of individual funds of hedge funds. For each fund having at least 36 monthly return observations, we estimate the Fung & Hsieh model $r_{p,t} = \alpha_p + \sum_{j=1}^J \beta_{i,j} f_{j,t} + \epsilon_{p,t}$ where $r_{p,t}$ is the return on each individual fund in month t . The explanatory variables are $\sum_{j=1}^J f_j$, the Fung and Hsieh seven factors. We also estimate the same model but with standardized risk factors in order to get the sum of absolute risk exposures $\sum_{j=1}^J |\beta_j|$. Simultaneously, we estimate an MA(2) model on $r_{p,t}$. Portfolios are formed in ranking each fund according to its weight of the current return on its reported returns θ_0 , so the portfolio Low is the portfolio with the lowest θ_0 . The sample period is January 1994 - February 2015. For each decile portfolio, we report the average serial correlation parameter θ_0 , the risk-adjusted return α and their t-statistics. We also report the average serial correlation parameter θ_0^i , the average of absolute betas $|\beta|$ and its high-minus-low t-statistic.

In order to dig deeper into the relationship between serial correlation, risk-adjusted returns and risk exposures, we use a rolling-window framework. We first use a non-parametric portfolio approach : we form quintile portfolios in sorting individual funds of hedge funds every month with respect to their 36 months weights $\theta_{0,t}^i$ on the current "true" returns in reported returns. We then estimate the average portfolios' risk-adjusted returns and sum of systematic risk exposures. We report the results for these quintile portfolios in Table 1.21. There is a monotonically decreasing relationship between the rank of the portfolio and the average risk-adjusted returns, indicating that more serially correlated funds of hedge funds exhibit higher measured alphas. Furthermore, the sum of risk exposures is increasing with the rank of the portfolio, showing that funds having higher serial correlation, i.e. lower θ_0 , have lower measured betas with respect to the Fung and Hsieh seven hedge fund risk factors. There is an average monthly alpha spread of -0.3%, highly statistically significant with t-statistics of -10.39. All the absolute betas spreads are positive and highly statistically significant, indicating that for every risk exposure the most serially correlated funds are less exposed than the least serially correlated, consistent with our biasing hypothesis.

We then develop a 36-months rolling window Fama and McBeth cross-sectional regression framework in order to test the reliability of the cross-sectional relationships between serial correlation and risk-adjusted returns and risk estimates. We estimate over a fixed 36 months window in first stage time-series regressions the risk-adjusted returns α , the sum of absolute exposure to standardized risk factors $\sum_{j=1}^J |\beta_j|$ and the weight of current returns in the reported returns θ_0 . We follow by two cross sectional regressions of the risk adjusted returns and the sum of risk exposures on the coefficient θ_0 , a measure inversely proportional to the amount of serial correlation in funds of hedge funds' reported returns. We roll this estimation procedure over the period January 1997 to February 2015, keeping a fixed estimation window of 36 months.

Table 1.21 presents the time-series averages and t-statistics in parentheses of the intercepts and slopes for the cross-sectional regressions. Results show that more serially correlated funds of hedge funds, i.e. funds having lower θ_0 , have higher measured risk-adjusted returns and lower risk exposures : the average slopes for the coefficient θ_0 are -0.22% and 2.23% with associated t-statistics of -7.81 and 15.94 respectively. These results confirm our findings found for hedge funds and our previous results for funds of hedge funds that serial correlation have an impact on risk factors' estimates in an economically significant way.

Finally, we check for the proportion of funds of hedge funds having positive and statistically significant risk-adjusted returns and false discoveries with and without taking into account for serial correlation. We employ a procedure similar to Barras et al. (2010). We begin by estimating, using the bootstrap method of Storey (2002), the prior proportion of "zero alpha" funds of hedge funds $\hat{\pi}_0$ in the global population of funds of hedge funds using risk-adjusted returns p-values as in Eq (1.21). We then compute the prior proportion of "lucky funds", i.e. funds of hedge funds having positive and statistically significant alphas by luck alone $E[S_\gamma^+]$ for different significance levels γ . We then retrieve this proportion of lucky funds to the estimated proportion of funds having a positive and statistically significant alpha at the significance level γ to get the proportion of "truly skilled" funds $E[T_\gamma^+]$. Finally, the False Discoveries Rate fdr_γ^+ for the significance level γ is the expected proportion of "zero alpha" funds among the funds of hedge funds exhibiting a positive and statistically significant alpha.

	α	<i>PTFSBD</i>	<i>PTFSFX</i>	<i>PTFSCOM</i>	<i>SP500</i>	<i>Size</i>	<i>Bond</i>	<i>Credit</i>
Intercept	0.61	-1.1	-0.83	-1.48	15.22	-1.1	-0.17	0.17
t_{NW}	(10.84)***	(-3.13)***	(-2.88)***	(-4.91)***	(6.38)***	(-3.13)***	(-0.23)	(1.11)
t_{GMM}	(11.38)***	(-3.22)***	(-2.97)***	(-5.13)***	(6.7)***	(-3.22)***	(-0.22)	(1.12)
λ_{θ_0}	-0.45	4	2.94	4.26	10.02	4	4.88	1.13
t_{NW}	(-6.08)***	(8.21)***	(7.23)***	(9.88)***	(3.06)***	(8.21)***	(4.88)***	(5.39)***
t_{GMM}	(-6.38)***	(8.49)***	(7.49)***	(10.39)***	(3.21)***	(8.49)***	(4.65)***	(5.43)***
R^2	3.36	8.1	8.74	11.22	0.86	8.1	4.5	3.06

TABLE 1.20 – Risk-adjusted returns' and absolute betas Fama-McBeth on θ_0 for individual funds of hedge funds
 Estimates of monthly cross-sectional regressions of individual funds of hedge funds' risk-adjusted returns α and absolute risk exposures $\sum_{j=1}^J |\beta_j|$ on the weight of current "true" returns in reported returns θ_0 . These serial correlation parameters estimated with a first-stage time-series MA(2) as in Eq (8). The monthly sample is 01/1994-02/2015. R^2 is the adjusted coefficient of determination in percentage. Generalized methods-of-moments t_{GMM} and Newey-West t_{NW} t-statistics in parantheses adjust for cross-asset correlation in the residuals and for estimation error of the time-series betas.

TABLE 1.21 – Rolling-window relation between absolute betas and serial-correlation

	α	PTFSBD	PTFSCOM	PTFSFX	SP500	Bond	Size	Credit
Intercept	0.59 (17.33)***	0.59 (4.76)***	0.9 (9.69)***	0.54 (4.44)***	19.8 (28.11)***	2.14 (10.28)***	0.9 (19.01)***	3.15 (17.68)***
λ_{θ_0}	-0.22 (-7.81)***	2.78 (15.9)***	1.7 (17.53)***	2.73 (14.38)***	7.73 (8.82)***	3.74 (13.74)***	0.99 (14.75)***	1.29 (7.76)***

(a) Rolling-window Fama-McBeth cross-sectional regressions of individual funds of hedge funds Fung and Hsieh 7 factors absolute betas on θ_0

	α	PTFSBD	PTFSCOM	PTFSFX	SP500	Bond	Size	Credit
Low θ_0	0.56	1.85	1.42	1.44	17.25	3.39	1.21	3.37
2	0.47	1.97	1.72	1.84	23.36	4.03	1.36	3.76
3	0.45	2.26	1.99	2.25	27.37	4.71	1.58	4.19
4	0.37	2.76	2.33	2.9	29.99	5.1	1.8	4.37
High θ_0	0.26	4.57	3.41	4.62	31.29	7.43	2.25	4.93
High θ_0 - Low θ_0	-0.3 (-10.39)***	2.72 (19.94)***	1.99 (35.2)***	3.18 (21.21)***	14.04 (15.21)***	4.04 (24.04)***	1.04 (23.39)***	1.56 (9.13)***

(b) **Rolling-window quintile portfolios of funds of hedge funds Fung and Hsieh's 7-factors absolute betas sorted by θ_0**

Panel (a) presents cross-sectional estimates of hedge fund Fung and Hsieh 7 factors' absolute exposures regressed on the serial-correlation coefficient θ_0 . θ_0 is defined as the current return's weight on contemporary return. It is estimated through a moving average-process. λ_{θ_0} is the mean slope of monthly cross-sectional regression of hedge fund sum of exposures to standardized risk factors on θ_0 . The exposures are estimated in a first-stage time-series regression (a regression with the Fung and Hsieh 7 factors for the absolute risk exposures and separately a MA(2) for the serial correlation parameter θ_0). The monthly sample is 01/1997-02/2015.

Panel (b) presents quintile portfolios formed every month by sorting individual hedge funds on their past 36-month financial intermediaries' risk exposure. The sample goes from 01/1997 to 01/2015. Quintile 1 is the portfolio of hedge funds with the lowest θ_0 and quintile 5 is the portfolio of hedge funds with the highest θ_0 . For each quintile portfolio, we report the average 36-month Fung and Hsieh 7 standardized factors' sum of betas.

Table 1.22 reports the results for funds of hedge funds over the sample period January 1994 - February 2015 for three empirical specifications : regressions on reported returns with ordinary least-squares estimates, regressions on reported returns with Newey and West (1987) estimates obtained with an automatic lag selection similar to Newey and West (1994) and regressions on returns filtered for serial correlation with ordinary least-squares estimates. We first notice that the estimated prior proportion of zero-alpha funds of hedge funds $\hat{\pi}_0$ varies strongly from one specification to the other : it goes from 17.83% for the standard estimates to 8.92% with Newey West estimates, while it is 65.13% with returns filtered for serial correlation. The really higher prior proportion of zero-alpha funds when we filter for serial correlation in reported returns advocates for the economic importance of serial-correlation in biasing upwards the risk-adjusted returns estimates and their statistical significance.

TABLE 1.22 – Proportion of "truly" skilled funds of hedge funds

This table provides the results of the FDR approach for the alphas for different econometric specification. $\hat{\pi}_0$ is the estimated proportion of zero-alpha funds, $E[S_\gamma^+]$ is the proportion of funds having a positive and significant alpha, $E[F_\gamma]$ is the proportion of funds having a positive/negative and significant alpha by luck, $E[T_\gamma^+]$ is the true porportion of skilled funds. Risk-adjusted returns are estimated with respect to the seven factors of Fung and Hsieh. The sample period goes from January 1994 to February 2015.

	Funds of Hedge Funds											
	Standard $\hat{\pi}_0 = 17.83$				Newey West $\hat{\pi}_0 = 8.92$				Unsmoothed $\hat{\pi}_0 = 65.13$			
significance level γ	1%	5%	10%	20%	1%	5%	10%	20%	1%	5%	10%	20%
lucky funds $E[F_\gamma]$	0.09	0.45	0.89	1.78	0.04	0.22	0.44	0.89	0.33	1.63	3.26	6.51
significant funds $E[S_\gamma^+]$	27.78	37.63	43.25	51.89	23.94	35.18	41.55	50.38	14.09	24.03	30.63	39.32
skilled funds $E[T_\gamma^+]$	27.69	37.18	42.36	50.11	23.9	34.96	41.11	49.49	13.76	22.4	27.37	32.81
fdr_γ^+	0.32	1.19	2.06	3.43	0.17	0.63	1.06	1.77	2.34	6.78	10.64	16.56

This increase in the number of zero-alpha funds when we take into account serial-correlation is paired with a reduction of the proportion of funds having positive and statistically significant alphas : for ordinary least-squares estimates on serially-correlated returns, there is 27.78% of the funds exhibiting statistically significant positive risk-adjusted returns at the 1% significance level while this proportion falls to 14.78% when hedge fund returns are filtered for serial correlation. This results in a proportion of "trully skilled" funds of hedge funds more than divided by two, going from 27.69% of the funds of hedge funds to 13.76%. The false discoveries rate fdr_γ^+ , measuring the percentage of "zero alpha" funds among the funds having positive and statistically significant risk-adjusted returns, sharply increases, from 0.32% to 2.34% at the 1% significance level, and 3.43% to 16.56% at the 20% level.

All these results on the sample of funds of hedge funds confirm those obtained with individual hedge funds. A higher level of serial correlation is associated with a higher measured risk-adjusted return and lower risk exposures. Controlling for serial-correlation strongly decreases the proportion of funds of hedge funds perceived as being trully skilled, i.e. funds having a positive alpha not being lucky.

Chapitre 2

Serial-correlation without liquidity risk in the hedge fund industry

Un des faits stylisés les plus connus des *hedge funds* est que leurs rendements affichés au sein des bases de données sont autocorrélés. Il a été démontré pour la première fois par Brooks et Kat en 2002 et a depuis été documenté dans un grand nombre d'études académiques. Si de nombreuses explications ont été proposées à ce phénomène, Getmansky et al. (2004) démontrent que seules deux d'entre elles peuvent être envisagées raisonnablement : le lissage des variations des rendements par les gérants afin d'améliorer la performance et l'illiquidité du portefeuille d'actifs sous-jacent.

Ce chapitre distingue entre les deux explications dans la coupe transversale des *hedge funds*. Il part d'une intuition simple, qui est que si l'autocorrélation se manifeste à cause de la présence d'illiquidité dans le portefeuille, alors les fonds ayant des rendements plus autocorrélés devraient avoir de plus fortes expositions au risque de liquidité. Ce chapitre commence par tester directement cette relation. Une analyse non-paramétrique montre que les fonds les plus et moins autocorrélés sont ceux ayant les plus et moins fortes expositions au risque de liquidité mais qu'il n'y a pas de relation monotone entre les variables. De plus, une méthodologie paramétrique Fama et McBeth (1973) démontre qu'il n'y a pas de relation linéaire entre l'exposition à ce risque et l'autocorrélation des rendements des *hedge funds*.

Notre seconde manière de tester l'existence de cette relation est de chercher, en cohérence avec la théorie financière et les résultats empiriques sur les *hedge funds*, l'existence d'une prime de risque associée à l'autocorrélation. Une telle prime de risque indiquerait l'existence d'un risque de liquidité, dont Sadka (2010) a montré qu'il était un déterminant majeur des rendements des *hedge funds*. Les résultats empiriques ne confirment cependant pas l'existence d'une telle prime de risque : aucune relation significative n'apparaît entre autocorrélation des fonds individuels et leur rendement espéré et l'autocorrélation n'est pas un prédicteur des rendements, ce qui d'après Bali et al. (2011) est une condition essentielle à la validation d'un facteur de risque pour les *hedge funds*.

Les résultats de ce chapitre sont importants car ils contredisent les prémisses d'articles académiques récents, comme Kruttli et al. (2015), selon lesquels l'autocorrélation dans les rendements des *hedge funds* est le pur reflet de l'illiquidité de leurs portefeuilles sous-jacents. Ils montrent également que le lissage des variations des rendements par les gérants est perversif, ce qui pose des problèmes de gouvernance et d'alignement des intérêts entre investisseurs et gérants. Enfin, du point de vue des investisseurs, ce chapitre souligne l'importance de la *due diligence* sur le report des rendements par le gérant au même titre que d'autres risques opérationnels.

Serial-correlation without liquidity risk in the hedge fund industry

Hedge funds' returns are notoriously serially correlated. Two potentially complementary explanations has been given in the literature for this phenomenon. The first one is illiquidity in the underlying portfolio and the second one is artificial return smoothing by the fund's manager. This paper isolates the two effects in testing the relationship between serial correlation in hedge fund returns and liquidity risk in the cross-section of individual hedge fund reported returns. Results show that the liquidity risk exposures are partially linked to the amount of serial correlation in reported returns, but that serial correlation does not command a risk premium and hence smoothing by the fund managers is a major determinant of hedge fund serial correlation.

Key-words : hedge funds, serial-correlation, liquidity risk

2.1 Introduction

One of the most famous stylized facts about hedge fund reported returns is their autocorrelated nature. It has been first noticed by Brooks and Kat (2002) and has been documented since in a large number of academic studies (see getmansky et al. (2004) or Krutli et al. (2015)). The existence of such serial correlation seems anomalous with respect to the levels found in other asset classes and efficient market theories. Getmansky et al. (2004) test numerous explanations for this serial-correlation and find that only two can reasonably be kept : illiquidity of the underlying portfolio of assets and artificial smoothing of the reported returns by the fund manager in order to increase performance measures. Serially correlated returns exhibit a lower volatility and lower correlations with other asset classes, dangerously deflating risk measures for portfolio construction as shown by Geltner (1993). Furthermore, Loudon et al. (2006) show that serial correlation greatly reduces the Value-at-Risk.

This article intends to disentangle these two explanations in the cross-section of the amount of serial correlation in hedge fund reported returns. The premise is that, if serial correlation is driven by illiquidity, it should co-move with systematic liquidity measures to which hedge funds are exposed to. To test this idea, we first thoroughly investigate the relation between serial correlation and liquidity exposures in individual fund returns. In sorting funds with respect to the amount of serial correlation in their reported returns or to their exposure to liquidity risk, we find that the most and least serially correlated funds are also the most and least exposed to liquidity risk, and vice versa. However, two-stage cross-sectional regressions show there is no linear relationship between the amount of serial correlation in reported hedge fund returns and the exposure to liquidity risk, indicating that artificial smoothing may cause an important part of the phenomenon. Tests are conducted with the liquidity factors of Sadka (2006), known to price the cross-section of individual hedge fund returns, but in an appendix we also conducted our empirical testing strategy with the Pastor and Stambaugh (2003) liquidity proxies in order to control for the risk of a misspecified liquidity model.

To deeper investigate the liquidity explanation of serial correlation in hedge fund returns, we hypothesize that funds having more serially correlated reported returns should earn larger expected returns. Indeed, Sadka (2010) shows that liquidity risk is priced in the cross-section of hedge fund returns. We test this hypothesis in sorting funds by serial correlation and comparing decile portfolio average returns. We find that the most serially correlated funds earn larger average returns than the least serially correlated ones, but there is no evidence of a linear relation between serial correlation and expected return in the cross-section. Moreover, serial-correlation does not predict future hedge fund returns. These results clearly indicate that liquidity cannot be taken as the sole cause for serial correlation in hedge fund reported returns, as proxied for example by Krutli et al. (2015), and that smoothing should be considered a major explanation of the phenomenon.

The results of this paper give a better understanding on the determinants of serial correlation in hedge fund reported returns. It highlights the complex nature of the autocorrelation process and show that known hedge fund liquidity risk factors are only marginally able to explain it. It also shed light on the importance of artificial return smoothing in the hedge fund industry.

Our paper is linked with the literature on hedge fund serial correlation and liquidity. Brooks & Kat (2002) are the first to identify high levels of serial correlation in hedge fund index returns. Such properties can lead to biased risk estimates : Asness et al. (2001) show that hedge fund indices are correlated both with contemporaneous and lagged equity returns while Patton (2009) unsmooths market neutral hedge fund returns and finds that a portion of these funds have exposure to the equity market once we take into account their returns' autocorrelation. Getmansky et al. (2004) develop an econometric model of individual hedge fund serial correlation. They

also state that autocorrelation in hedge fund returns can only come from illiquidity of the underlying assets or artificial smoothing by the fund manager. The former explanation seems intuitive due to the fact that hedge funds are significantly exposed to liquidity risk (see Sadka (2012) for example). Some studies, such as Krutli et al. (2015), have directly proxied liquidity risk exposure by the amount of serial correlation in hedge fund returns.

The liquidity risk of hedge fund returns is a developed theme in the literature. Cao et al. (2013) find that a subset of hedge fund successfully time market liquidity and hence the dynamic nature of liquidity exposure should be taken into account. Aragon (2007) shows the existence of a funding liquidity risk premium among hedge funds : funds having more lockups and share restrictions outperform due to the greater capacity of investing in illiquid assets. Teo (2011) argues that funds manage their funding liquidity risk in order to attract investor flows, creating a mismatch between asset and liability liquidity. Hong (2014) exhibits dynamics in hedge fund share restrictions and that hedge funds actively manage their funding liquidity risk.

Another strand of literature focuses on hedge fund discretionary reporting of performance. Lo (2002) demonstrates that serial correlation inflates Sharpe Ratios and hence there is an incentive for fund managers to inflate their returns. Bollen and Pool (2008) argue that the full reporting of gains but a delayed reporting of losses by hedge fund managers may induce the observed hedge fund return serial correlation and find empirical evidence of conditional return smoothing. Furthermore, Bollen and Pool (2009) find that there is a discontinuity in the pooled distribution of hedge fund returns, suggesting artificial return smoothing by managers. Agarwal et al. (2011) show a "December spike" in the returns for funds having incentives to misreport¹. Finally, Cao et al. (2016), using a proprietary database on separate accounts from Lyxor, show that serial correlation is 25.1% lower for separate accounts with respect to their hedge fund counterparts.

The rest of this paper is organized as follows. Section 2 describes the data used in the article. Section 3 investigates the cross-sectional relation between serial correlation in hedge fund returns and exposure to liquidity risk. Section 4 analyses the existence of a risk premium in serial correlation. Section 5 concludes.

2.2 Data and variables

Our monthly individual hedge fund returns come from the Lipper TASS database. We select funds having at least 36 observations over the sample period January 1994 - December 2012, reporting their returns at a monthly frequency and net of fees in US dollars. We exclude Funds of Hedge Funds to avoid double counting, i.e. a Fund of Hedge Funds having invested in an individual hedge fund already included in the database. Table 2.1 reports average summary statistics for the whole database as for individual hedge funds grouped according to ten investment styles : Convertible-Arbitrage, Dedicated Short Bias, Emerging Markets, Equity Market Neutral, Event Driven, Fixed-Income Arbitrage, Global Macro, Long/Short Equity, Multi-Strategies and Options. Our sample contains 4,641 individual hedge funds, having an average return of 0.76% and an average volatility of 4.41%. We find that, on average, individual hedge funds report returns that are negatively skewed, with a coefficient of -0.25, and have a kurtosis of 7.72, in excess to a gaussian distribution.

The most important statistic in our case is the amount of serial correlation, proxied here by θ_0 the weight of the current "true" return in reported returns : a value of one indicates no serial correlation in reported returns while the closer to zero, the more serially correlated the reported returns. To model and measure serial-correlation in hedge funds' reported returns, we rely on the methodology developed by Getmansky et al. (2004). We denote

1. gain in incentives fees or fear of a capital withdrawal

TABLE 2.1 – **Basic statistics of individual hedge funds**

This table provides the mean summary statistics for each hedge fund strategy in the Lipper TASS database for the period January 1994 - December 2012. This includes the mean (μ), standard deviation (σ), kurtosis, skewness and the Sharpe ratio (SR). The full sample contains 4,641 funds with both live funds and dead funds to avoid survivorship bias.

	numObs	μ	σ	skewness	kurtosis	SR
All	4,641	0.76	4.41	-0.25	7.72	0.27
Convertible-Arbitrage	172	0.61	2.63	-1.07	12.06	0.45
Dedicated-Short	40	0.22	6.18	0.34	5.62	0.06
Emerging-Markets	606	0.75	5.77	-0.44	7.82	0.2
Macro	300	0.71	4.27	0.33	6.23	0.19
Equity-Market-Neutra	300	0.81	4.98	-0.3	8.2	0.27
Event-Driven	532	0.82	3.03	-0.49	8.13	0.42
Fixed-Income	205	0.6	2.48	-1.3	15.93	0.69
Long-Short Equity	2,003	0.83	4.86	0.02	6.24	0.21
Multi-Strategies	467	0.59	3.34	-0.47	8.8	0.3
Options	16	0.72	3.34	-0.77	16.6	0.25

R_t the "true" economic return of a hedge fund at date t , i.e. returns that prevail if there was no artificial smoothing or frictions in marking-to-market due to illiquidity. R_t follows linear single factor model :

$$R_t = \mu + \beta\Lambda_t + \epsilon_t, \quad E[\Lambda_t] = E[\epsilon_t] = 0, \quad \epsilon_t, \Lambda_t \sim IID \tag{2.1}$$

$$Var(R_t) = \sigma^2$$

These true returns represent the returns updated with the contemporaneous flow of information in a frictionless market, determining the equilibrium value of the fund's underlying assets. However, investors only observe the smoothed returns R_t^0 which are weighted averages of the true returns over the most recent $k + 1$ and current periods :

$$R_t^0 = \theta_0 R_t + \theta_1 R_{t-1} + \dots + \theta_k R_{t-k} \tag{2.2}$$

$$\theta_j \in [0, 1], j = 0, \dots, k$$

$$1 = \theta_0 + \theta_1 + \dots + \theta_k$$

Furthermore, we define ξ the Herfindahl index of the smoothing weights in reported returns, a measure of the concentration of the smoothing process :

$$\xi = \sum_j^k \theta_j^2 \tag{2.3}$$

A lower value of ξ implies a more marked smoothing process, while a greater value indicates a low serial correlation in reported returns. If $\xi = 1$, there is no evidence of serial correlation in the reported returns.

To estimate the smoothing coefficients, we follow Getmansky et al. (2004) that have used a moving average procedure. We define the de-meaned observed returns process X_t with the following properties :

$$\begin{aligned}
X_t &= R_t^0 - \mu & (2.4) \\
X_t &= \theta_0 \eta_t + \theta_1 \eta_{t-1} + \dots + \theta_k \eta_{t-k} \\
\eta &\sim N(0, \sigma_\eta^2)
\end{aligned}$$

The parameters are obtained through maximum likelihood optimization. Once the weights are estimated, we can recover unsmoothed returns with the following identification :

$$R_t = \frac{R_t^0 - \hat{\theta}_1 R_{t-1}^0 - \dots - \hat{\theta}_k R_{t-k}^0}{\hat{\theta}_0} \quad (2.5)$$

In practice, we follow Getmansky et al. (2004) and fix $k = 2$, meaning that we stop after a lag at the order two. Table 2.2 presents the average empirical results for the whole sample as for the different trading styles.

TABLE 2.2 – Means and standard deviations of the smoothing estimates

This table presents the average (Mean) and the standard deviation (SD) of the MA(2) smoothing process $R_t^0 = \theta_0 R_t + \theta_1 R_{t-1} + \theta_2 R_{t-2}$ and $\xi = \theta_0^2 + \theta_1^2 + \theta_2^2$ is the index of smoothing (the smaller it is, the greater the smoothing is). The sample period is from January 1994 to December 2012.

Serial correlation statistics										
Category	N	$\hat{\theta}_0$		$\hat{\theta}_1$		$\hat{\theta}_2$		ξ		
		Mean	SD	Mean	SD	Mean	SD	Mean	SD	
All	4,641	0.8	0.34	0.14	0.2	0.06	0.2	0.86	0.38	
Convertible Arbitrage	172	0.61	0.14	0.27	0.13	0.11	0.1	0.51	0.21	
Dedicated Short	40	0.98	0.24	0.08	0.16	-0.05	0.17	1.07	0.6	
Emerging Markets	606	0.78	0.16	0.17	0.11	0.06	0.13	0.69	0.3	
Equity Market Neutral	300	0.84	0.24	0.11	0.17	0.05	0.16	0.83	0.58	
Event Driven	532	0.71	0.2	0.2	0.13	0.09	0.13	0.62	0.6	
Fixed Income	205	0.7	0.21	0.2	0.16	0.1	0.13	0.63	0.42	
Long-Short Equity	2,003	0.83	0.35	0.12	0.2	0.05	0.2	0.91	0.55	
Macro	300	0.94	0.32	0.06	0.21	0	0.22	1.07	1.37	
Multi Strategy	467	0.79	0.59	0.15	0.3	0.06	0.33	1.21	0.33	
Options	16	0.81	0.17	0.15	0.15	0.04	0.12	0.74	0.29	

Consistent with Asness et al. (2001), we find that hedge funds' reported returns exhibit serial correlation, with an average weight on the first lag return of 14%. We further notice that average serial correlations vary greatly across different hedge fund strategies. For example, the average weight on the current "true" return, which can be taken as a proxy for the amount of serial correlation, goes from 61% for Convertible Arbitrage to 98% to Dedicated Short. These first results advocate to investigate at the individual fund level and not at the index level due to the heterogeneity in individual funds' serial correlation profiles.

However, another striking feature of our data is the amount of intra-style variability in serial-correlation, with cross-sectional standard-deviation of the contemporaneous return's weight parameter θ_0 going from 14%

for Convertible Arbitrage to 59% for Multi Strategy. Individual hedge funds returns are then widely differently serially correlated within a strategy. This confirms the interest of doing the analysis at the individual fund level and not the index level due to the non-uniformity of individual funds within a strategy.

Most of the serial-correlation is present at the order one, with low coefficients at the order two. Estimates for lag two goes from -5% for Dedicated Short to 11% for Convertible Arbitrage. The Herfindhal index ξ shows a great variability, with an average of 0.86 for a standard-deviation 0.38 : hedge funds report, on average, serially correlated returns but this amount of serial correlation is far from uniform. This wide dispersion in serial correlation, both inter and intra-strategy, enables us to properly test if its variation is explained by variation in exposure to liquidity risk factors.

TABLE 2.3 – Summary statistics of the risk factors

This table provides summary statistics for our risk factors for the period January 1994 - December 2012. This includes the mean (μ), standard deviation (σ), kurtosis, skewness, the Sharpe Ratio (SR) and the serial correlation (AR(1)) parameter, as measured with an autoregressive process at the order 1 with a constant.

	μ	σ	skewness	kurtosis	SR	AR(1)
transitory price impact	0.01	0.13	4.2	39.39	0.1	12.24
permanent price impact	0.05	0.59	-0.84	8.88	0.08	9.12
S&P 500	0.59	4.49	-0.66	3.95	0.13	9.31

Finally, we use the transitory and permanent market-wide price impact factors of Sadka (2006)² to proxy for the liquidity risk exposure of hedge funds and the S&P 500 for the equity market exposure over the period January 1994 to December 2012. These measure aggregate permanent and transitory price impact measures of Glosten & Harris (1988) across individual firms in the TAQ database every month. Table 2.3 presents the summary statistics for these risk factors. The transitory price impact risk factor presents a strong positive skewness of 4.2 and an even stronger kurtosis of 39.39, implying small but frequent negative returns and rare huge positive returns. The two other risk factors have negative skewness and kurtosis in excess to a gaussian distribution, as observed in most hedge fund returns profiles. We notice that there is a small amount of serial correlation in all three factors, with serial correlation going from 9.12% for the permanent price impact factor to 12.24% for the transitory price impact factor.

2.3 Serial correlation and liquidity exposure

Getmansky et al. (2004) show that illiquidity and artificial smoothing are responsible for serial correlation in hedge fund returns far above the levels found in equities by Campbell et al. (1993) for example.

2. these liquidity factors can be found at Sadka personal web-page <https://www2.bc.edu/ronnie-sadka/>

	Low	2	3	4	5	6	7	8	9	High	High-Low
All	θ_0	0.49	0.62	0.68	0.72	0.79	0.83	0.89	0.96	1.26	0.77
	$\beta_{transit}$	11.46 (11.43)***	10.08 (12.65)***	10.07 (11.41)***	7.99 (10.57)***	7.19 (10.29)***	5.19 (6.94)***	6.41 (9.15)***	3.91 (4.39)***	-0.80 (-0.18)	1.89 (2.3)**
Convertible-Arbitrage	θ_0	0.41	0.49	0.52	0.55	0.61	0.64	0.68	0.72	0.87	0.47
	$\beta_{transit}$	10.57 (3.55)***	7.58 (2.85)***	7.27 (3.59)***	5.37 (2.4)***	4.82 (2.93)***	7.49 (3.39)***	7.2 (3.97)***	3.84 (2.36)***	2.38 (1.71)*	11.99 (1.95)*
Dedicated-Short	θ_0	0.71	0.75	0.83	0.87	0.9	0.98	1.03	1.19	1.54	0.83
	$\beta_{transit}$	3.63 (1.77)*	-13.55 (-2.46)***	3.66 (1.23)	-5.43 (-1.08)	3.8 (1.04)	-0.96 (-0.22)	2.48 (3.05)***	2.58 (3.18)***	8.98 (3.59)***	7.12 (1.48)
Emerging-Markets	θ_0	0.54	0.64	0.68	0.71	0.78	0.8	0.84	0.9	1.1	0.56
	$\beta_{transit}$	18.64 (5.59)***	15.64 (7.82)***	15.84 (6.09)***	16.69 (6.58)***	13.14 (6.99)***	10.85 (5.18)***	9.06 (4.53)***	14.77 (4.69)***	4.72 (2.31)**	5.02 (1.85)*
Equity Market-Neutral	θ_0	0.53	0.64	0.7	0.75	0.82	0.87	0.93	1.02	1.35	0.82
	$\beta_{transit}$	5.37 (3.41)***	1.38 (1.72)*	0.76 (0.57)	2.39 (1.31)	0.9 (0.52)	2.69 (2.74)***	8.09 (1.92)*	4.21 (3.16)***	-7.2 (-0.95)	5.44 (3.02)***
Event-Driven	θ_0	0.49	0.57	0.6	0.63	0.69	0.73	0.78	0.83	1.06	0.57
	$\beta_{transit}$	12.12 (3.43)***	11.86 (5.69)***	11.27 (6.01)***	10.14 (5.84)***	12.39 (3.12)***	5.32 (4.69)***	6.45 (3.7)***	2.55 (1.21)	6.96 (3.41)***	4.28 (3.1)***
Fixed-Income	θ_0	0.39	0.5	0.58	0.63	0.7	0.75	0.8	0.87	1.08	0.69
	$\beta_{transit}$	4.47 (1.14)	8.09 (2.34)***	5.22 (3.15)***	3.47 (1.72)*	12.96 (2.13)**	2.98 (1.39)	7.21 (2.67)***	5.89 (3)***	5.68 (3.94)***	6.28 (2.03)**
Long-Short Equity	θ_0	0.54	0.68	0.72	0.76	0.83	0.86	0.91	0.98	1.24	0.7
	$\beta_{transit}$	12.26 (6.18)***	9.48 (7.55)***	8.17 (6.47)***	6.67 (5.68)***	5.79 (4.21)***	5.52 (5.81)***	4.26 (3.49)***	4.09 (4.1)***	0.97 (1.17)	-0.1 (-0.07)
Macro	θ_0	0.62	0.72	0.77	0.81	0.9	0.94	1	1.12	1.6	0.97
	$\beta_{transit}$	2.54 (1.23)	4.2 (1.51)	5.64 (1.67)*	1.93 (1.3)	-3.55 (-0.58)	9.61 (1.31)	-0.04 (-0.02)	8.07 (3.29)***	5.37 (1.74)	0.64 (0.26)
Multi-Strategies	θ_0	0.47	0.57	0.62	0.66	0.7	0.8	0.85	0.95	1.36	0.89
	$\beta_{transit}$	10.1 (3.9)***	13.31 (5.93)***	12.87 (4.97)***	10.8 (4.23)***	6.69 (4.99)***	4.97 (3.62)***	4.95 (3.32)***	3.11 (1.86)*	8.16 (2.05)**	1.47 (0.88)
Options	θ_0	0.47	0.57	0.62	0.66	0.7	0.8	0.84	0.95	1.36	0.89
	$\beta_{transit}$	10.1 (3.9)***	13.31 (5.93)***	12.87 (4.97)**	10.8 (4.23)***	6.69 (4.99)***	4.97 (3.62)***	4.95 (3.22)***	3.11 (1.86)*	8.16 (2.05)**	1.47 (0.88)

TABLE 2.4 – Decile portfolios of hedge funds transitory price impact exposures sorted by serial correlation

This table reports properties of equal-weighted decile portfolios of individual hedge funds. For each fund having at least 36 monthly return observations, we estimate the following liquidity risk model $r_{i,t} = \alpha^i + \beta^i_{transit} F_{transit,t} + \beta^i_{perma} F_{perma,t} + u^i_t$ where $r_{i,t}$ is the return on each individual fund in month t , $\beta^i_{transit}$ is the exposure to innovations in the market-wide transitory price-impact of fund i and β^i_{perma} is the exposure to innovations in the market-wide permanent price-impact of fund i . Simultaneously, we estimate an MA(2) model on $r_{i,t}$. Portfolios are formed in ranking each fund according to its weight of the current return on its reported returns θ_0 , so the portfolio Low is the portfolio with the lowest θ_0 . The sample period is January 1994 - December 2012. For each decile portfolio, we report the average serial correlation parameter θ_0 , the exposure $\beta_{transit}$ and its t-statistic.

The first hypothesis that illiquidity causes serial-correlation in hedge fund returns is often taken for granted : for example, Krutli et al. (2015) build a measure of aggregate illiquidity of hedge fund portfolios as the cross-sectional average first-order autocorrelation of hedge fund returns. However, to our knowledge, there has been no formal test of the relation between hedge fund serial correlation and the liquidity of their underlying portfolio. Does cross-sectional differences in serial-correlation is related to differences in liquidity measures ?

To answer this question, we first investigate the link between the amount of serial correlation through a simple non-parametric portfolio approach. Sadka (2010) demonstrated that exposures to shocks to the permanent and transitory market-wide price impact in the equity market explains the cross-section of hedge fund returns. Therefore, we use both permanent price-impact exposure and transitory price-impact beta as measures of the illiquidity of a given hedge fund underlying portfolio. We sort individual hedge fund returns into decile portfolios, based on their weight θ_0 of the current "true" return in reported returns, measured with Eq. (2.4). The higher this coefficient, the lower is the serial correlation. We simultaneously measure the individual hedge funds' liquidity exposures with the following factor model :

$$r_{i,t} = \alpha^i + \beta_{transit}^i F_{transit,t} + \beta_{perma}^i F_{perma,t} + u_t^i \quad (2.6)$$

where $r_{i,t}$ is the return of fund i in month t , α^i is the risk-adjusted return of fund i , $\beta_{transit}^i$ is the exposure to innovations in the market-wide transitory price-impact of fund i , $F_{transit,t}$ is the realization in month t of the innovation in the market-wide transitory price-impact, β_{perma}^i is the exposure to innovations in the market-wide permanent price-impact of fund i , $F_{perma,t}$ is the realization in month t of the innovation in the market-wide permanent price-impact and u_t^i is the residual of fund i in month t .

For each decile, we compute the average coefficients θ_0 , $\beta_{transit}$ and β_{perma} . Tables 2.4-2.5 present the results for the decile portfolios. The resulting weights on current "true" returns in reported returns θ_0 go from an average of 0.49 for the lowest decile to an average of 1.26 for the last decile. Table 2.4 shows that, for the global sample of individual hedge funds, there is a high-minus-low difference in exposure to the transitory market-wide impact factor of -9.56%, highly statistically significant with an associated t-statistic of -7.59. This result shows that the most serially correlated hedge funds, i.e. funds having lower θ_0 , are more exposed to liquidity risk than the lowest serially correlated funds, consistent with the interpretation that serial correlation in hedge fund returns is the byproduct of illiquidity in the underlying portfolio.

When we look at the strategies' decile portfolios cross-sectional differences in exposures to the transitory market impact factor, we find that half of the ten strategies -Emerging Markets, Event-Driven, Long/Short Equity, Multi-Strategies and Options- have negative and statistically significant high-minus-low spreads. All the the other strategies have non-statistically significant spreads, indicating a lack of relationship between serial-correlation and this measure of liquidity risk. There seems to be a global relationship between liquidity exposures of hedge funds and the amount of serial correlation in their reported returns, but this relation is imperfect and does not hold for every strategy sub-sample of individual funds.

	Low	2	3	4	5	6	7	8	9	High	High-Low
All	θ_0	0.49	0.62	0.68	0.72	0.75	0.79	0.83	0.89	1.26	0.77
	β_{perma}	0.58	0.58	0.72	0.59	0.68	0.68	0.54	0.47	-0.54	-0.63
		(9.33)***	(9.7)***	(12.95)***	(8.81)***	(11.96)***	(11.51)***	(9.59)***	(6.45)***	(-0.39)	(-5.1)***
Convertible-Arbitrage	θ_0	0.41	0.49	0.52	0.55	0.58	0.61	0.64	0.68	0.72	0.47
	β_{perma}	1	1.03	0.31	0.11	0.41	0.2	0.73	0.58	0.36	-0.81
		(2.58)***	(2.71)***	(1.7)*	(0.5)	(0.94)	(0.87)	(1.94)*	(2.37)***	(1.48)	(-1.45)
Dedicated-Short	θ_0	0.71	0.75	0.83	0.87	0.9	0.95	0.98	1.03	1.19	0.83
	β_{perma}	0	-1.32	-0.91	-0.59	-0.32	-0.83	-1.06	-0.65	-0.79	-3.8
		(0)	(-1.86)*	(-3.47)***	(-0.94)	(-0.7)	(-4.28)***	(-2.78)***	(-0.73)	(-2.68)***	(-1.37)
Emerging-Markets	θ_0	0.54	0.64	0.68	0.71	0.74	0.78	0.8	0.84	0.9	0.56
	β_{perma}	1.38	1.03	1.21	1.42	1	1.52	0.98	0.84	1.2	0.47
		(5.51)***	(7.49)***	(5.25)***	(6.49)***	(6.61)***	(6.37)***	(4.83)***	(5.69)***	(4.72)***	(-2.14)**
Equity Market-Neutral	θ_0	0.53	0.64	0.7	0.75	0.78	0.82	0.87	0.93	1.02	0.82
	β_{perma}	-0.28	0.12	0.17	0.31	0.29	0.31	0.47	0.23	-7.66	0.77
		(-1.03)	(0.93)	(1.01)	(3.45)***	(2.39)***	(2.15)**	(2.49)***	(1.35)	(-0.93)	(1.79)*
Event-Driven	θ_0	0.49	0.57	0.6	0.63	0.66	0.69	0.73	0.78	0.83	0.57
	β_{perma}	0.4	0.96	0.63	0.57	0.45	0.57	0.74	0.38	0.16	0.26
		(3.71)***	(5.6)***	(6.74)***	(4.85)***	(4.46)***	(5.13)***	(5.44)***	(1.78)*	(0.81)*	(3.96)***
Fixed-Income	θ_0	0.39	0.5	0.58	0.63	0.66	0.7	0.75	0.8	0.87	0.69
	β_{perma}	0.06	0.61	0.84	0.93	0.54	0.23	0.58	0.1	0.33	-0.13
		(0.51)	(2.42)**	(3.55)***	(3.34)***	(1.87)*	(1.08)	(3.21)***	(0.54)	(0.74)	(-0.39)
Long-Short Equity	θ_0	0.54	0.68	0.72	0.76	0.79	0.83	0.86	0.91	0.98	0.7
	β_{perma}	0.34	0.78	0.46	0.74	0.68	0.68	0.54	0.39	0.23	-0.45
		(2.92)***	(9.1)***	(4.15)***	(8.21)***	(8.63)***	(7.68)***	(5.92)***	(4.08)***	(2.19)***	(-2.01)**
Macro	θ_0	0.62	0.72	0.77	0.81	0.86	0.9	0.94	1	1.12	0.97
	β_{perma}	0.53	0.22	0.27	0.47	0.16	0.32	-0.15	0.07	0.12	-0.79
		(2.5)***	(0.71)	(1.47)	(2.67)***	(0.38)	(0.99)	(-0.77)	(0.54)	(0.7)	(-1.73)*
Multi-Strategies	θ_0	10.1	13.31	12.87	10.8	6.69	4.97	4.95	3.11	8.16	-8.63
	β_{perma}	0.4	0.85	0.89	0.38	0.48	0.38	0.51	0.41	0.35	-0.73
		(2.89)***	(5.98)***	(6.66)***	(2.11)**	(4.06)***	(3.11)***	(3.95)***	(3.45)***	(2.77)***	(-2.42)***
Options	θ_0	0.47	0.57	0.62	0.66	0.7	0.74	0.8	0.84	0.95	0.89
	β_{perma}	0.4	0.85	0.89	0.38	0.49	0.38	0.51	0.41	0.35	-0.73
		(2.89)***	(5.98)***	(6.66)***	(2.11)**	(4.06)***	(3.11)***	(3.95)***	(3.45)***	(2.77)***	(-2.42)***

TABLE 2.5 – Decile portfolios of hedge funds permanent price impact exposures sorted by serial correlation

This table reports properties of equal-weighted decile portfolios of individual hedge funds. For each fund having at least 36 monthly return observations, we estimate the following liquidity risk model $r_{i,t} = \alpha^i + \beta_{transit}^i F_{transit,t} + \beta_{perma}^i F_{perma,t} + u_t^i$ where $r_{i,t}$ is the return on each individual fund in month t , $\beta_{transit}^i$ is the exposure to innovations in the market-wide transitory price-impact of fund i and β_{perma}^i is the exposure to innovations in the market-wide permanent price-impact of fund i . Simultaneously, we estimate an MA(2) model on $r_{i,t}$. Portfolios are formed in ranking each fund according to its weight of the current return on its reported returns θ_0 , so the portfolio Low is the portfolio with the lowest θ_0 . The sample period is January 1994 - December 2012. For each decile portfolio, we report the average serial correlation parameter θ_0 , the exposure β_{perma} and its t-statistic.

Table 2.5 presents the results for the relation between serial correlation and exposure to changes in the permanent market-wide permanent price impact. For the whole sample of individual funds, there is a negative high-minus-low average difference in exposure to this liquidity risk factor, highly statistically significant with a t-statistic of -5.1. However, only four strategies -Emerging-markets, Long/Short Equity, Multi-Strategies and Options- exhibit negative and statistically significant at the 5% risk level high-minus-low differences, indicating that for most strategies there is a lack of intra-style cross-sectional difference in liquidity risk exposures between the lowest and highest serially correlated hedge funds.

If liquidity is the main cause of serial-correlation, the relation should go both ways, with the most serially correlated funds having the highest exposures to liquidity risk and vice-versa. In order to test this relationship, we estimate liquidity betas as in Eq. (2.6) and sort individual hedge fund into deciles according to their exposures to shocks in market-wide transitory market impact. We then look at the average serial correlation parameter θ_0 for each decile. Results are presented in Table 2.6. The resulting market-wide transitory market impact exposures range from an average of -18.51% for decile 1 to an average of 44.39% for decile 10. For the global sample of individual hedge funds, there is a high-minus-low average spread in serial correlation coefficient θ_0 of -0.19, highly statistically significant with a t-statistic of -6.38. This indicates that the funds the most exposed to liquidity risk are more serially correlated, i.e. have lower θ_0 , than the least exposed funds, consistent with the prediction that portfolio illiquidity drives serial correlation in hedge fund returns.

This difference in serial correlation varies greatly from a strategy subsample to another, and is only negative and statistically significant at the 5% risk level for five strategies over ten, Long/Short Equity, Multi-Strategies, Emerging Markets, Event-Driven and Options. The relation between serial correlation and liquidity risk exposure seems not monotone. This indicates a noisy relationship between the amount of serial-correlation in reported returns and the exposure to liquidity risk in the cross-section of individual hedge fund : liquidity is clearly not the sole driver of serial correlation .

We also check for the relation when we sort individual hedge funds into decile portfolios with respect to their exposures to changes in permanent market-wide price impact. Table 2.7 shows the results. The exposures to this liquidity risk goes from an average of -2.49% for the lowest decile to and average of 3.21% for the highest decile, giving a high-minus-low spread of 5.69% in exposure to permanent price-impact risk. at the global level, the high-minus-low portfolio of individual hedge funds exhibits a negative spread in the weight θ_0 of current "true" returns in reported returns of -0.05%, non-statistically significant with an associated t-statistic of -1.45. Only two strategies, Emerging-Markets and Fixed Income, have negative and statistically significant spreads in this liquidity risk, with coefficients of both -0.11% and associated t-statistics of -2.97 and -2.42 respectively. The other strategies sub-samples of individual funds have no statistically significant spreads of serial correlation.

	Low	2	3	4	5	6	7	8	9	High	High-Low
All	$\beta_{transit}$ θ_0	-2.57 0.86 (32.64)***	-0.72 0.81 (79.43)***	0.41 0.75 (25.34)***	1.54 0.77 (82.94)***	3.24 0.82 (72.99)***	5.96 0.8 (93.88)***	10.59 0.78 (90.62)***	18.28 0.75 (92.32)***	44.39 0.74 (92.08)***	62.9 -0.19 (-6.38)***
Convertible Arbitrage	$\beta_{transit}$ θ_0	0.43 0.62 (19.16)***	0.92 0.62 (22.39)***	1.32 0.61 (16.04)***	1.94 0.61 (31.85)***	3.1 0.57 (27.43)***	6.03 0.62 (21.35)***	9.61 0.61 (21.92)***	15.41 0.59 (23.18)***	26.74 0.55 (15.8)***	29.83 -0.13 (-2.28)***
Dedicated-Short	$\beta_{transit}$ θ_0	-5.66 0.81 (14.79)***	-0.81 0.96 (7)***	1.15 0.91 (19.02)***	1.96 0.94 (10.21)***	3.08 1.03 (6.12)***	3.61 0.94 (36.24)***	4.59 1.21 (8.55)***	8.01 0.89 (9.09)***	15.32 1.23 (7.38)***	34.27 0.4 (2.82)***
Emerging-Markets	$\beta_{transit}$ θ_0	-1.47 0.83 (40.8)***	0.44 0.74 (31.24)***	2.35 0.78 (36.75)***	4.4 0.78 (35.53)***	7.77 0.77 (31.88)***	13.42 0.76 (69.63)***	19.43 0.75 (38.09)***	29.97 0.73 (48.14)***	56.4 0.74 (39.4)***	66.46 -0.12 (-4.98)***
Equity Market-Neutral	$\beta_{transit}$ θ_0	-2.22 0.84 (33.98)***	-0.92 0.89 (21.57)***	0.01 0.82 (16.94)***	0.68 0.76 (31.02)***	1.55 0.85 (20.14)**	2.74 0.94 (13.61)***	5.15 0.81 (24.72)***	9.75 0.78 (18.27)***	27.73 0.9 (22.45)***	113.01 0.09 (1.95)*
Event-Driven	$\beta_{transit}$ θ_0	-0.45 0.77 (30.11)***	0.21 0.73 (28.71)***	0.96 0.77 (15.26)***	1.96 0.68 (41.07)***	3.65 0.71 (43.69)***	7.95 0.69 (31.95)***	14.22 0.71 (28.93)***	20.52 0.65 (40.56)***	38.8 0.65 (38.67)***	47.01 -0.12 (-3.97)***
Fixed-Income	$\beta_{transit}$ θ_0	-0.84 0.71 (11.88)***	-0.07 0.68 (11.62)***	0.35 0.61 (12.11)***	0.95 0.65 (13.9)***	1.61 0.69 (24.8)***	3.31 0.7 (22.56)***	7.88 0.78 (10.32)***	14.84 0.72 (21.89)***	38.28 0.72 (16.84)***	42.29 -0.03 (-0.46)
Long-Short Equity	$\beta_{transit}$ θ_0	-4.14 0.88 (55.17)***	-1.67 0.86 (47.38)***	-0.3 0.84 (60.42)***	1.01 0.75 (11.61)***	2.89 0.83 (75.8)***	5.11 0.85 (62.84)***	8.82 0.81 (70.54)***	16.15 0.8 (67.19)***	44.33 0.77 (66.15)***	60.38 -0.15 (-7.42)***
Macro	$\beta_{transit}$ θ_0	-4.57 1.02 (9.51)***	-1.96 0.92 (24.65)***	-0.59 0.91 (17.51)***	0.56 0.9 (27.43)***	1.69 0.96 (14.85)***	3.52 1.01 (11.99)***	6.53 0.86 (32.15)***	12.4 0.92 (20.92)***	39.48 0.93 (25.06)***	62.11 -0.09 (-0.8)
Multi-Strategies	$\beta_{transit}$ θ_0	-2.15 0.8 (4.84)***	-0.24 0.74 (26.12)***	0.92 0.77 (21.35)**	2.11 0.73 (25.12)***	4.74 0.76 (29.21)***	8.44 0.78 (31.1)***	11.77 0.73 (10.97)***	19.09 0.69 (25.39)***	38.34 0.65 (27.64)***	50.7 -0.6 (-2.27)**

TABLE 2.6 – Decile portfolios of hedge funds sorted by exposure to transitory price impact liquidity risk

This table reports properties of equal-weighted decile portfolios of individual hedge funds. For each fund having at least 36 monthly return observations, we estimate the following liquidity risk model $r_{i,t} = \alpha^i + \beta_{transit}^i F_{transit,t} + \beta_{perma}^i F_{perma,t} + u_t^i$ where $r_{i,t}$ is the return on each individual fund in month t , $\beta_{transit}^i$ is the exposure to innovations in the market-wide transitory price-impact of fund i and β_{perma}^i is the exposure to innovations in the market-wide permanent price-impact of fund i . Simultaneously, we estimate an MA(2) model on $r_{i,t}$. Portfolios are formed in ranking each fund according to its exposure $\beta_{transit}^i$. The sample period is January 1994 - December 2012. For each decile portfolio, we report the average exposure $\beta_{transit}$, the average serial correlation parameter θ_0 and its t-statistic.

These results for the different decile portfolios show that, globally, the most serially correlated hedge funds are more exposed to liquidity risk than the least serially correlated funds, and that conversely the funds that are the most exposed to liquidity risk have more serially correlated returns than the least exposed. These findings hold for both liquidity risk factors and are consistent with the idea that illiquidity explains hedge fund returns' serial correlation. However, this does not hold for the majority of strategies sub-samples, with high-minus-low decile portfolios that have non-statistically significant spreads.

To continue to investigate if there is a monotonic relation between individual funds' serial correlation and liquidity risk, we use a parametric regression approach. More precisely, we use two-stage cross-sectional regressions similar to Fama and McBeth (1973). For each individual hedge fund i , we estimate in a first-stage regression its exposure to the liquidity risk factors as in Eq. (2.6). We estimate simultaneously its coefficient θ_0^i , which measures the weight of current "true" returns in reported returns as in Eq. (2.4). We then run a cross-sectional regression of these serial-correlation parameters on each liquidity risk exposure in second-stage regressions :

$$\hat{\theta}_0^i = \gamma + \lambda_{\beta_{transit}} \hat{\beta}_{transit}^i + \nu^i \quad (2.7)$$

where $\hat{\theta}_0^i$ is the estimated weight on current "true" returns in reported returns for fund i , γ is the intercept, $\lambda_{\beta_{transit}}$ is the cross-sectional slope coefficient, $\hat{\beta}_{transit}^i$ is the estimated exposure to transitory price impact risk for fund i and ν^i is the residual for fund i .

We repeat the procedure with the market-wide permanent impact risk factor :

$$\hat{\theta}_0^i = \gamma + \lambda_{\beta_{perma}} \hat{\beta}_{perma}^i + \nu^i \quad (2.8)$$

where $\hat{\theta}_0^i$ is the estimated weight on current "true" returns in reported returns for fund i , γ is the intercept, $\lambda_{\beta_{perma}}$ is the cross-sectional slope coefficient, $\hat{\beta}_{perma}^i$ is the estimated exposure to permanent price impact risk for fund i and ν^i is the residual for fund i .

Table 2.8 presents results for the exposures to the innovations in transitory market-wide price impact. The cross-sectional second-stage regression for the global sample of individual hedge funds exhibits a negative slope of -0.06%, non-statistically significant with both Newey and West (1987) and Hansen's (1992) generalized method of moments t-statistics. These statistical procedures adjust standard deviations of estimates for cross-sectional correlation among funds and errors in variables. The number of lags in the Newey-West procedure is selected automatically as in Newey and West (1994). This result confirms that, globally, there is no linear relation between serial correlation as measured by θ_0 and the transitory price-impact risk, even if there are statistically significant spreads for high-minus-low portfolios. For individual hedge funds, transitory market impact risk seems to explain the difference between the lowest exposed and the highest exposed funds, but is not the sole explanatory variable.

	Low	2	3	4	5	6	7	8	9	High	High-Low
All Arbitrage	β_{perma}	-0.46	-0.11	0.1	0.32	0.54	0.77	1.09	1.59	3.21	5.69
	θ_0	(27.38)***	(79.66)***	(70.37)***	(77.33)***	(96.06)***	(30.05)***	(104.19)***	(96.12)***	(65.45)***	(-1.45)
Convertible-	β_{perma}	-1.76	-0.7	-0.28	0	0.56	0.8	1.17	1.16	2.93	4.69
	θ_0	(20.5)***	(15.5)***	(15.15)***	(15.04)***	(17.29)***	(29.18)***	(39.03)***	(25.8)***	(13.34)***	(-0.7)
Dedicated-Short	β_{perma}	-5	-1.81	-1.37	-0.98	-0.79	-0.56	-0.32	0.21	1.02	6.02
	θ_0	(4.69)***	(7.13)***	(25.66)***	(10.55)***	(12.98)***	(7.81)***	(7.14)***	(15.92)***	(7.24)***	(15.4)***
Emerging-Markets	β_{perma}	-1.52	-0.22	0.12	0.45	0.71	1.33	1.8	2.57	4.63	6.15
	θ_0	(27.48)***	(32.27)***	(29.31)***	(57.4)***	(52.22)***	(53.16)***	(46.43)***	(40.6)***	(37.86)***	(-2.97)***
Equity Market-Neutral	β_{perma}	-9.83	-0.51	-0.16	0.02	0.18	0.52	0.71	1.01	2.15	11.98
	θ_0	(15.99)***	(22.87)***	(27.15)***	(20.84)***	(25.29)***	(26.32)***	(19.27)***	(28.22)***	(20.75)***	(13.6)***
Event-Driven	β_{perma}	-1.24	-0.11	0.07	0.25	0.4	0.77	0.99	1.37	2.34	3.57
	θ_0	(30.69)***	(14.99)***	(22.1)***	(23.73)***	(39.12)***	(38.17)***	(32.65)***	(28.14)***	(38.37)***	(42.53)***
Fixed-Income	β_{perma}	-1.21	-0.41	-0.12	-0.03	0.09	0.51	0.72	1.26	2.64	3.85
	θ_0	(21.47)***	(10.85)***	(14.36)***	(13.65)***	(13.89)***	(17.97)***	(19.89)***	(25.34)***	(12.75)***	(23.56)***
Long-Short Equity	β_{perma}	-2.32	-0.52	-0.12	0.11	0.31	0.8	1.13	1.62	3.13	5.45
	θ_0	(12.72)***	(54.57)***	(56.4)***	(67.76)***	(81.62)***	(74.81)***	(93.54)***	(90.91)***	(66.76)***	(41.18)***
Macro	β_{perma}	-2.24	-0.77	-0.42	-0.24	-0.05	0.43	0.67	1.02	3.14	5.38
	θ_0	(9.48)***	(12.28)***	(24.72)***	(35.25)***	(15.55)***	(17.16)***	(27.46)***	(26.34)***	(25.06)***	(16.41)***
Multi-Strategies	β_{perma}	-1.47	-0.38	-0.06	0.12	0.32	0.73	0.97	1.34	2.17	3.64
	θ_0	(18.6)***	(25.93)***	(23.42)***	(24.18)***	(22.63)***	(29.74)***	(5.19)***	(4.49)***	(30.94)***	(32.92)***

TABLE 2.7 – Decile portfolios of hedge funds sorted by permanent price impact liquidity risk exposure

This table reports properties of equal-weighted decile portfolios of individual hedge funds. For each fund having at least 36 monthly return observations, we estimate the following liquidity risk model $r_{i,t} = \alpha^i + \beta_{transit}^i F_{transit,t} + \beta_{perma}^i F_{perma,t} + u_t^i$ where $r_{i,t}$ is the return on each individual fund in month t , $\beta_{transit}^i$ is the exposure to innovations in the market-wide transitory price-impact of fund i and β_{perma}^i is the exposure to innovations in the market-wide permanent price-impact of fund i . Simultaneously, we estimate an MA(2) model on $r_{i,t}$. Portfolios are formed in ranking each fund according to its exposure β_{perma}^i . The sample period is January 1994 - December 2012. For each decile portfolio, we report the average exposure β_{perma} , the average serial correlation parameter θ_0 and its t-statistic.

When we look at the results for trading styles sub-samples of individual hedge funds, we find that four strategies -Emerging Markets, Equity Market-Neutral, Event-Driven and Fixed Income- over ten have negative and statistically significant cross-sectional slopes for the coefficients $\beta_{transit}$, indicating a positive linear relationship between the amount of serial correlation and the exposure to changes in transitory market-wide price-impact. The strategy Dedicated Short exhibits the converse relation with a positive and statistically significant coefficient, which goes contrary to our intuition that serial correlation in hedge fund reported returns is explained by illiquidity of the underlying portfolio. The other half hedge fund strategies do not exhibit statistically significant slopes. This lack of pricing shows that there is no clear linear relation between serial correlation and liquidity.

We then look at the results for Eq. (2.8), for the permanent price impact factor, presented in Table 2.9. Again, there is no statistically significant relation between the weight θ_0 of current "true" returns in reported returns and liquidity risk, here proxied by the exposure to shocks in permanent price-impact. Three strategies -Dedicated Short, Emerging Markets and Multi-Strategies- have negative slopes statistically significant at the 5% risk level and no strategies have a positive and statistically significant slopes. This is interesting because we have seen previously that Dedicated Short had a statistically significant positive slope for $\lambda_{\beta_{transit}}$. These contradictory results for the two measures of liquidity risk indicates that liquidity is an elusive concept and that both factors proxies for different aspects of the phenomenon.

Although there is no global relation between serial correlation and measures of liquidity risk, some strategies sub-samples exhibit statistically negative relation between θ_0 and measured exposures to liquidity risk. It might be that we need to take into account the differences in the liquidity risks captured by the two factors and that interactions between the two might help explaining changes in amounts of serial correlation. To do so, we estimate bivariate two-stage cross-sectional regressions. As previously, we estimate in a first-stage regression the exposures to the liquidity factors with Eq. (2.6) and the serial correlation parameters θ_0^i with Eq. (2.4). We then run the following cross-sectional regression :

$$\hat{\theta}_0^i = \gamma + \lambda_{\beta_{transit}} \hat{\beta}_{transit}^i + \lambda_{\beta_{perma}} \hat{\beta}_{perma}^i + \nu^i \quad (2.9)$$

where $\hat{\theta}_0^i$ is the estimated weight on current "true" returns in reported returns for fund i , γ is the intercept, $\lambda_{\beta_{transit}}$ is the cross-sectional slope coefficient for the transitory price-impact risk factor exposure, $\hat{\beta}_{transit}^i$ is the estimated exposure to transitory price impact risk for fund i , $\lambda_{\beta_{perma}}$ is the cross-sectional slope coefficient for the permanent price-impact risk factor exposure, $\hat{\beta}_{perma}^i$ is the estimated exposure to permanent price impact risk for fund i and ν^i is the residual for fund i .

	All	Convertible-Arbitrage	Dedicated Short	Emerging	Equity MN	Event Driven	Fixed-Income	LS Equity	Macro	Multi-Strat	Options
Intercept	80	61	96.17	79.23	83.92	72.22	70.26	84.24	93.84	87.48	81.14
t_{NW}	(130.53)***	(40.05)***	(29.77)***	(86.54)***	(56.02)***	(68.38)***	(40.98)***	(99.18)***	(46.1)***	(11.67)***	(21.1)***
t_{GMM}	(126.32)***	(40)***	(35.77)***	(81.22)***	(51.57)***	(65.95)***	(39.51)***	(10.2.06)***	(43.45)***	(11.79)***	(32.23)***
$\lambda_{\beta_{transit}}$	-0.06	-0.03	1.12	-0.14	-0.01	-0.15	0.02	-0.17	-0.08	-1.13	-0.02
t_{NW}	(-1.4)	(-0.14)	(2.8)***	(-3.31)***	(-5.47)***	(-3.07)***	(0.18)	(-5.11)***	(-0.96)	(-1.49)	(-0.02)
t_{GMM}	(-1.4)	(-0.14)	(2.78)***	(-3.22)***	(-5.27)***	(-3.09)***	(0.18)	(-5.04)***	(-0.94)	(-1.5)	(-0.03)
R^2	0.46	0	1.59	2.66	0	1.58	0	0.77	0	9.74	0
nb funds	4,641	172	40	606	300	300	532	205	2,003	467	16

TABLE 2.8 – Cross-sectional regressions θ_0 on transitory price impact liquidity risk

Mean slopes estimates of monthly cross-sectional regressions of individual hedge funds' weight of current "true" returns in reported returns θ_0 on exposures to the liquidity risk $\beta_{transit}$. These exposures are estimated in a first-stage time-series regression. The monthly sample is 01/1994-12/2012. R^2 is the adjusted coefficient of determination in percentage. Generalized methods-of-moments t_{GMM} and Newey-West t_{NW} t-statistics in parentheses adjust for cross-asset correlation in the residuals and for estimation error of the time-series betas.

Table 2.10 presents the results for this bivariate cross-sectional regression. We see that, globally, the transitory market-impact liquidity factor has a negative cross-sectional slope of -0.14%, statistically significant with Newey-West and GMM t-statistics of -1.99. There is no linear relation between the weight on current "true" return in reported returns θ_0^i and the permanent price-impact liquidity factor. This implies that, for the global sample of individual hedge funds, the amount of serial correlation, i.e. the inverse of θ_0^i , is positively related to the amount of exposure to the transitory market-impact liquidity risk.

When we look at the results for strategies' sub-samples of individual hedge funds, the strategies Emerging Markets, Event Driven and Long-Short Equity have negative and statistically significant negative cross-sectional slopes for the exposure to transitory market-impact risk. Dedicated Short is the only trading strategy having a positive and statistically significant cross-sectional slope for this coefficient, while the rest of the strategies all present insignificant coefficients for this liquidity risk factor. Furthermore, when we look at the cross-sectional slopes for the permanent price-impact liquidity risk factor exposures, the only trading style having a negative and statistically significant coefficient is Dedicated Short, confirming its apart status. Every other strategy has an insignificant cross-sectional slope. This shows that globally, there are only weak relationships between the amount of serial correlation and the exposures to the two liquidity risk factors, with even for one strategy a reverse relationship.

To summarize our results, we have seen that the most serially-correlated individual hedge funds, i.e. funds having the lowest coefficients θ_0^i , are more exposed both to transitory and permanent price-impact liquidity risk factors. When we look at the inverse relation, we notice that the funds the most exposed to the transitory price impact have more serially correlated reported returns, while this is not the case for the funds the most exposed to the permanent price-impact factor. A two-stage cross-sectional regression analyses confirm that there is only a bijective relation between serial correlation in hedge fund reported returns and liquidity risk for the transitory market-impact. The amount of serial correlation a fund exhibits in its reported returns is dependent of the level of exposure to liquidity risk, but it not seems to be the only factor determining cross-sectional variations in serial-correlation.

2.4 Serial correlation and expected returns

We have seen previously that there is a mixed relation between hedge fund return serial correlation in reported returns and their exposure to liquidity risk. In this section, we will investigate if there is a link between individual hedge fund average returns and the amount of serial correlation in their returns, which could indicate the presence of risk premia for serial-correlation, consistent with a liquidity risk explanation of the phenomenon.

	All	Convertible-Arbitrage	Dedicated Short	Emerging	Equity MN	Macro	Event-Driven	Fixed-Income	LS Equity	Multi-Strat	Options
Intercept	80.25	61.84	91.87	78.72	84.92	84.46	71.56	71.15	83.45	81.01	81.15
t_{NW}	(151.3)***	(54.85)***	(27.43)***	(76.93)***	(56.07)***	(45.45)***	(67.25)***	(41.82)***	(63.78)***	(31.1)***	(19.69)***
t_{GMM}	(145.86)***	(56.19)***	(31.72)***	(72.49)***	(51.43)***	(42.19)***	(67.36)***	(36.88)***	(64.9)***	(31.27)***	(30.98)***
$\lambda_{\beta_{perma}}$	-0.28	-1.34	-5.52	-1.08	-0.04	-5.04	-1.14	-1.89	-0.37	-4.34	0.59
t_{NW}	(-1.41)	(-1.53)	(-5.34)***	(-2.18)**	(-1.47)	(-1.47)	(-1.71)*	(-1.39)	(-0.28)	(-2.39)**	(0.15)
t_{GMM}	(-1.42)	(-1.52)	(-4.99)***	(-2.12)**	(-1.71)*	(-1.49)	()***	(-1.71)*	(-0.28)	(-2.36)**	(0.14)
R^2	0.08	0.99	20.45	1.26	0	5.7	0.2	0.62	0	0.44	0
nb funds	4,641	172	40	606	300	300	532	205	2,003	467	16

TABLE 2.9 – Cross-sectional regressions θ_0 on permanent price impact liquidity risk

Mean slopes estimates of monthly cross-sectional regressions of individual hedge funds' weight of current "true" returns in reported returns θ_0 on exposures to the liquidity risk β_{perma} . These exposures are estimated in a first-stage time-series regression. The monthly sample is 01/1994-12/2012. R^2 is the adjusted coefficient of determination in percentage. Generalized methods-of-moments t_{GMM} and Newey-West t_{NW} t-statistics in parentheses adjust for cross-asset correlation in the residuals and for estimation error of the time-series betas.

	All	Convertible-Arbitrage	Dedicated Short	Emerging	Equity MN	Event Driven	Fixed-Income	LS Equity	Macro	Multi-Strat	Options
Intercept	80.61	61.71	91.51	79.82	84.07	72.46	70.96	84.22	94.45	86.82	81.26
t_{NW}	(136.99)***	(39.76)***	(30.25)***	(71.29)***	(59.40)***	(62.39)***	(37.47)***	(66.35)***	(43.58)***	(14.06)***	(20.5)***
t_{GMM}	(132.38)***	(39.99)***	(32.58)***	(66.88)***	(50.89)***	(60.54)***	(36.35)***	(67.63)***	(41.37)***	(14.25)***	(32.65)***
$\lambda_{\beta_{transit}}$	-0.14	0.02	0.92	-0.12	-0.14	-0.14	0.03	-0.17	0	-1.2	-0.22
t_{NW}	(-1.99)**	(0.12)	(3.88)***	(-2.99)***	(-1.17)	(-2.95)***	(0.34)	(-4.84)***	(0.05)	(-1.32)	(-0.21)
t_{GMM}	(-1.99)**	(0.12)	(3.81)***	(-2.91)***	(-1.04)	(-3.02)***	(0.34)	(-4.75)***	(0.05)	(-1.33)	(-0.28)
$\lambda_{\beta_{perma}}$	0.89	-1.4	-4.77	-0.73	1.28	-0.57	-1.93	0.04	-0.05	2.65	1.6
t_{NW}	(1.32)	(-1.83)*	(-6.79)***	(-1.58)	(1.12)	(-0.88)	(-1.35)	(0.03)	(-1.47)	(0.4)	(0.31)
t_{GMM}	(1.33)	(-1.83)*	(-6.85)***	(-1.55)	(0.99)	(-0.86)	(-1.32)	(0.03)	(-1.49)	(0.4)	(0.33)
R^2	0.72	0.44	30.73	3.11	0.16	1.49	0.17	0.71	5.38	9.75	0
nb funds	4,641	172	40	606	300	300	532	205	2,003	467	16

TABLE 2.10 – **Bivariate cross-sectional regressions θ_0 on liquidity risk**

Mean slopes estimates of monthly cross-sectional regressions of individual hedge funds' weight of current "true" returns in reported returns θ_0 on exposures to the liquidity risks $\beta_{transit}$ and β_{perma} . These exposures are estimated in a first-stage time-series regression. The monthly sample is 01/1994-12/2012. R^2 is the adjusted coefficient of determination in percentage. Generalized methods-of-moments t_{GMM} and Newey-West t_{NW} t-statistics in parentheses adjust for cross-asset correlation in the residuals and for estimation error of the time-series betas.

2.4.1 The cross-section of individual serial-correlation and returns

Another way to test for the illiquidity hypothesis for hedge fund returns' autocorrelation is to directly test the impact of serial correlation in hedge fund expected returns. The rationale is that, if serial correlation is the byproduct of illiquidity in the underlying portfolio, serially-correlated hedge funds should earn a risk premium for loading on this non-diversifiable source of risk, as demonstrated for liquidity-loading hedge funds by Sadka (2010). This direct testing procedure enables us to bypass the liquidity measurement problem, i.e. the fact that there exists a large panel of liquidity measures. Lo (2002) has demonstrated that serial-correlation in hedge fund returns can bias performance estimates. However, as shown by Getmansky et al. (2004), it does not affect the measures of expected return, ensuring the consistency of our estimates.

We want to investigate if differences in serial correlation in individual hedge funds reported returns explain differences in expected returns. To answer this question, we first follow a simple non-parametric approach and sort individual hedge funds with respect to their weight θ_0^i of current "true" returns in reported returns into decile portfolios. We then compare the average return $\hat{E}[R_{i,t}]$ of each decile portfolio to compare differences in expected returns.

Table 2.11 reports the results for the global sample of individual hedge funds and for the strategies subsamples. Globally, there is an economically meaningful difference in average return : while the lowest portfolio has an average monthly expected return of 0.75%, the highest portfolio earns an average return of 0.43% per month, which means a high-minus-low portfolio spread in monthly average return of -0.32%, highly statistically significant with an associated t-statistic of -6.29. This high-minus-low spread in expected returns could be seen as an evidence of pricing of serial correlation in the cross-section of individual hedge funds. Furthermore, this high-minus-low expected return spread is negative and statistically significant at the 5% risk level for seven of our ten hedge fund strategies : Convertible Arbitrage, Emerging Markets, Equity Market Neutral, Long/Short Equity, Multi-Strategies and Options. No strategy subsample exhibits a positive and statistically significant high-minus-low spread, indicating no evidence of negative pricing of serial-correlation. These results argue in favor of a risk premium explanation for the presence of autocorrelation in hedge fund returns, consistent with the underlying portfolio illiquidity explanation of serial-correlation.

However, the lack of a clear monotonous relationship between the rank of the decile and the expected returns casts doubt on the ability of serial correlation to purely reflect a risk premium due to an exposure to liquidity risk, and hence favors other explanations such as smoothing.

If serial correlation proxies for illiquidity, it should earn a risk premium. Another way to test this idea is through a parametric regression approach, in order to directly test if serial correlation is priced in the cross-section of individual hedge fund returns : indeed, if a characteristic -here serial correlation in returns- is a proxy for an exposure to a non-diversifiable systematic source of risk such as liquidity risk, there should be a relation between expected return and differences in this characteristic to compensate for bearing the risk.

	Low	2	3	4	5	6	7	8	9	High	High-Low
All	θ_0	0.49	0.62	0.72	0.76	0.8	0.83	0.89	0.97	1.26	0.76
	$E[R_t]$	0.75 (18.62)***	0.74 (17.23)***	0.77 (20.99)***	0.87 (26.2)***	0.82 (27.02)***	0.77 (27.15)***	0.69 (18.36)***	0.72 (22.9)***	0.83 (5.09)***	0.43 (13.47)***
Convertible-Arbitrage	θ_0	0.41	0.5	0.53	0.56	0.62	0.67	0.72	0.81	0.92	0.51
	$E[R_t]$	0.59 (4.69)***	0.66 (7.75)***	0.52 (4.67)***	0.8 (8.62)***	0.67 (9.46)***	0.65 (10.24)***	0.63 (3.06)***	0.5 (6.21)***	0.17 (1.49)	-0.11 (-0.95)
Dedicated-Short	θ_0	0.71	0.75	0.83	0.87	0.94	0.98	1.04	1.19	1.43	0.73
	$E[R_t]$	0.14 (0.22)	0.97 (1.07)	0.28 (1.06)	-0.17 (-1.07)	-0.1 (-0.4)	-0.14 (-1.64)	0.29 (2.06)**	0.67 (4.67)***	0.13 (0.35)	0.12 (0.5)
Emerging-Markets	θ_0	0.54	0.65	0.69	0.72	0.78	0.81	0.85	0.93	1.12	0.58
	$E[R_t]$	0.81 (5.56)***	0.17 (0.86)	0.88 (8.05)***	0.78 (7.21)***	0.93 (10.99)***	0.83 (10.34)***	0.56 (6.95)***	0.59 (6.79)***	0.77 (6.36)***	0.45 (4.06)***
Equity Market-Neutral	θ_0	0.53	0.64	0.7	0.74	0.82	0.86	0.93	1.02	1.32	0.79
	$E[R_t]$	0.88 (4.61)***	0.53 (8.13)***	0.6 (6.67)***	0.57 (9.44)***	0.62 (6.38)***	0.61 (7.07)***	0.47 (5.49)***	0.52 (8.81)***	0.31 (1.22)	0.2 (3.73)***
Event-Driven	θ_0	0.49	0.57	0.6	0.63	0.66	0.73	0.78	0.84	1.05	0.56
	$E[R_t]$	0.83 (6.42)***	0.95 (8.26)***	0.81 (13.5)***	0.91 (9.02)***	0.84 (5.48)***	0.83 (12.66)***	0.8 (11.53)***	0.77 (7.63)***	0.78 (10.83)***	0.51 (3.85)***
Fixed-Income	θ_0	0.39	0.51	0.58	0.63	0.67	0.75	0.8	0.88	1.09	0.7
	$E[R_t]$	0.86 (7.85)***	0.83 (4.11)***	0.61 (5.24)***	0.79 (7.95)***	0.51 (3.27)***	0.55 (9.32)***	0.69 (7.04)***	0.23 (1.48)	0.2 (1.87)*	0.32 (2.53)***
Long-Short Equity	θ_0	0.54	0.68	0.72	0.76	0.79	0.86	0.91	0.98	1.23	0.69
	$E[R_t]$	0.89 (13.59)***	0.96 (18.02)***	1.02 (18.99)***	0.96 (20.6)***	0.82 (18.28)***	0.8 (17.99)***	0.82 (18.87)***	0.79 (18.97)***	0.74 (8.25)***	0.57 (12.78)***
Macro	θ_0	0.61	0.71	0.77	0.81	0.86	0.95	1.01	1.13	1.51	0.9
	$E[R_t]$	0.39 (1.29)	0.72 (6.02)***	0.64 (4.79)***	0.81 (9.19)***	0.99 (4.89)***	0.63 (6.59)***	0.73 (7.43)***	0.53 (5.93)***	0.36 (2.99)***	0.51 (2.64)***
Multi-Strategies	θ_0	0.47	0.57	0.62	0.66	0.7	0.81	0.86	0.95	1.33	0.86
	$E[R_t]$	0.75 (7.27)***	0.79 (11.73)***	0.5 (3.66)***	0.43 (3.93)***	0.71 (8.35)***	0.51 (6.35)***	0.57 (6.73)***	0.69 (2.83)***	0.47 (5.6)***	0.32 (3.34)***
Options	θ_0	0.58	0.62	0.65	0.69	0.84	0.88	0.92	0.93	1.05	0.47
	$E[R_t]$	1.35 (22.78)***	1.16 (11.28)***	0.99 (2.22)**	0.75 (12.77)***	0.78 (33.31)***	0.42 (1.72)*	1.66 (44.87)***	1.63 (1.49)	0.47 (1.53)	0.74 (2.63)***

TABLE 2.11 – Decile portfolios of hedge funds returns sorted by serial correlation

This table reports properties of equal-weighted decile portfolios of individual hedge funds. For each fund having at least 36 monthly return observations, we estimate MA(2) model on $r_{p,t}$, its time-series of returns, in order to get its serial correlation parameters. Portfolios are formed in ranking each fund according to its weight of the current return on its reported returns θ_0 , so the portfolio Low is the portfolio with the lowest θ_0 . A lower coefficient θ_0 indicates a higher level of serial correlation. The sample period is January 1994 - December 2012. For each decile portfolio, we report the average serial correlation parameter θ_0 , the average return $E[R_t]$ and its t-statistic.

For each individual hedge fund i , we estimate in a first-stage step the weight θ_0^i of current "true" returns in reported returns as in Eq. (2.4). We then run a cross-sectional regression of average individual returns on this estimated serial-correlation factor :

$$\hat{E}[R_t^i] = \gamma + \lambda_{\theta_0} \hat{\theta}_0^i + \nu^i \quad (2.10)$$

where $\hat{E}[R_t^i]$ is the average return of fund i , γ is the intercept, λ_{θ_0} is the risk slope coefficient, $\hat{\theta}_0^i$ is fund i 's estimated weight of current "true" returns in reported returns and ν^i is the residual for fund i .

Table 2.12 presents results for Fama and McBeth (1973) two-stage regressions of individual hedge funds average returns on serial-correlation, as proxied by θ_0^i : the higher the coefficient, the lower is the serial-correlation. We find that, for the whole sample of individual hedge funds, there is a negative slope of -0.15%, but only statistically significant at the 10% risk level. This relation indicates a mixed evidence of positive risk pricing in the cross-section of individual hedge funds. When we look at subsamples of strategies, six -Convertible arbitrage, Macro, Event-Driven, Fixed-Income, Multi-Strategies and Options- out of ten have statistically significant negative slopes, indicating evidence of positive risk pricing of serial correlation. This mixed results show that, on the one hand, a majority of strategies display intra-style evidence of risk pricing for serial-correlation, but on the other hand this does not work for the global sample of individual funds and some strategies. This last point pleads for a mixed view of hedge fund returns' serial correlation, in which illiquidity is not the only determinant of the autocorrelation level.

2.4.2 Does serial-correlation predict hedge fund returns ?

While most studies focus on contemporaneous relations between a given risk factor and returns, Bali et al. (2011) highlight the importance of the predictive power of risk exposures and characteristics in the cross-section of hedge fund returns. For a particular characteristic to be considered as a compensation for a non-diversifiable source of risk, it musts predicts future hedge fund returns.

We follow Bali et al. (2001) in using both parametric and non-parametric tests to investigate if serial-correlation predicts future hedge fund returns. First and foremost, we begin with the parametric procedure to test if the coefficients θ_0^i , measuring the weight of current "true" returns in reported returns, predict one-month ahead individual hedge fund returns. We first derive monthly time-series estimates of serial correlation parameters $\theta_{0,t}^i$ over a rolling-window and second use Fama and McBeth regressions of one-month ahead hedge fund returns on these estimates. If the average slope of the Fama and McBeth cross-sectional regressions is statistically significantly negative, it indicates that higher serial correlation predicts stronger future average hedge fund returns.

	All	Convertible-Arbitrage	Dedicated Short	Emerging	Equity MN	Macro	Event-Driven	Fixed-Income	LS Equity	Multi-Strat	Options
Intercept	0.86	1.26	0.65	0.98	0.6	0.94	1.19	1.12	0.93	0.69	1.77
t_{NW}	(12.71)***	(6.2)***	(1.05)	(3.42)***	(1.37)	(5.68)***	(9.41)***	(6.84)***	(7.68)***	(10.53)***	(5.71)***
t_{GMM}	(12.74)***	(5.79)***	(1.01)	(3.58)***	(1.36)	(5.61)***	(9.28)***	(6.52)***	(7.71)***	(9.93)***	(7.51)***
λ_{θ_0}	-0.15	-1.17	-0.46	-0.38	0.23	-0.33	-0.55	-0.78	-0.11	-0.15	-1.09
t_{NW}	(-1.79)*	(-3.67)***	(-0.82)	(-1.15)	(0.29)	(-2.08)**	(-3.37)***	(-3.48)**	(-0.77)	(-2.26)**	(-2.43)***
t_{GMM}	(-1.79)*	(-3.45)***	(-0.76)	(-1.19)	(0.29)	(-2.06)*	(-3.32)***	(-3.35)**	(-0.77)	(-2.27)**	(-3.2)***
R^2	0.12	10.65	0	0.25	0	0.87	1.75	7.4	0.17	0.82	5.8
nb funds	4,864	195	41	640	325	309	554	209	2,073	492	26

TABLE 2.12 – Fama-McBeth regressions on θ_0 for individual hedge funds

Risk price estimates for the serial correlation parameter θ_0 . Risk prices are the mean slopes of monthly cross-sectional regressions of individual hedge funds' returns on the weight on current "true" return in reported returns θ_0 as in Eq. (2.4). For each fund having at least 36 monthly return observations, we estimate MA(2) model on $r_{p,t}$, its time-series of returns, in order to get its serial correlation parameter. The monthly sample is 01/1994-12/2012. R^2 is the adjusted coefficient of determination in percentage. Generalized methods-of-moments t_{GMM} and Newey-West t_{NW} t-statistics in parentheses adjust for cross-asset correlation in the residuals and for estimation error of the time-series betas. Coefficients are reported in percentage.

In the first stage, monthly weights of current "true" returns in reported returns are estimated for each fund as in Eq. (2.6) over a three-year rolling-window period. Thirty six months provide sufficient observations for the maximum likelihood estimation procedure, while it allows for time-variation in estimates. In the second stage, the cross-section of one month ahead individual fund returns is regressed on the funds' weights of current "true" returns in reported returns $\theta_{0,t}^i$ for the period January 1997-February 2015. More specifically, we start with the reported returns from January 1994 to December 1996 to estimate serial correlation parameters for each fund in the sample and then we estimate rolling maximum likelihood procedures with a fixed estimation window of 36 months to get the time-series of first-stage weights on current "true" returns $\theta_{0,t}^i$.

Then, in the second stage, starting from January 1997, we estimate Fama and McBeth cross-sectional regressions of one-month ahead individual hedge fund returns on the estimated weights of current "true" returns in reported returns :

$$R_{t+1}^i = \omega_t + \lambda_t \cdot \tilde{\theta}_{0,t}^i + \epsilon_{t+1}^i \quad (2.11)$$

where R_{t+1}^i is the excess return on fund i in month $t + 1$ and $\tilde{\theta}_{0,t}^i$ is the weight of current "true" return in reported returns for fund i in month t estimated using Eq. (2.6). ω_t and λ_t are, respectively, the monthly intercepts and slope coefficients from the Fama and McBeth regressions. We roll the estimation procedure over the sample, keeping a fixed estimation window of 36 months.

Our second framework to investigate if serial correlation predicts future individual hedge fund returns is to form quintile portfolios every month by sorting individual hedge fund according to their weights $\theta_{0,t}^i$ of current "true" returns in reported returns, estimated over a fixed 36-months window. We then average each quintile individual hedge funds' returns to investigate if there is a statistically significant difference in the future return of the high θ_0 quintile minus the low θ_0 quintile. We roll this estimation procedure each month over the period January 1997 - February 2015.

Table 2.13 panel (a) shows the time-series average intercept and slope coefficients for estimates of Eq. (2.11) over the sample period January 1997 - February 2015. The corresponding t-statistics are reported in parentheses. Results for the global sample of individual hedge funds show that there is no statistically significant average slope for the serial correlation parameter $\theta_{0,t}^i$. Furthermore, the only strategy sub-sample showing a negative coefficient statistical significance at the 10% risk level is Long/Short Equity. The fact that only one strategy exhibits mixed evidence of predictive power for serial correlation advocates for an absence of a true risk premium in hedge fund serial correlation.

We then look at the results for quintile portfolios, reported in Table 2.13 panel (b). There is no statistical significance for the high-minus-low portfolio at the global sample of individual hedge funds level, and only the strategies Event-Driven and Fixed-Income exhibit negative and statistically significant high-minus-low spreads in one-month ahead returns of -0.21% and -0.47% respectively.

TABLE 2.13 – Rolling-window relation between expected returns and serial-correlation

	All	Convertible-Arbitrage	Dedicated Short	Emerging	Equity MN	Event-Driven	Fixed-Income	LS Equity	Macro	Multi-Strat
Intercept	0.68 (3.87)***	0.8 (3.29)***	0.03 (0.04)	0.65 (1.89)*	-1.08 (-0.54)	0.81 (6.04)***	0.96 (6.58)***	0.9 (4.26)***	0.44 (2.75)***	0.8 (5.11)***
λ_0	-0.02 (-0.24)	-0.39 (-0.87)	0.19 (0.24)	0.11 (0.34)	0.02 (0.83)	-0.27 (-1.62)	-0.69 (-3.39)***	-0.18 (-1.84)*	0.16 (1.08)	-0.24 (-1.07)

(a) Rolling-window Fama-McBeth cross-sectional regressions of individual hedge fund average return on θ_0

	All	Convertible-Arbitrage	Dedicated Short	Emerging	Equity MN	Event Driven	Fixed-Income	LS Equity	Macro	Multi-Strat
Low θ_0	0.68 (6.21)***	0.72 (5.58)***	0.15 (0.55)	0.68 (2.79)***	0.51 (6.83)***	0.7 (6.91)***	0.61 (6.11)***	0.8 (4.71)***	0.5 (4.11)***	0.69 (6.27)***
2	0.68 (4.77)***	0.51 (3.2)***	-0.04 (-0.11)	0.73 (2.25)**	0.57 (7.22)***	0.66 (5.42)***	0.6 (6.12)***	0.86 (4.28)***	0.43 (3.26)***	0.61 (6.07)***
3	0.69 (4.1)***	0.48 (3.46)***	-0.34 (-1.01)	0.8 (2.42)***	0.66 (6.17)***	0.68 (5.93)***	0.7 (8.02)***	0.79 (3.86)***	0.66 (4.93)***	0.64 (6.54)***
4	0.64 (3.75)***	0.56 (3.58)***	0.19 (0.57)	0.73 (2.24)**	0.47 (5.43)***	0.56 (4.23)***	0.4 (3.55)***	0.72 (3.51)***	0.66 (4.38)***	0.64 (5.14)***
High θ_0	0.63 (4.18)***	0.69 (3.5)***	0.06 (0.14)	0.67 (2.01)**	1.82 (5.43)***	0.48 (3.39)***	0.14 (1.15)	0.61 (3.18)***	0.6 (3.79)***	0.56 (3.89)***
High θ_0 - Low θ_0	-0.05 (-0.31)	-0.04 (-0.25)	-0.09 (-0.19)	-0.01 (-0.06)	1.31 (0.95)	-0.21 (-2.19)**	-0.47 (-3.62)***	-0.18 (-1.47)	0.1 (0.63)	-0.13 (-0.87)

(b) Rolling-window quintile portfolios of hedge funds average returns sorted by θ_0

Panel (a) presents cross-sectional estimates of individual hedge fund average return regressed on the serial-correlation coefficient θ_0 . θ_0 is defined as the current return's weight on contemporary return. It is estimated through a moving average-process. λ_0 is the mean slope of monthly cross-sectional regression of hedge fund average returns on θ_0 . The serial correlation parameters θ_0 are estimated in a first-stage MA(2). The monthly sample is 01/1996-02/2015.

Panel (b) presents quintile portfolios formed every month by sorting individual hedge funds on their past 36-month serial correlation parameter $\theta_{0,t}^i$. The sample goes from 01/1996 to 02/2015. Quintile 1 is the portfolio of hedge funds with the lowest θ_0 and quintile 5 is the portfolio of hedge funds with the highest θ_0 . For each quintile portfolio, we report the average return and its t-statistic.

These results for both parametric and non-parametric tests show only very weak evidence of the serial correlation predictive power for one-month individual hedge fund returns. This lack of pricing indicates that serial-correlation is not a characteristic fully reflecting the exposure to an underlying systematic risk whose command a risk premium. As demonstrated by Sadka (2010), liquidity risk is priced in the cross-section of hedge fund returns, and hence if serial-correlation is merely the product of liquidity issues, it should also be priced. The fact that it is not shows that liquidity is not the only and major driver of hedge fund serial correlation and that a large part of the cross-sectional variation comes from the smoothing of returns by the manager.

2.5 Conclusion

This paper presents only mixed empirical evidence for the liquidity explanation of serial correlation in hedge fund reported returns. We show that the most serially correlated hedge funds are more exposed to both the transitory and permanent market wide price impact factors, consistent with the view that serial correlation in hedge fund returns comes from the illiquidity in the underlying portfolio. However, when we rank funds according to their liquidity risk betas, only the transitory price-impact exhibits a significant difference in its high-minus-low portfolio serial-correlation. A cross-sectional regression analysis confirms that only the transitory price-impact has a statistically significant linear relation with the amount of serial-correlation.

This noisy cross-sectional relation between serial-correlation and liquidity exposure is further confirmed by an analysis of the link between serial correlation and average return. The idea here is that, if serial-correlation occurs due to exposure to liquidity risk, hedge fund having more serially correlated returns should earn a risk premium, due to the supposedly associated loading on liquidity risk. A portfolio analysis of hedge funds sorted according to their amount of serial correlation in their reported returns shows that the most serially correlated hedge funds outperform the least serially correlated, both for the global sample of funds and when we look at the intra-style level. However, a cross-sectional regression approach yields only a weakly statistically significant slope for the amount of serial correlation. The amount of past serial correlation does not predict future expected returns, showing that the link between serial correlation and liquidity seems noisy. Serial-correlation does not command a risk premium, highlighting the fact that it is non-systematically linked to liquidity risk. Hence, we can conclude that smoothing is a major explanation of serial correlation in hedge fund returns.

The results of this paper highlights the complexity of serial correlation in hedge fund reported returns. While recent papers, such as Krutli et al. (2015), directly proxy hedge fund exposures to liquidity risk with the amount of serial correlation in their reported returns, this articles shows that the relation is not as clear-cut as it was previously thought. Other factors as well might explain differences in hedge fund serial correlation, making it a noisy proxy for liquidity exposure. Among such factors, artificial smoothing of reported returns by the fund manager seems to be the most likely explanation.

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2.6 Appendix A : Robustness checks with alternative liquidity factors

In this appendix, we revisit our results with alternative liquidity risk proxies. Indeed, liquidity is an elusive concept whose different aspects cannot be captured by a significant measure. Is it possible that our previous results are driven by a particular restrictive definition of liquidity risk? To investigate this possibility, we use the liquidity factors of Pastor and Stambaugh (2003) as new proxies for liquidity risk. These liquidity factors are the aggregate level of liquidity in the equity market and its innovations.

We then re-test the hypothesis that serial-correlation in hedge fund reported returns is mainly driven by the illiquidity of the underlying portfolio. We first sort individual hedge fund returns into decile portfolios, according to their weight θ_0^i of the current "true" returns in reported returns. We then measure the individual hedge fund liquidity risk exposures with a bivariate factor model :

$$r_{i,t} = \alpha^i + \beta_{global}^i F_{global,t} + \beta_{innov}^i F_{innov,t} + u_t^i \quad (2.12)$$

where $r_{i,t}^i$ is the return of fund i in month t , α^i is the risk-adjusted return of fund i , β_{global}^i is the exposure to changes in the aggregate liquidity, $F_{global,t}$ is the realisation in month t of this change in aggregate liquidity, β_{innov}^i is the exposures to innovations in the changes in aggregate equity market liquidity, $F_{innov,t}$ is the realisation in month t of the innovations in liquidity and u_t^i is the residual of fund i in month t .

We compute the average of coefficients θ_0^i , β_{global}^i and β_{innov}^i for each decile portfolios. Results are reported in Table 2.14 and Table 2.15. The resulting coefficients θ_0 for the whole sample of individual hedge funds goes from 0.49 for decile 1 to 1.26 decile 10, displaying a high-minus-low difference of 0.77. There is an high-minus-low difference in β_{global} of -5.07% and in β_{innov} of 4.28%, both statistically significant with respective t-statistics of -4.66 and 3.33. These results indicate that the most serially correlated individual hedge funds, i.e. funds having the lowest θ_0^i , are significantly more exposed to the aggregate liquidity risk and significantly less exposed to the risk contained in its innovations. This is a different result from those obtained with the market-impact factors of Sadka (2008), for which both liquidity risk exposures are negatively related with the coefficient θ_0 .

When we look at the intra-style cross-sectional relations, we see that the strategies Emerging Markets, Macro and Multi-Strategies have negative and statistically significant high-minus-low negative exposure to β_{global} of -10.9%, -8.51% and -6.17% respectively, with associated t-statistics of -2.45, -4.35 and -2.14. Only the Options trading-style exhibits the converse relation with an average high-minus-low exposure of 5.31% with an associated t-statistic of 6.09. Furthermore, the strategies Dedicated Short, Event-Driven and Long-Short Equity all have positive high-minus-low differences in average exposures β_{innov} with coefficients of 9.5%, 5.9% and 5.46% respectively. No strategy has a statistically significant negative high-minus-low average difference in β_{innov} .

	Low	2	3	4	5	6	7	8	9	High	High-Low
All											
θ_0	0.49	0.62	0.68	0.72	0.76	0.8	0.83	0.89	0.97	1.26	0.77
β_{global}	3.84 (8.3)***	4.53 (8.13)***	4.36 (7.2)***	2.94 (6.35)***	4.25 (8.1)***	3.26 (6.03)***	2.13 (2.93)***	2.61 (3.93)***	-7.04 (-0.81)	-1.23 (-1.25)	-5.07 (-4.66)***
Convertible-Arbitrage											
θ_0	0.41	0.5	0.53	0.56	0.59	0.62	0.67	0.72	0.81	0.92	0.51
β_{global}	2.98 (1.42)	2.2 (0.88)	1.23 (0.98)	1.7 (1.4)	-0.82 (-0.8)	1.42 (1)	2.08 (1.15)	0.82 (0.59)	2.96 (1.2)	3.51 (2.2)**	0.53 (0.25)
Dedicated-Short											
θ_0	0.71	0.75	0.83	0.87	0.9	0.94	0.98	1.04	1.19	1.43	0.73
β_{global}	7.56 (1.8)*	-7.46 (-1.3)	1.26 (0.84)	2.47 (0.3)	-7.03 (-0.84)	-7.07 (-2.42)***	-0.09 (-0.02)	3.89 (0.33)	33.23 (1.79)*	10.54 (3.32)***	2.98 (0.9)
Emerging-Markets											
θ_0	0.54	0.65	0.69	0.72	0.75	0.78	0.81	0.85	0.93	1.12	0.58
β_{global}	9.86 (3.48)***	6.21 (3.23)***	7.44 (5.88)***	4.1 (3.25)***	4.3 (2.91)***	6.63 (2.86)***	3.01 (2.23)**	0.43 (0.26)	1.47 (0.51)	-1.04 (-0.31)	-10.9 (-2.45)***
Equity Market-Neutral											
θ_0	0.53	0.64	0.7	0.74	0.78	0.82	0.86	0.93	1.02	1.32	0.79
β_{global}	4.26 (2.74)***	1.44 (1.46)	1.45 (1.38)	-0.49 (-0.59)	0.05 (0.5)	-0.51 (-0.23)	1.51 (1.2)	1.3 (1.02)	-1.39 (-0.99)	-0.59 (-0.32)	-4.85 (-1.85)*
Event-Driven											
θ_0	0.49	0.57	0.6	0.63	0.66	0.69	0.73	0.78	0.84	1.05	0.56
β_{global}	4.24 (3.41)***	4.41 (3.73)***	5.06 (5.07)***	3.5 (4.78)***	1.7 (1.23)	3.1 (3.67)***	3.33 (3.79)***	1.42 (0.87)	2.79 (2.89)***	0.82 (0.42)	-3.42 (-1.44)
Fixed-Income											
θ_0	0.39	0.51	0.59	0.63	0.67	0.71	0.75	0.8	0.88	1.09	0.7
β_{global}	0.73 (0.58)	0.5 (0.37)	1.77 (1.16)	5.62 (2.48)**	5.4 (2.53)***	-6.03 (-1.89)*	-0.53 (-0.38)	6.42 (2.21)**	-1.08 (-0.43)	3.87 (2.4)***	3.14 (1.75)*
Long-Short Equity											
θ_0	0.54	0.68	0.72	0.76	0.79	0.83	0.86	0.91	0.98	1.23	0.69
β_{global}	5.48 (5.61)***	5.91 (7.14)***	4.02 (5.02)***	5.02 (6.15)***	3.72 (4.26)***	4.63 (5.27)***	2.11 (2.33)***	2.8 (3.47)***	1.33 (1.04)	-3.03 (-1.93)*	-8.51 (-4.35)***
Macro											
θ_0	0.61	0.71	0.77	0.81	0.86	0.91	0.95	1.01	1.13	1.51	0.9
β_{global}	-3.83 (-0.73)	2.2 (1.25)	2.12 (1.44)	0.16 (0.07)	7.36 (1.45)	6.91 (1.78)*	1.6 (0.81)	5.1 (2.65)***	-2.51 (-0.64)	0.08 (0.02)	3.91 (0.53)
Multi-Strategies											
θ_0	0.47	0.58	0.62	0.66	0.7	0.75	0.81	0.86	0.95	1.34	0.86
β_{global}	3.36 (2.29)**	4.72 (3.8)***	4.25 (4.83)***	2.33 (1.94)*	3.03 (3.13)***	2.69 (1.93)**	-0.28 (-0.06)	-2.02 (-0.75)	3.79 (2.17)**	-2.81 (-1.07)	-6.17 (-2.14)**
Options											
θ_0	0.58	0.62	0.65	0.69	0.8	0.84	0.88	0.92	0.93	1.06	0.47
β_{global}	-2.45 (-1.31)	-2.37 (-1.01)	-0.42 (-0.22)	-0.81 (-0.26)	1.59 (7.52)***	-2.18 (-0.52)	4.58 (0.14)	-12.24 (-10.3)***	2.41 (0.79)	2.85 (2.85)***	5.31 (6.09)***

TABLE 2.14 – Decile portfolios of hedge funds’ innovations liquidity risk exposures sorted by serial correlation

This table reports properties of equal-weighted decile portfolios of individual hedge funds. For each fund having at least 36 monthly return observations, we estimate the following liquidity risk model $r_{i,t} = \alpha^i + \beta_{global}^i F_{global,t} + \beta_{innov}^i F_{innov,t} + u_t^i$ where $r_{i,t}$ is the return on each individual fund in month t , β_{global}^i is the exposure to the aggregate liquidity risk factor of fund i and β_{innov}^i is the exposure to innovations in liquidity risk factor of fund i . Simultaneously, we estimate an MA(2) model on $r_{i,t}$. Portfolios are formed in ranking each fund according to its weight of the current return on its reported returns θ_0 , so the portfolio Low is the portfolio with the lowest θ_0 . The sample period is January 1994 - February 2015. For each decile portfolio, we report the average serial correlation parameter θ_0 , the exposure β_{global} and its t-statistic.

These results imply that serial correlation is positively related to changes in aggregate liquidity conditions but inversely related to its unexpected changes. To further explore these relations, we sort hedge funds into portfolio according to their liquidity risk exposures β_{global} and β_{innov}^i and then looking at their weights θ_0^i of the current "true" returns in their reported returns. Table 16 reports the results for the exposures to the aggregate liquidity factor β_{global} . The idea is that, if serial correlation is negatively driven by differences in exposures to aggregate liquidity risk, the funds the most exposed to this particular liquidity risk should be more serially correlated. However, we find a global high-minus-low decile θ_0 of -0.05, non-statistically significant with a t-statistic of -1.21. Over the ten strategy subsamples, only Emerging Markets and Event-Driven have negative and statistically significant relations, while Options has a statistically significant relation.

Table 2.16 shows the results for portfolio sorted according to β_{global}^i . For the global sample of individual hedge funds, there is a negative but statistically non-significant high-minus-low spread of -0.05 for the coefficient θ_0 . Among the ten different strategies, no strategy exhibits a negative and statistically significant high-minus-low spread while the strategy Event Driven has the converse relationship of a positive and statistically significant high-minus-low coefficient. These results indicate that, globally, the funds loading the most on the global liquidity factor do not have a higher amount of serial correlation in their reported returns, i.e. they do not have statistically significant lower coefficients θ_0^i .

We now sort funds into decile portfolios according to β_{innov}^i and present the results in Table 2.17. Once again, there is no statistically significant high-minus-low θ_0 , indicating that the funds the most exposed to this liquidity factors are not statistically significantly more serially correlated than the funds the least exposed. No strategy subsample exhibit a negative and statistically significant high-minus-low θ_0 while the strategy Event Driven has a positive and statistically significant θ_0 spread.

We can conclude that, if the most serially correlated funds are more exposed to liquidity risk when we take the Pastor and Stambaugh (2003) liquidity risk factors as proxies for liquidity risk, the converse is not true, indicating that the liquidity procies are not the sole cross-sectional determinants of serial-correlation.

In order to further explore the link between individual funds' serial correlation in reported returns and exposures to liquidity risk, we now conduct two-stage cross-sectional regressions. For each individual fund i , we estimate its exposure to the global liquidity factor in a first-stage univariate regression and simultaneously estimate its weight of the current "true" return in reported returns θ_0^i . Then, in a second stage, we run a cross-sectional regression of the serial correlation parameters θ_0^i on the liquidity risk exposures :

$$\hat{\theta}_0^i = \gamma + \lambda_{\beta_{global}} \hat{\beta}_{global}^i + \nu^i \tag{2.13}$$

	Low	2	3	4	5	6	7	8	9	High	High-Low
All											
θ_0	0.49	0.62	0.68	0.72	0.76	0.8	0.83	0.89	0.97	1.26	0.77
β_{innov}	3.49 (8.27)***	4.83 (7.98)***	5.46 (7.49)***	6.86 (10.7)***	7.46 (12.26)***	7.1 (11.06)***	6.93 (8.44)***	6.39 (8.53)***	10.67 (2.3)***	7.76 (6.5)***	4.28 (3.33)***
Convertible-Arbitrage											
θ_0	2.98	2.2	1.23	1.7	-0.82	1.42	2.08	0.82	2.96	3.51	0.53
β_{innov}	2.02 (1.46)	1.61 (1.31)	2.28 (3.08)***	0.51 (0.5)	4.72 (3.27)***	4.64 (2.77)***	5.98 (2.42)***	3 (1.78)*	11.66 (1.69)*	3.53 (1.72)*	1.51 (0.64)
Dedicated-Short											
θ_0	0.71	0.75	0.83	0.87	0.9	0.94	0.98	1.04	1.19	1.43	0.73
β_{innov}	-14.81 (-2.9)***	-0.71 (-0.11)	-14.7 (-2.34)**	-16.59 (-2.87)***	0.12 (0.01)	-19.03 (-3.11)***	-21.27 (-5.79)***	-17.65 (-1.37)	-49.72 (-2.65)***	-14.34 (-2.21)**	0.47 (0.07)
Emerging-Markets											
θ_0	0.54	0.65	0.69	0.72	0.75	0.78	0.81	0.85	0.93	1.12	0.58
β_{innov}	5.5 (1.85)*	9.72 (4.65)***	11.01 (5.01)***	15.23 (7.02)***	12.77 (6.8)***	9.43 (4.42)***	13.11 (6.92)***	16.22 (5.52)***	16.67 (3.54)***	15 (5.15)***	9.5 (2.39)***
Equity Market-Neutral											
θ_0	0.53	0.64	0.7	0.74	0.78	0.82	0.86	0.93	1.02	1.32	0.79
β_{innov}	1.73 (1.59)	1.83 (1.43)	2.84 (1.83)*	3.83 (3.02)***	1.44 (1.09)	3.49 (2.22)**	2.08 (0.94)	-0.26 (-0.15)	0.77 (1.05)	0.03 (1.19)	1.4 (0.53)
Event-Driven											
θ_0	0.49	0.57	0.6	0.63	0.66	0.69	0.73	0.78	0.84	1.05	0.56
β_{innov}	1.52 (1.96)**	3.89 (3.42)***	4.13 (3.69)***	5.14 (5.2)***	5.98 (2.3)**	5.44 (4.83)***	5.93 (4.37)***	6.16 (4.91)***	7.24 (4.12)***	7.42 (2.86)***	5.9 (2.16)**
Fixed-Income											
θ_0	0.39	0.51	0.59	0.63	0.67	0.71	0.75	0.8	0.88	1.09	0.7
β_{innov}	-0.28 (-0.16)	2.71 (1.55)	2.87 (1.95)*	1.29 (0.84)	-0.23 (-0.1)	6.37 (2.91)**	3.63 (2.29)**	0.73 (0.46)	3.79 (2.06)**	0.82 (0.51)	1.1 (0.56)
Long-Short Equity											
θ_0	0.54	0.68	0.72	0.76	0.79	0.83	0.86	0.91	0.98	1.23	0.69
β_{innov}	5.18 (5.04)***	5.02 (5.2)***	7.09 (6.66)***	7.85 (7.69)***	7.14 (7.78)***	7.36 (8.01)***	8.92 (8.55)***	6.41 (5.98)***	8.03 (6.78)***	10.64 (5.37)***	5.46 (2.51)***
Macro											
θ_0	0.61	0.71	0.77	0.81	0.86	0.91	0.95	1.01	1.13	1.51	0.9
β_{innov}	8.13 (1.47)	0.2 (0.11)	6.1 (2.87)***	4.07 (1.73)*	-3.95 (-1)	-2.23 (-0.77)	2.39 (1.02)	5.04 (2.47)***	4.03 (0.74)	1.02 (0.2)	-7.11 (-0.88)
Multi-Strategies											
θ_0	0.47	0.58	0.62	0.66	0.7	0.75	0.81	0.86	0.95	1.34	0.86
β_{innov}	3.44 (3.49)***	3.62 (4.41)***	4.82 (3.09)***	6.65 (5.38)***	4.18 (3.23)***	5.76 (4.67)***	5.02 (1.94)*	0.83 (0.19)	2.03 (1.16)	8.44 (3.07)***	5 (1.63)
Options											
θ_0	0.58	0.62	0.65	0.69	0.8	0.84	0.88	0.92	0.93	1.06	0.47
β_{innov}	-1.88 (-1.58)	6.35 (0.58)	-16.46 (-7.67)**	-13.29 (-33.11)***	6.27 (0.76)	-4.75 (-1.57)	11.46 (1.63)	25.98 (12.61)***	-5.75 (-1.18)	3.04 (0.2)	4.93 (0.35)

TABLE 2.15 – Decile portfolios of hedge funds innovations in liquidity risk sorted by serial correlation

This table reports properties of equal-weighted decile portfolios of individual hedge funds. For each fund having at least 36 monthly return observations, we estimate the following liquidity risk model $r_{i,t} = \alpha^i + \beta_{global}^i F_{global,t} + \beta_{innov}^i F_{innov,t} + u_t^i$ where $r_{i,t}$ is the return on each individual fund in month t , β_{global}^i is the exposure to the aggregate liquidity risk factor of fund i and β_{innov}^i is the exposure to innovations in liquidity risk factor of fund i . Simultaneously, we estimate an MA(2) model on $r_{i,t}$. Portfolios are formed in ranking each fund according to its weight of the current return on its reported returns θ_0 , so the portfolio Low is the portfolio with the lowest θ_0 . The sample period is January 1994 - February 2015. For each decile portfolio, we report the average serial correlation parameter θ_0 , the exposure β_{innov} and its t-statistic.

where $\hat{\theta}_0^i$ is the estimated weight on current "true" returns in reported returns for fund i , γ is the intercept, $\lambda_{\beta_{global}}$ is the cross-sectional slope coefficient, $\hat{\beta}_{global}^i$ is the estimated exposure to the global liquidity risk for fund i and ν^i is the residual for fund i .

Results are presented in Table 2.18. We find that, for the whole sample of individual hedge funds, as the global exposure to the global liquidity factor increases of 1%, the coefficient θ_0^i decreases of -0.92%, indicating that there is a positive link between exposure to the aggregate liquidity risk and serial correlation. When we look at the cross-sectional regressions results for strategies' subsamples, we find that three strategies, Emerging Markets, Equity Market-Neutral and Event-Driven, have negative slopes of -17.26%, -0.44% and -24.69% respectively, statistically significant with associated Newey and West (1994) t-statistics of -2.77, -8.55 and -2.43. This signifies that this relationship is not universally shared among hedge fund strategies.

We repeat the procedure with the innovations in liquidity risk factor :

$$\hat{\theta}_0^i = \gamma + \lambda_{\beta_{innov}} \hat{\beta}_{innov}^i + \nu^i \quad (2.14)$$

where $\hat{\theta}_0^i$ is the estimated weight on current "true" returns in reported returns for fund i , γ is the intercept, $\lambda_{\beta_{innov}}$ is the cross-sectional slope coefficient, $\hat{\beta}_{innov}^i$ is the estimated exposure to innovations in liquidity risk for fund i and ν^i is the residual for fund i .

With this liquidity proxy, Table shows that there is a positive but statistically non-significant cross-sectional slope, indicating a lack of relation between the exposure to innovations in liquidity and the amount of serial correlation. at the intra-style level, only the strategy Dedicated Short reports a negative and statistically significant slope, while the strategies Convertible Arbitrage, Emerging Markets, Equity Market-Neutral and Event Driven have positive and statistically significant slopes, indicating that, for these strategies subsamples, the more individual funds are exposed to innovations in liquidity, the higher their weight in current "true" returns in reported returns are, i.e. the less serially-correlated their reported returns are.

We have seen that, for some trading style subsamples, individual hedge funds loading more on the aggregate liquidity risk factor have more serially correlated reported returns while funds loading more on the innovations in liquidity are less serially correlated. This means that hedge fund serial correlation is positively related to exposure to ex-ante liquidity risk, while negatively related to ex-post contemporaneous unexpected illiquidity.

To test for the potential conjoint effect of these two exposures on hedge fund reported returns' serial correlation, we estimate a bivariate version of our two-past cross-sectional regression frameworks :

$$\hat{\theta}_0^i = \gamma + \lambda_{\beta_{global}} \hat{\beta}_{global}^i + \lambda_{\beta_{innov}} \hat{\beta}_{innov}^i + \nu^i \quad (2.15)$$

	Low	2	3	4	5	6	7	8	9	High	High-Low	
All	β_{global} θ_0	-29.41 0.89 (30.34)***	-5.72 0.83 (77.96)***	-2.24 0.81 (84.71)***	0 0.75 (86.37)***	1.4 0.76 (99.63)***	3.2 0.78 (95.21)***	5.31 0.78 (106.99)***	7.97 0.78 (95.69)***	12.24 0.8 (38.8)***	26.9 0.84 (41.43)***	56.31 -0.05 (-1.21)
Convertible-Arbitrage	β_{global} θ_0	-10.11 0.72 (13.46)***	-3.86 0.54 (26.93)***	-2.27 0.61 (22.95)***	-1.16 0.64 (26.95)***	0.99 0.6 (24.52)***	2.66 0.65 (18.83)***	6.06 0.73 (20.31)***	6.06 0.73 (20.54)***	8.63 0.69 (20.54)***	16.62 0.64 (19.55)***	26.73 -0.08 (-1.22)
Dedicated-Short	β_{global} θ_0	-23.91 1.09 (5.24)***	-11.67 0.94 (37.55)***	-9.61 0.87 (16.59)***	-3.8 0.91 (24.25)***	2.1 0.81 (15.05)***	4.98 1.05 (9.86)***	9.22 1.25 (6.92)***	9.22 1.25 (6.92)***	15.58 0.86 (7.7)***	25.87 1.13 (12.4)***	49.79 0.04 (0.14)
Emerging-Markets	β_{global} θ_0	-24.58 0.89 (32.77)***	-6.9 0.79 (41.3)***	-2.35 0.78 (44.73)***	0.1 0.76 (36.96)***	5.16 0.78 (52.9)***	7.71 0.74 (53.47)***	11.09 0.77 (49.76)***	11.09 0.77 (49.76)***	15.52 0.75 (45.14)***	34.03 0.8 (30.04)***	58.61 -0.09 (-2.62)***
Equity Market-Neutral	β_{global} θ_0	-153.78 0.93 (16.78)***	-5 0.88 (21.62)***	-2.87 0.83 (24.66)***	-1.18 0.88 (20.56)***	1.03 0.79 (22)***	2.44 0.78 (29.26)***	4.18 0.77 (28.62)***	4.18 0.77 (28.62)***	7.31 0.88 (13.9)***	16.14 0.86 (17.02)***	169.92 -0.08 (-1.04)
Event-Driven	β_{global} θ_0	-11.56 0.75 (30.44)***	-2.4 0.79 (14.47)***	-0.27 0.73 (23.69)***	0.74 0.69 (35.45)***	2.95 0.7 (42.02)***	4.66 0.69 (42.23)***	6.59 0.71 (35.78)***	6.59 0.71 (35.78)***	8.97 0.68 (35.82)***	17.79 0.67 (36.29)***	29.35 -0.08 (-2.55)***
Fixed-Income	β_{global} θ_0	-13.28 0.73 (22.3)***	-5.91 0.73 (21.81)***	-2.24 0.73 (22.03)***	-1.17 0.72 (19.84)***	1.16 0.63 (15.46)***	2.81 0.66 (18.72)***	5.29 0.71 (14.26)***	5.29 0.71 (14.26)***	9.46 0.92 (10.57)***	20.57 0.7 (19.97)***	33.86 -0.03 (-0.46)
Long-Short Equity	β_{global} θ_0	-22.67 0.88 (13.53)***	-6.45 0.88 (57.07)***	-2.38 0.85 (71.39)***	0.07 0.81 (80.92)***	4.13 0.82 (74.93)***	6.2 0.81 (70.76)***	8.97 0.8 (92.46)***	8.97 0.8 (92.46)***	13.26 0.8 (61.77)***	28.13 0.85 (43.82)***	50.81 -0.03 (-0.47)
Macro	β_{global} θ_0	-27.49 1.05 (13.39)***	-8.29 0.93 (27.71)***	-4.55 0.88 (25.08)***	-2.29 0.93 (15.51)***	1.59 0.91 (30.49)***	3.46 0.95 (19.19)***	7.48 0.87 (27.76)***	7.48 0.87 (27.76)***	14.2 0.99 (12.04)***	32.02 0.96 (21.13)***	59.52 -0.08 (-0.84)
Multi-Strategies	β_{global} θ_0	-21.81 0.84 (26.44)***	-4.91 0.78 (27.28)***	-1.86 0.78 (27.29)***	-0.21 0.71 (26.31)***	2.96 0.74 (25.88)***	4.5 0.8 (32.91)***	6.54 0.72 (49.18)***	6.54 0.72 (49.18)***	10.39 0.75 (25.19)***	21.54 1.09 (4.44)***	43.35 0.25 (1)
Options	β_{global} θ_0	-22.91 0.82 (19.03)***	-12.25 0.92 (612.19)***	-6.52 0.87 (21.92)***	-4.52 0.6 (28.47)***	-0.07 0.71 (7.69)***	1.43 0.73 (9.56)***	1.94 0.95 (10.85)***	1.94 0.95 (10.85)***	3.1 0.88 (4.38)***	11.26 1.13 (8.43)***	31.16 0.31 (3.39)***

TABLE 2.16 – Decile portfolios of hedge funds sorted by global liquidity risk exposure

This table reports properties of equal-weighted decile portfolios of individual hedge funds. For each fund having at least 36 monthly return observations, we estimate the following liquidity risk model $r_{i,t} = \alpha^i + \beta_{global}^i F_{global,t} + \beta_{innov}^i F_{innov,t} + u_t^i$ where $r_{i,t}$ is the return on each individual fund in month t , β_{global}^i is the exposure to aggregate liquidity risk of fund i and β_{innov}^i is the exposure to innovations in liquidity risk of fund i . Simultaneously, we estimate an MA(2) model on $r_{i,t}$. Portfolios are formed in ranking each fund according to its exposure β_{global}^i . The sample period is January 1994 – February 2015. For each decile portfolio, we report the average exposure β_{global} , the average serial correlation parameter θ_0 and its t-statistic.

where $\hat{\theta}_0^i$ is the estimated weight on current "true" returns in reported returns for fund i , γ is the intercept, $\lambda_{\beta_{global}}$ is the cross-sectional slope coefficient for $\hat{\beta}_{global}^i$, the estimated exposure to the global liquidity risk for fund i , $\lambda_{\beta_{innov}}$ is the cross-sectional slope coefficient for $\hat{\beta}_{innov}^i$, the estimated exposure to the innovations in illiquidity for fund i and ν^i is the residual for fund i .

Results Table 2.20 show that, globally, there is no statistically significant cross-sectional relation between the amount of serial correlation in individual hedge fund reported returns and exposures to the Pastor and Stambaugh (2003) liquidity risk factors. No strategy subsample has a statistically significant negative slope for the exposures to aggregate liquidity risk and innovations in illiquidity. The strategy Options has a statistically significant positive slope for both exposures, while Convertible Arbitrage has only a positive and statistically significant slope for the innovations in illiquidity.

This shows us that, globally, there is no cross-sectional linear relation between individual hedge fund reported returns' serial correlation and the exposures to the Pastor and Stambaugh (2003) liquidity risk factors. However, the portfolio sorts have showed that high-minus-low portfolios, sorted according to the weight on current "true" returns in reported returns θ_0^i , have statistically significant negative differences in average exposure to the aggregate liquidity risk and positive exposure to innovations in illiquidity. These mixed results indicates that at least the most and least serially-correlated portfolios of individual hedge funds statistically significantly differ in their exposures to these liquidity risk factors.

To summarize, our results are similar with Pastor and Stambaugh (2003) liquidity factors. We notice a cross-sectional noisy relation between serial correlation and liquidity exposures : funds that are more serially correlated are more exposed to the aggregate liquidity risk factor and less exposed to the innovations in liquidity risk factor, but the converse does not hold. There is a cross-sectional linear relation between exposure to the aggregate liquidity risk factor and serial correlation.

	Low	2	3	4	5	6	7	8	9	High	High-Low	
All	β_{innov}	-19.04	-4.29	-0.63	1.45	3.32	5.55	8.16	11.68	17.98	38.18	57.21
	θ_0	0.91	0.82	0.73	0.75	0.77	0.78	0.8	0.81	0.81	0.87	-0.04
		(32.98)***	(73.19)***	(88.29)***	(97.06)***	(90.61)***	(81.01)***	(93.58)***	(102.84)***	(29.4)***	(76.5)***	(-1.4)
Convertible-Arbitrage	β_{innov}	-7.72	-1.41	0.02	0.97	1.87	2.53	3.94	6.02	9.18	19	26.72
	θ_0	0.68	0.61	0.55	0.61	0.71	0.65	0.57	0.67	0.58	0.73	0.05
		(14.82)***	(24.49)***	(18.09)***	(26.06)***	(20.56)***	(21.16)***	(18.48)***	(18.95)***	(22.24)***	(15.45)***	(0.71)
Dedicated-Short	β_{innov}	-59.46	-33.55	-26.27	-20.84	-18.86	-15.32	-11.71	-6.79	-3.33	8.46	0.68
	θ_0	1.31	0.99	1.11	0.87	1.01	0.89	0.88	1.03	0.79	0.97	-0.33
		(10.15)***	(17.12)***	(5.52)***	(11.57)***	(15.9)***	(16.33)***	(17.31)***	(6.36)***	(18.3)***	(6.97)***	(-1.43)
Emerging-Markets	β_{innov}	-17.75	-1.62	1.17	3.99	7.41	10.97	15.89	22.4	30.15	52.06	69.82
	θ_0	0.8	0.72	0.73	0.8	0.77	0.81	0.81	0.76	0.81	0.85	0.05
		(35.4)***	(35.61)***	(44.57)***	(47.45)***	(58.38)***	(45.96)***	(33.95)***	(39.09)***	(43.98)***	(35.16)***	(1.33)
Equity Market-Neutral	β_{innov}	-14.61	-6.34	-2.86	-0.52	0.93	2.84	4.81	7.03	10.54	20.88	35.49
	θ_0	0.99	0.83	0.82	0.79	0.76	0.84	0.78	0.85	0.83	0.92	-0.06
		(14.01)***	(20.28)***	(28.03)***	(19.78)***	(25.46)***	(25.81)***	(21.48)***	(18.55)***	(22.5)***	(19.51)***	(-0.84)
Event-Driven	β_{innov}	-9.48	-1.63	0.42	1.69	2.96	4.4	5.83	7.45	11.63	26.85	36.33
	θ_0	0.73	0.68	0.63	0.7	0.67	0.71	0.74	0.7	0.73	0.83	0.09
		(26.11)***	(49.36)***	(32.93)***	(39.97)***	(35.38)***	(23.77)***	(15.42)***	(32.93)***	(40.67)***	(31.03)***	(2.29)**
Fixed-Income	β_{innov}	-13.7	-4.88	-1.81	-0.31	0.66	1.95	3.06	5.14	8.8	17.1	30.78
	θ_0	0.83	0.76	0.64	0.63	0.67	0.71	0.69	0.81	0.66	0.72	-0.11
		(9.56)***	(14.24)***	(16.5)***	(14.51)***	(15.15)***	(20.13)***	(20.66)***	(16.67)***	(28.06)***	(19.02)***	(-1.17)
Long-Short Equity	β_{innov}	-18.73	-5.08	-0.58	2.2	4.54	7.17	10.2	13.93	20.13	39.16	57.88
	θ_0	0.87	0.85	0.8	0.8	0.82	0.81	0.82	0.85	0.8	0.9	0.03
		(43.44)***	(57.52)***	(75.63)***	(72.91)***	(65.47)***	(72.43)***	(81.53)***	(78.27)***	(12.68)***	(47.28)***	(1)
Macro	β_{innov}	-33.88	-8.07	-2.98	-0.46	1.89	3.63	5.72	8.39	12.44	32.94	66.82
	θ_0	1	0.85	1.04	0.87	0.86	0.9	0.92	1.03	0.9	0.98	-0.01
		(23.93)***	(19.44)***	(11.49)***	(26.39)***	(22.09)***	(18.84)***	(34.57)***	(20.02)***	(22.83)***	(14.25)***	(-0.18)
Multi-Strategies	β_{innov}	-18.06	-2.84	0	1.56	2.92	4.94	6.94	9.15	12.59	25.15	43.21
	θ_0	1.17	0.77	0.69	0.74	0.74	0.7	0.78	0.73	0.79	0.82	-0.35
		(4.77)***	(27.52)***	(24.43)***	(29.22)***	(31.53)***	(29.75)***	(23.62)***	(32.5)***	(29.93)***	(27.68)***	(-1.42)
Options	β_{innov}	-18.81	-14	-11.37	-6.23	-1.82	0.26	4.14	15.92	18.35	22.2	41
	θ_0	0.73	0.68	1	0.72	0.82	0.92	0.9	0.71	0.83	0.85	0.12
		(9.99)***	(23.04)***	(13.71)**	(6.80)***	(24.58)***	(2.68)***	(119.34)***	(7.74)***	(4.11)***	(11.75)***	(0.83)

TABLE 2.17 – Decile portfolios of hedge funds sorted by innovations in liquidity risk exposure

This table reports properties of equal-weighted decile portfolios of individual hedge funds. For each fund having at least 36 monthly return observations, we estimate the following liquidity risk model $r_{i,t} = \alpha^i + \beta_{i,innov}^i F_{i,global,t} + \beta_{i,global}^i F_{i,global,t} + u_{i,t}^i$ where $r_{i,t}$ is the return on each individual fund in month t , $\beta_{i,global}^i$ is the exposure to aggregate liquidity risk of fund i and $\beta_{i,innov}^i$ is the exposure to innovations in liquidity risk of fund i . Simultaneously, we estimate an MA(2) model on $r_{i,t}$. Portfolios are formed in ranking each fund according to its exposure $\beta_{i,innov}$. The sample period is January 1994 – February 2015. For each decile portfolio, we report the average exposure $\beta_{i,innov}$, the average serial correlation parameter θ_0 and its t-statistic.

	All	Convertible-Arbitrage	Dedicated Short	Emerging	Equity MN	Event Driven	Fixed-Income	LS Equity	Macro	Multi-Strat	Options
Intercept	80.36	63.91	97.65	79.28	84.28	71.85	70.65	83.51	93.39	79.03	82.44
t_{NW}	(169.29)***	(45.85)***	(25.38)***	(93.75)***	(56.49)***	(73.87)***	(45.93)***	(91.54)***	(52.52)***	(33.64)***	(27.67)***
t_{GMM}	(161.1)***	(44.91)***	(25.51)***	(93.66)***	(52.54)***	()***	(70.14)***	42.13(93.08)***	(50.43)***	(33.07)***	(30.86)***
$\lambda_{\beta_{global}}$	-0.92	-4.85	20.46	-17.26	-0.44	-24.69	20.18	-10.67	-3.68	9.66	32.52
t_{NW}	(-1.96)**	(-0.28)	(1.11)	(-2.77)***	(-8.55)***	(-2.43)***	(1.6)	(-1.28)	(-0.33)	(0.54)	(1.72*)
t_{GMM}	(-1.97)**	(-0.27)	(1.22)	(-2.54)***	(-8.05)***	(-2.37)***	(1.64)	(-1.29)	(-0.33)	(0.54)	(1.96)**
R^2	0	0	0.24	3.37	0	1.14	0.36	0.16	0	0	0.91
nb funds	4,864	195	41	640	309	554	209	2,073	325	492	26

TABLE 2.18 – Cross-sectional regressions θ_0 on global liquidity risk

Mean slopes estimates of monthly cross-sectional regressions of individual hedge funds' weight of current "true" returns in reported returns θ_0 on exposures to the liquidity risk β_{global} . These exposures are estimated in a first-stage time-series regression. The monthly sample is 01/1994-02/2015. R^2 is the adjusted coefficient of determination in percentage. Generalized methods-of-moments t_{GMM} and Newey-West t_{NW} t-statistics in parentheses adjust for cross-asset correlation in the residuals and for estimation error of the time-series betas.

	All	Convertible-Arbitrage	Dedicated Short	Emerging	Equity MN	Event Driven	Fixed-Income	LS Equity	Macro	Multi-Strat	Options
Intercept	80.27	63.03	91.23	77.36	83.96	70.11	71.75	82.89	93.24	80.13	81.17
t_{NW}	(166.54)***	(50.02)***	(28.83)***	(90.38)***	(55.94)***	(73.38)***	(37.64)***	(114.54)***	(55.86)***	(24.29)***	(25.58)***
t_{GMM}	(157.93)***	(44.43)***	(34.55)***	(52.54)***	(52.1)***	(73.81)***	(35.11)***	(113.54)***	(51.1)***	(24.39)***	(29.4)***
$\lambda_{\beta_{innov}}$	1.12	19.33	-39.9	9.59	0.79	18.72	-40.47	3.74	3.22	-20.36	21.17
t_{NW}	(1.52)	(2.57)***	(-2.53)***	(3.17)***	(5.15)***	(2.08)**	(-1.04)	(0.71)	(0.25)	(-1.09)	(1.06)
t_{GMM}	(1.49)	(2.54)***	(-2.68)***	(3)***	(4.81)***	(2.06)**	(-1.03)	(0.71)	(0.25)	(-1.08)	(1.04)
R^2	0	1.58	10.2	1.56	0	1.09	2.01	0	0	0.07	0
nb funds	4,864	195	41	640	309	554	209	2,073	325	492	26

TABLE 2.19 – Cross-sectional regressions θ_0 on innovations in liquidity risk

Mean slopes estimates of monthly cross-sectional regressions of individual hedge funds' weight of current "true" returns in reported returns θ_0 on exposures to the liquidity risk β_{innov} . These exposures are estimated in a first-stage time-series regression. The monthly sample is 01/1994-02/2015. R^2 is the adjusted coefficient of determination in percentage. Generalized methods-of-moments t_{GMM} and Newey-West t_{NW} t-statistics in parentheses adjust for cross-asset correlation in the residuals and for estimation error of the time-series betas.

	All	Convertible-Arbitrage	Dedicated Short	Emerging	Event Driven	Fixed-Income	Equity MN	LS Equity	Macro	Multi-Strat	Options
Intercept	80.53	63.08	90.05	78.95	70.99	71.65	84.28	83.81	93.33	79.97	81.89
t_{NW}	(143.25)***	(46.6)***	(19.65)***	(62.97)***	(55.29)***	(33.36)***	(49.74)***	(75.67)***	(55.11)***	(27.1)***	(25.58)***
t_{GMM}	(133.13)***	(43.27)***	(24.37)***	(62.46)***	(55.88)***	(29.46)***	(45.89)***	(76.2)***	(52.38)***	(27.09)***	(33.45)***
$\lambda_{\beta_{global}}$	-2.08	-2.49	-15.27	-15.65	-15.75	3.46	-6.03	-12.81	-2.55	5.29	47.4
t_{NW}	(-1.37)	(-0.16)	(-0.44)	(-1.86)*	(-1.38)	(0.18)	(-0.53)	(-1.39)	(-0.2)	(0.33)	(2.02)**
t_{GMM}	(-1.27)	(-0.15)	(-0.53)	(-1.73)*	(-1.39)	(0.18)	(-0.51)	(-1.4)	(-0.19)	(0.32)	(2.91)***
$\lambda_{\beta_{innov}}$	-2.19	19.19	-49.18	2.14	11.17	-38.4	-10.62	-3.08	1.52	-19.13	34.95
t_{NW}	(-0.75)	(2.63)***	(-1.55)	(0.48)	(1.1)	(-0.82)	(-0.49)	(-0.66)	(0.09)	(-1.2)	(1.74)*
t_{GMM}	(-0.7)	(2.67)***	(-1.78)*	(0.48)	(1.1)	(-0.81)	(-0.47)	(-0.64)	(0.09)	(-1.18)	(2.00)**
R^2	0	1.09	8.74	3.27	1.25	1.55	0	0.12	0	0	4.45
nb funds	4,864	195	41	640	309	554	209	2,073	325	492	26

TABLE 2.20 – **Bivariate cross-sectional regressions θ_0 on liquidity risk**

Mean slopes estimates of monthly cross-sectional regressions of individual hedge funds' weight of current "true" returns in reported returns θ_0 on exposures to the liquidity risks β_{global} and β_{innov} . These exposures are estimated in a first-stage time-series regression. The monthly sample is 01/1994-12/2012. R^2 is the adjusted coefficient of determination in percentage. Generalized methods-of-moments t_{GMM} and Newey-West t_{NW} t-statistics in parentheses adjust for cross-asset correlation in the residuals and for estimation error of the time-series betas.

2.7 Appendix B : Robustness checks with Funds of Hedge Funds

We previously excluded funds of hedge funds in our global data sample of individual hedge funds in order to avoid any double counting of a particular hedge fund investment and hence ensure the statistical soundness of our results. In this appendix, we test our previous results on the relation between serial correlation in the reported funds' returns and exposure to liquidity factors.

Our sample of funds of hedge funds comprehends 2,243 individual funds with at least 36 monthly returns observations over the period January 1994 - December 2012. These individual funds' returns have a monthly average of 0.38% with an average volatility of 2.54%, giving an average Sharpe ratio of 0.31. As for their hedge fund counterparts, individual funds of hedge funds' returns exhibit an average negative skewness of -0.77 and an average kurtosis of 7.83. More importantly for our analysis, their average serial correlation, estimated with an autoregressive process at the order one, is 22.83%. This average amount of serial correlation is superior than those of individual hedge funds. Furthermore, the cross-sectional standard-deviation for the serial-correlation is 19.19%, indicating a fairly wide dispersion in estimates, which helps in cross-sectional testing of the impact of serial correlation on other characteristics.

To investigate the potential link between funds of hedge funds' serial correlation and liquidity exposure, we begin in sorting them over the period January 1994 - December 2012 in decile portfolios with respect to their weight θ_0^i of the current "true" returns in their reported returns. This coefficient proxies for serial correlation : the lower it is, the more serially correlated reported returns are. Because we want to see if there is a connection between liquidity and serial correlation, and if so if serially correlated funds of hedge funds earn a risk premia, we report the average portfolio return $E[R_t^i]$ and the average liquidity betas $\beta_{transit}^i$ and β_{perma}^i .

Table 2.21 reports the results of the three parameters for our decile portfolios. The serial correlation parameter θ_0 goes from 0.53 for the first decile to 1.19 for the highest decile, showing large differences in the amount of serial-correlation among decile portfolios of funds of hedge funds. We find that, as θ_0 increases, i.e. as the amount of serial correlation present in reported returns decreases, the exposures to innovations in the market wide transitory impact $\beta_{transit}$ and permanent impact β_{perma} are globally decreasing. They present spreads of -7.3% and 0.47% respectively, highly statistically significant with t-statistics of -5.57 and 4.68. These results are consistent with the idea that the more a fund of hedge fund has serially correlated returns, the more it is exposed to liquidity risk.

If serial-correlation in funds of hedge fund returns is a by-product of liquidity exposures, funds that have more serially correlated returns, i.e. that have lower θ_0 , should earn a risk premium to bear this non-diversifiable systematic liquidity risk, as demonstrated by Sadka (2010). Consistent with this idea, high-minus-low decile portfolio sorted on θ_0 earns a monthly average return of -0.23%, statistically significant with an associated t-statistic of -4.92. This result seems to confirm the intuition that more serially correlated funds of hedge funds earn higher average returns to compensate the liquidity-risk bearing.

	Low	2	3	4	5	6	7	8	9	High	High-Low
FoHF											
θ_0	0.53	0.61	0.65	0.68	0.71	0.74	0.77	0.82	0.9	1.19	0.66
$E[R_t]$	0.43 (10.52)***	0.36 (12.95)***	0.41 (11.57)***	0.43 (18.12)***	0.36 (14.74)***	0.42 (15.26)***	0.39 (15.95)***	0.43 (16.46)***	0.33 (10.03)***	0.19 (7.04)***	-0.23 (-4.92)***
$\beta_{transit}$	9.66 (9.99)***	10.16 (10.87)***	8.25 (14.51)***	8.96 (9.61)***	7.76 (11.35)***	6.43 (8.89)***	6.11 (9.12)***	6.02 (7.52)***	6 (5.87)***	2.37 (2.72)***	-7.3 (-5.57)***
β_{perma}	0.63 (12.13)***	0.75 (11.3)***	0.67 (16.6)***	0.58 (13.23)***	0.65 (17.36)***	0.62 (11.43)***	0.54 (12.75)***	0.44 (6.03)***	0.22 (2.69)***	0.16 (2.11)**	-0.47 (-4.68)***

TABLE 2.21 – Decile portfolios of hedge funds sorted by serial correlation

This table reports estimates for equal-weighted decile portfolios of individual funds of hedge funds. For each fund having at least 36 monthly return observations, we estimate the following liquidity model : $r_{i,t} = \alpha^i + \beta_{transit}^i F_{transit,t} + \beta_{perma}^i F_{perma,t} + u_i$ where $r_{i,t}$ is the return on each individual fund in month t , α^i is the regression intercept, $\beta_{transit}^i$ is the exposure of fund i to the transitory market-impact factor, $F_{transit,t}$ is the realization month t of the transitory liquidity factor, β_{perma}^i is the exposure of fund i to the permanent market-impact factor and $F_{perma,t}$ is the realization month t of the permanent liquidity factor. Simultaneously, we estimate an MA(2) model on $r_{i,t}$ to get θ_0^i the weight of fund i of its current "true" return in its reported returns. Portfolios are formed in ranking each fund according to its θ_0^i , so the portfolio Low is the portfolio with the lowest θ_0 , i.e. the portfolio of the most-serially correlated hedge funds. The sample period is January 1994 - December 2012. For each decile portfolio, we report the average serial correlation parameter θ_0 , the average return $E[R_t]$, the average liquidity betas $\beta_{transit}$ and β_{perma} and their t-statistics.

	$\beta_{transit}^i$	β_{perma}^i	$E[R_t^i]$
Intercept	1,417.88	108.84	0.61
t_{NW}	(7.65)***	(11.58)***	(13.76)***
t_{GMM}	(10.59)***	(11.87)***	(14.4)***
$\lambda_{\theta_0^i}$	-925.92	-74.15	-0.31
t_{NW}	(-3.78)***	(-5.85)***	(-5.96)***
t_{GMM}	(-3.35)***	(-5.67)***	(-6.19)***
R^2	2.22	2.79	1.79

TABLE 2.22 – **Fama-McBeth cross-sectional regressions on θ_0 for individual funds of hedge funds**
Estimates of monthly cross-sectional regressions of individual funds of hedge funds' average returns $E[R_t^i]$, transitory market-impact liquidity factor exposure $\beta_{transit}^i$ and permanent market-impact liquidity factor beta β_{perma}^i on the weight of current "true" returns in reported returns θ_0^i . These serial correlation parameters are estimated with a first-stage time-series MA(2) as in Eq. (4). The monthly sample is 01/1994-12/2012. R^2 is the adjusted coefficient of determination in percentage. Generalized methods-of-moments t_{GMM} and Newey-West t_{NW} t-statistics in parentheses adjust for cross-asset correlation in the residuals and for estimation error of the time-series betas.

To further investigate the relationship between serial correlation and liquidity, we estimate univariate cross-sectional regressions in the spirit of Fama and McBeth (1973). We run three of them, each time with θ_0 the weight of current "true" returns in reported returns as the explanatory variable and with $\beta_{transit}^i$ the exposure to market-wide transitory impact risk, β_{perma}^i the exposure to market-wide permanent impact risk and $E[R_t^i]$ the average return as the dependent variables.

Results for these two-stage cross-sectional regressions are presented in Table 2.22. We see that there is a negative slope of -925.92% and -74.15% for the parameter θ_0 for both exposures to liquidity risk $\beta_{transit}^i$ and β_{perma}^i respectively, statistically significant at the 1% risk level with both Hansen's (1982) generalized-method-of-moments and Newey and West (1994) estimators. These results show that the more a fund of hedge fund has serially correlated returns, i.e. the lower its coefficient θ_0 , the higher its liquidity betas are. Furthermore, the Fama and McBeth regression of average individual funds' returns on their amount of serial correlation explicits the existence of risk premium, with a negative slope of -0.31%, highly statistically significant, for the coefficient θ_0 .

As with individual hedge funds, we also run bivariate two-stage cross-sectional regressions of the amount of serial-correlation, proxied with θ_0^i on both liquidity exposures, as in Eq. (2.9). Results in Table 2.23 show that both exposures have a negative and highly statistically significant slope, confirming the strong link between funds of hedge funds' serial correlation and liquidity.

We have seen that the most serially correlated funds of hedge funds are more exposed to liquidity risk than the least serially correlated ones. However, if liquidity is the main driver of serial correlation in funds of hedge fund autocorrelation, the converse relation should also hold, i.e. the individual funds of hedge funds the most exposed to liquidity risk should present more serially correlated returns. To explore this issue, we sort individual funds of hedge funds into decile portfolio according to their liquidity betas $\beta_{transit}^i$ and β_{perma}^i and present the average weight θ_0 of current "true" returns in reported returns as a proxy for serial correlation.

Results for both methods of sorting funds in decile portfolios are presented in Table 2.24. When we sort funds of hedge funds in decile with respect to their exposure to market-wide transitory impact risk $\beta_{transit}^i$, we see that these exposures go from -4.82 to 33.11, showing a great dispersion. The high-minus-low decile portfolio exhibit

	θ_0
Intercept	78.93
t_{NW}	(107.28)***
t_{GMM}	(103.65)***
$\lambda_{\beta_{transit}}$	-0.2
t_{NW}	(-2.74)***
t_{GMM}	(-2.72)***
$\lambda_{\beta_{perma}}$	-3.29
t_{NW}	(-4.75)***
t_{GMM}	(-4.69)***
R^2	4.2

TABLE 2.23 – **Bivariate cross-sectional regression of θ_0 on liquidity risk exposures for individual funds of hedge funds**

Mean slopes estimates of monthly cross-sectional regressions of individual funds of hedge funds' weight of current "true" returns in reported returns θ_0 on exposures to the liquidity risks $\beta_{transit}$ and β_{perma} . These exposures are estimated in a first-stage time-series regression. The monthly sample is 01/1994-12/2012. R^2 is the adjusted coefficient of determination in percentage. Generalized methods-of-moments t_{GMM} and Newey-West t_{NW} t-statistics in parentheses adjust for cross-asset correlation in the residuals and for estimation error of the time-series betas.

a difference in θ_0 of -0.2, highly statistically significant with an associated t-statistic of -8.56 : the funds loading the most on this proxy of liquidity risk have higher serial correlation in their returns, i.e. lower coefficients θ_0^i , than funds loading the least on this particular liquidity risk. We reach the same conclusion for the exposure to unexpected changes in market-wide permanent impact β_{perma} . These exposure goes from -0.89 for decile 1 to 2.09 for decile 10, and the high-minus-low portfolio has a difference in average θ_0^i of -0.13, statistically significant at the 1% risk level with a t-statistic of -6.11.

Bali et al. (2011) emphasize the importance of the predictive power of a given risk exposure or characteristic on future returns to be considered as a source of a risk premium. We follow their methodology and both form rolling portfolio estimated with a fixed window of 36 months with respect to $\theta_{0,t}^i$ and rolling-window two-stage cross-sectional regressions over the same window's length. For the portfolios, we get an average high-minus-low one-month ahead return spread of -0.2%, only statistically significant at the 10% risk-level with a t-statistic of -1.94. However, there is an average negative slope of -0.26% for the cross-sectional regressions of one-month ahead returns on $\theta_{0,t}^i$, the past weight on current "true" returns in reported returns, statistically significant with an associated t-statistic of -2.32. There is evidence that a higher serial correlation, i.e. a lower $\theta_{0,t}^i$, predicts higher future expected returns.

We can conclude that there is a strong relationship between funds of hedge fund serial correlation and exposure to liquidity risk, and this relation goes both way with the most serially correlated funds of hedge funds being more exposed to liquidity risk and the funds the most exposed to liquidity risk are more serially correlated. Both univariate and bivariate cross-sectional two-stage regressions confirm this finding and there is evidence of a risk premium of being serially-correlated, which is not the case for individual hedge funds.

	Low	2	3	4	5	6	7	8	9	High	High-Low
FoHF											
$\beta_{transit}$	-4.82	-0.2	0.71	1.49	2.82	5.08	7.7	10.5	14.54	33.11	37.93
θ_0	0.91	0.78	0.74	0.75	0.78	0.74	0.75	0.70	0.69	0.71	-0.2
	(49.03)***	(51.78)***	(62.3)***	(53.1)***	(55.83)***	(85.74)***	(55.51)***	(99.52)***	(73.31)***	(53.95)***	(-8.56)***
FoHF											
β_{perma}	-0.89	-0.05	0.18	0.33	0.45	0.56	0.67	0.82	1.04	2.09	2.99
θ_0	0.88	0.79	0.8	0.78	0.72	0.72	0.69	0.72	0.71	0.75	-0.13
	(53.35)***	(46.22)***	(51.09)***	(57.33)***	(75.61)***	(73.93)***	(90.76)***	(67.57)***	(49.43)***	(57.05)***	(-6.11)***

TABLE 2.24 – Decile portfolios of hedge funds sorted by liquidity risk exposure

This table reports estimates for equal-weighted decile portfolios of individual funds of hedge funds. For each fund having at least 36 monthly return observations, we estimate the following liquidity model : $r_{i,t} = \alpha^i + \beta_{transit}^i F_{transit,t}^i + \beta_{perma}^i F_{perma,t}^i + u_t^i$ where $r_{i,t}$ is the return on each individual fund in month t , α^i is the regression intercept, $\beta_{transit}^i$ is the exposure of fund i to the transitory market-impact factor, $F_{transit,t}^i$ is the realization month t of the transitory liquidity factor, β_{perma}^i is the exposure of fund i to the permanent market-impact factor and $F_{perma,t}^i$ is the realization month t of the permanent liquidity factor. Simultaneously, we estimate an MA(2) model on $r_{i,t}$ to get θ_0^i the weight of fund i of its current "true" return in its reported returns. Portfolios are formed in ranking each fund according to its liquidity betas $\beta_{transit}^i$ and β_{perma}^i , so the portfolio Low is the portfolio with the lowest $\beta_{transit}^i$ or β_{perma}^i , i.e. the portfolio of the least exposed to liquidity risk. The sample period is January 1994 - December 2012. For each decile portfolio, we report the average liquidity betas $\beta_{transit}$ or β_{perma} , the average serial correlation parameter θ_0 and its t-statistic.

Chapitre 3

Hedge funds and limits-to-arbitrage : does financial intermediaries' risk predict hedge fund returns ?

Les *hedge funds*, tant par leur arrangement institutionnel que du fait de leurs stratégies complexes, sont en interaction fréquente avec des intermédiaires financiers. Ces derniers sont contreparties au trading de produits négociés de gré-à-gré, structurent des produits exotiques et prêtent des capitaux ou encore des titres afin de pouvoir effectuer de la vente à découvert.

Ce chapitre interroge le risque posé par ces relations. Il part de l'idée que, quelle que soit la nature de la stratégie employée par un *hedge fund*, elle va être porteuse d'un risque de "limite à l'arbitrage" comme théorisé par Shleifer et Vishny (1997). Ces derniers démontrent que les prix des actifs financiers peuvent dévier en pratique de leurs prix théoriques du fait du risque posé sur les arbitrageurs par l'action de corriger ces déviations, impliquant l'usage de capitaux externes et le risque de financement associé. Ainsi, pour mettre en oeuvre leurs stratégies exploitant les différences entre prix théoriques et observés, les *hedge funds* sont obligés d'interagir avec des intermédiaires financiers tels que leurs *prime brokers* par exemple, et s'exposent au risque de brusque variation dans le capital de ces derniers. En effet, un tel évènement va soudainement rendre beaucoup plus coûteuse la vente à découvert ou l'usage du levier avec des appels de marge, et va grandement écarter les fourchettes de prix cotées par les teneurs de marchés des instruments de gré-à-gré.

L'hypothèse faite dans ce chapitre est qu'il existe une relation entre le rendement d'une stratégie *hedge fund* et le niveau de risque de capital des intermédiaires financiers auquel elle est exposée. Comme He et al. (2017), nous prenons comme approximation du secteur des intermédiaires financiers les *primary dealers*, c'est-à-dire les contreparties à la *Federal Reserve Bank of New York* pour sa mise en oeuvre de la politique monétaire. Le risque de capital des intermédiaires financiers est le choc inattendu, issu d'un modèle autorégressif, sur le ratio de capital agrégé des *primary dealers*.

Les résultats empiriques démontrent unanimement l'existence d'un lien entre le rendement des *hedge funds* et leur exposition au risque de capital. Afin de s'assurer de la robustesse des résultats et d'écarter le risque de "fausse découverte", nous utilisons des méthodes paramétriques et non-paramétriques ainsi que des procédures de validation croisée, et nous les appliquons tant aux rendements bruts des *hedge funds* qu'à leurs rendements ajustés du risque. Nous contrôlons, en plus des sept facteurs de Fung et Hsieh (2004), l'inclusion du risque de liquidité et des marchés émergents.

Ce chapitre souligne l'importance d'un risque jusque-là omis dans la coupe transversale des rendements des *hedge funds*. Il permet d'expliquer une plus grande partie des variations des rendements et de la surperformance que l'explication obtenue avec les facteurs de Fung et Hsieh uniquement, diminuant l'"anomalie" de l'*alpha* des *hedge funds*. Les résultats obtenus permettent aux investisseurs une meilleure compréhension de leurs investissements *hedge funds* et de structurer leurs portefeuilles de fonds de manière à s'exposer au risque des intermédiaires financiers selon leur profil d'aversion au risque. De plus, il met en exergue le rôle posé par les contreparties des *hedge funds* dans le risque de ces derniers et incite les régulateurs à contrôler les activités de *prime brokerage* (l'ensemble des services fournis aux *hedge funds*) des banques.

Hedge funds and limits-to-arbitrage : does financial intermediaries' risk predict hedge fund returns ?

This paper investigates the systematic role of limits to arbitrage in the risk and return profile of hedge funds. We follow He et al. (2017) and define these frictions in financial markets as the shocks to the equity capital ratio of primary dealer counterparties of the New York Federal Reserve. This paper demonstrates that this financial intermediaries risk is an important determinant in the cross-section of future hedge fund returns. Funds significantly loading on financial intermediaries' risk outperform low-loading funds in the next month by about 6.48% annually. The results are robust to the inclusion of other hedge fund risk factors. The paper highlights the importance of limits-to-arbitrage to understand the hedge fund industry and its risks.

Key-words : risk premia, hedge funds, intermediary capital, systemic risk, limits to arbitrage

3.1 Introduction

This paper analyzes the relation between financial intermediaries' risk exposures and the cross-section of hedge funds' risk and return.

Financial intermediaries' risk occurs because of an unexpected change in financing conditions in the global financial intermediaries sector due to a lack of costly capital. It can be linked to adverse returns in a large class of financial assets, a surge in financial risk-premia and tighter financing conditions for investors. Facing time-varying financing conditions and financial assets' expected returns, risk-averse investors might prefer trading strategies with higher payoffs in states of low financial intermediaries capital and will pay a market premium for assets having higher payouts when the capital in the financial intermediaries' sector is scarce. Indeed, Adrian et al. (2014) empirically show that the cross-section of stocks and bonds expected returns is determined by financing conditions in the broker-dealer sector. He et al. (2017) present evidences that innovations in the aggregate primary dealers' equity capital ratio price a large collection of asset classes, including complex and over-the-counter assets such as corporate and sovereign bonds, derivatives, commodities and currencies. The premium earned for bearing primary dealer financing risk is stable across asset classes, indicating strong evidence of the existence of a risk premium for financial intermediaries' risk.

To proxy for financial intermediaries' risk, we follow He et al. (2017) and focus on primary dealers, who serve as counterparties of the Federal Reserve Bank of New York in its implementation of monetary policy. Because primary dealers are large financial institutions operating in almost the entire universe of financial markets, they are potentially marginal investors in many markets, and henceforth represent the financial intermediaries hedge funds deal with in the implementation of their trading strategies. These institutions have brokerage units, make markets in over-the-counter and derivatives assets and offer prime brokerage services, making them suitable candidates to measure the financial intermediaries' risk faced by hedge funds. In order to measure the financing risk of these institutions, we compute the aggregate primary dealer sector's equity capital ratio and proxy its risks as unexpected shocks in an simple autoregressive model.

This study shows that financial intermediaries' risk, proxied by innovations in the aggregate equity capital ratio of the primary dealer sector, prices the cross-section of hedge fund returns. Consistent with a limits-to-arbitrage framework of pricing "anomalies" in financial markets (Shleifer and Vishny, 1997), hedge fund strategies that are more exposed to changes in the financing conditions of financial intermediaries earn higher expected returns. There is a risk-return trade-off for hedge fund investors, because strategies generating high expected return bear a higher financial intermediaries' risk. For example, in a cross-section spanning the 24 longest Hedge Fund Research (HFR) hedge fund indices, the single factor model we present explains 70% of the variation in average returns in this cross-section with a mean absolute pricing error around 1% per annum.

The major finding from this paper is the demonstration, using both parametric and non-parametric methods, of a positive relation between individual hedge fund exposure to financial intermediaries' risk and future hedge fund returns. Funds that significantly load on financial intermediaries' risk subsequently have higher one-month ahead returns by about 6.48% annually on average than low-loading funds over the period January 1994-February 2015. We provide evidence of financial intermediaries risk predictive power at longer horizons for hedge fund returns. This result implies that financial intermediaries' risk is a strong predictor of future one month-ahead hedge fund returns and henceforth is a true systematic non-diversifiable risk factor for hedge fund investors. Henceforth, hedge funds enable investors to load on financial intermediaries' risk in order to earn its associated risk premium.

While financial intermediaries' risk is an important topic for investment strategies globally, it should be a special concern for hedge funds for three reasons. First, contrary to mutual funds, hedge funds have an absolute-return objective, meaning that they try to provide uncorrelated returns with the global equity market for their investors. To achieve their goal of market neutrality, hedge funds hedge their positions through the use of financial derivatives and short selling, requiring the recourse of financial intermediaries for the financing of the short positions and the trading of the derivatives products. Duffie et al. (2007) show that over-the-counter financial products such as derivatives are subject to price jumps and liquidity frictions caused by common shocks on market-makers. D'Avolio (2002) documents that the market for borrowing stocks experience rare but significant negative supply shocks, generating a risk for short-sellers.

Second, a common feature of hedge funds is their heavy use of leverage to enhance their returns : Ang et al. (2011) present evidence for dynamic hedge fund leverage. If leveraging an investment strategy can increase its expected return, it is also a source of risk. For example, Adrian and Shin (2010) document that the use of margin requirements, such as those in contracts between hedge funds and their prime brokers, can lead to procyclical leverage, inducing occasional large adverse returns for the levered investor. A shock in financial intermediaries' capital can lead to a liquidity spiral for hedge funds, as exhibited in Brunnermeier and Pedersen (2009). Khandani and Lo (2011) detail the occurrence of such an event, the "Quant Meltdown" of August 2007. Furthermore, Buraschi et al. (2014) argue that the relatively small number of prime brokers financing hedge funds implies systematic correlation shocks affecting hedge fund returns.

Third, financial intermediaries may be direct hedge fund investors themselves via their funds-of-hedge funds, asset management or wealth management divisions. They may also provide capital introduction services, which consist of attempts by prime brokers to introduce its hedge fund clients to potential investors. A shock on the financial intermediaries' capital can lead them to clear their hedge fund investments or to stop providing capital for hedge fund fundraising, inducing a coordinated funding liquidity risk for the hedge fund industry, as theoretically demonstrated by Liu and Mello (2011).

Our work borrows from streams of the literature on hedge funds and asset pricing. First and foremost, our empirical results are consistent with a large and growing asset pricing literature on the link between financial institutions and asset prices. Modern finance theory explains that asset prices are determined by their co-variances with the stochastic discount factor (SDF), as in Cochrane (2001) for example. This SDF is usually linked to the marginal value of aggregate wealth of the relevant representative agent. Assets that pay-off in future states with high marginal value of wealth demand a premium. Traditional SDF theories and empirical investigations emphasize the role of households as marginal investors in financial markets, such as the Breeden's (1979) Consumption-CAPM. There are however growing recent empirical evidence, see for example Gabaix et al. (2007), Collin-Dufresne et al. (2001) or Garleanu et al. (2009), that the performance of many financial assets such as mortgage-based securities, corporate bonds and index options, depend on the health of the financial sector broadly defined. He and Krishnamurthy (2013) gave a theoretical framework to these findings in developing a model in which the stochastic discount factor is the financial intermediary sector's financial health. Their model is able to produce spikes in risk premia similar to those observed for financial assets during financial crises, an empirical feature Muir (2017) documents is not explained by changes in aggregate consumption.

Second, we complement the literature on hedge fund performance and risk evaluation. Contrary to the literature on mutual funds, a number of empirical studies such as Fung and Hsieh (1997) and Agarwal and Naik (2004) found evidence of a positive risk-adjusted performance (alpha) in hedge fund returns. Their results indicate that using traditional factors such as in Fama and French (1993) underestimates systematic risk for hedge

funds. A number of subsequent studies have provided more adequate risk factors for hedge funds. Focusing on managed futures hedge funds, Fung and Hsieh (2001) develop option-based trend-following factors on currencies, commodities and bonds, and show that these factors explain trend-following hedge fund returns. Since then, the literature on hedge fund risk factors has considerably grown, with Sadka's (2010) liquidity risk factor, the macroeconomic uncertainty and systematic risk factors of Bali et al. (2012, 2014), Burashi et al.'s (2014) correlation risk or the sentiment risk index of Chen et al. (2016).

Finally, we take into account a recent literature examines the statistical significance of previously found financial risk factors. Harvey et al. (2016) that the high number of studies finding risk factors explaining the cross-section of financial asset returns reflects a high number of false positives. Furthermore, Hou et al (2017) find that the vast majority of anomalies found in the literature cannot be replicated. We control for a large sample of other risk factors in our analysis, decreasing the risk that our risk factor is a mere proxy for another well-known hedge fund risk factor. Furthermore, we work with both index and individual hedge fund data, ensuring a strong robustness of our results, and we systematically look at the out-of-sample predictive power of financial intermediaries' risk exposure, limiting the risk of overfitting.

The rest of this paper is organized as follows. Section 2 describes the data and variables used for this study. Section 3 presents the empirical findings, for hedge fund indices. Section 4 looks at the predictive power of financial intermediaries' betas on future individual hedge fund returns. Section 5 investigates the link between risk-adjusted returns and financial intermediaries' risk. Section 6 checks the long run performance of portfolios sorted on financial intermediaries' risk. Section 7 concludes.

3.2 Data and variables

Data for monthly hedge fund strategies indices' returns comes from Hedge Fund Research Indices (HFRI) for the period January 1990 to August 2016. The initial database contains 62 different indices which classify the hedge fund world according to characteristics such as geographical location and strategy. However, in order to minimize estimation errors issues, we exclude indices having missing returns over the considered time-period, leaving us with 24 hedge fund indices. To be included in the HFRI indices, individual hedge fund must report monthly returns, net of all fees (management, incentive and other expenses) and in US dollars for comparability issues. Funds having less than 50 million dollars of assets under management are excluded. Our sample covers a wide range of strategies whose investments styles and returns profiles vary greatly.

Table 3.1 reports summary statistics for the 24 selected hedge fund indices. Average monthly returns goes from 0.02% for the Short Bias strategy to 0.95% for the style Equity-Hedge, exhibiting a wide dispersion in expected hedge fund strategies' returns. Although Brown and Goetzmann (2003) show that hedge fund style is self-reported and subject to ambiguity, the fact that the different indices collected here present a strong cross-sectional variation in average returns would be valuable for testing the potential impact of financial intermediaries risk.

There is also a wide dispersion in standard-deviation of returns, going from 0.89 for Equity Market-Neutral to 5.09 for Short Bias. It is interesting to note here that the strategy having the lowest average returns also exhibits the highest volatility, indeed giving the lowest Sharpe Ratio of 0.0034. Traditionally, investment products are ranked according to their couple average return/standard deviation, and this measure indicates an abysmally low performance in this framework. However, Cochrane (2001) explains that, in equilibrium, such a low performing

TABLE 3.1 – **Basic statistics of hedge fund indices**

This table provides the mean summary statistics for HFRI hedge funds' indices for the period January 1990 - August 2016. This includes the mean (μ), standard deviation (σ), kurtosis, skewness, the Sharpe Ratio (SR).

	μ	σ	skewness	kurtosis	SR
Distressed	0.87	1.87	-0.9	7.05	0.46
Merger Arbitrage	0.63	1.12	-1.95	11.57	0.56
Equity-Market-Neutral	0.52	0.9	-0.19	4.72	0.58
Quantitative	0.93	3.53	-0.39	4.09	0.26
Short Bias	0.02	5.09	0.27	5.68	0
Emerging	0.95	3.93	-0.78	6.72	0.24
Emerging Asia	0.8	3.82	-0.11	3.89	0.21
Equity-Hedge	0.95	2.57	-0.21	4.84	0.37
Event-Driven	0.86	1.92	-1.18	6.65	0.45
FoF Conservative	0.48	1.1	-1.61	10.46	0.44
FoF Defensive	0.52	1.65	-0.4	7.21	0.32
FoF Strategic	0.57	1.64	0.26	3.96	0.35
Fund Weighted	0.72	2.39	-0.43	6.6	0.3
CHF	0.82	1.94	-0.61	5.49	0.42
GBP	0.71	1.96	-0.65	5.42	0.36
JPY	0.93	1.97	-0.62	5.39	0.47
FoF	0.63	1.93	-0.63	5.23	0.33
Macro	0.55	1.61	-0.63	6.96	0.34
Macro Systematic	0.87	2.09	0.63	4.21	0.41
Relative-Value-Convertibles	0.8	2.14	0.14	2.63	0.371
Relative-Value Fixed-Income	0.66	1.82	-3.02	32.79	0.37
Relative-Value Multi-Strategy	0.61	1.81	-1.27	11.15	0.34
Relative-Value	0.76	1.23	-1.96	15.74	0.62

TABLE 3.2 – **Basic statistics of individual hedge funds**

This table provides the mean summary statistics for each hedge fund strategy in the Lipper TASS database for the period January 1994 - February 2015. This includes the mean (μ), standard deviation (σ), kurtosis, skewness, the Sharpe Ratio (SR). The full sample contains 5598 funds (live funds and dead funds).

	numObs	μ	σ	skewness	kurtosis	SR
All	5,338	0.68	4.3	-0.19	7.23	0.25
Convertible-Arbitrage	237	0.42	2.48	-0.82	10.09	0.34
Dedicated-Short	48	0.2	5.81	24.4	5.25	0.15
Emerging-Markets	742	0.59	5.6	-0.42	7.72	0.17
Macro	419	0.57	4.22	0.21	6.13	0.16
Equity-Market-Neutral	379	0.53	2.69	-0.27	7.32	0.26
Event-Driven	237	0.42	2.48	-0.82	10.09	34.4
Fixed-Income	245	0.52	2.41	-1.23	14.98	0.66
Long-Short Equity	2,404	0.81	4.84	0.03	6.09	0.21
Multi-Strategies	595	0.57	3.26	-0.42	8.23	0.32
Options	32	0.87	3.17	-0.79	11.92	0.34

investment can exist rationally if its returns are uncorrelated or negatively correlated with investors' stochastic

discount factors. Any potential hedge funds' stochastic discount factor should be able to explain this strong difference in performance among hedge fund indices.

Another striking feature of hedge fund returns at the index level is that almost every strategy but six (Short Bias, Funds-of-Funds Strategic, Macro Systematic and Relative-Value) exhibit negative skewness and all of them with the exclusion of Relative-Value Convertibles present excess kurtosis. This means that hedge funds' return distribution present thick left-tails, giving rise to potential extreme values for negative returns. This implies that any analysis trying to explain hedge fund returns statistical feature should replicate this stylized fact.

Monthly individual hedge-fund return data are obtained from the Lipper TASS dataset for the period January 1994-February 2015. The sample includes both "live" and "dead" funds, i.e funds that no longer report to TASS, which reduces the impact of survivorship bias on returns. Our analysis includes only funds that report their returns at a monthly frequency and net of fees in US dollars, for comparability issues. We also exclude funds having less than 24 observations, in order to get meaningful estimates, Funds of Funds to avoid double-counting of hedge funds in our analysis, for example a hedge fund and an investment in this particular hedge fund by a fund-of-hedge funds. Table 3.2 reports summary statistics of the sample used for this study. The sample contains 5,338 individual hedge funds overall with an average monthly return of 0.67% and an average time-series standard-deviation of returns of 4.02. As for indices, overall individual hedge funds exhibit a negative skewness (-0.19) coupled with a high kurtosis (7.23), meaning that a common feature of hedge funds is their propensity to experience rare but large negative returns.

We also reports average summary statistics for individual hedge funds grouped following 10 investment styles in Table 3.2 : Convertible-Arbitrage, Dedicated Short Bias, Emerging Markets, Equity Market Neutral, Event-Driven, Fixed-Income Arbitrage, Global Macro, Long/Short Equity , Multi-Strategies and Options. We observe strong differences across strategies, with Dedicated Short having the lowest Sharpe Ratio of 0.15 and Fixed-Income Arbitrage the highest with 0.66. Every investment style exhibits a high kurtosis and almost all, Dedicated-Short, Global Macro and Long/Short Equity excepted, negative skewness, confirming the pervasiveness of the existence of rare extreme negative returns across the hedge fund industry. This feature is important while trying to explain the risk-return profile of hedge funds : our financial intermediaries' risk factor should at least partially capture this stylized fact in order to correctly price the cross-section of hedge funds.

The financial intermediaries' risk measure used here is based on the aggregate equity capital ratio of primary dealers' factor constructed in He et al. (2017), which is extracted from CRSP/Compustat and Datastream data. The financial intermediary sector is defined as the set of primary dealers, which are the trading counterparties of the Federal Reserve Bank of New-York in its implementation of monetary policy. The primary dealer sector is a good candidate to approximate the representative financial intermediary for hedge funds because these institutions are large and are active intermediaries in virtually every asset class. They represent essentially half the broker-dealer sector and are the ones able to be intermediaries for complex hedge fund strategies involving over-the-counter and derivatives' assets, repo and other prime brokerage services such as securities lending. The historical list of primary dealers is available on the NY Fed's website and is hand-matched to data on their publicly-traded holding companies from CRSP/Compustat for US dealers and Datastream for foreign dealers. We use the term "financial intermediaries" to refer to these primary dealers throughout the paper.

Following He et al (2017), we define the intermediary's equity capital ratio as the equity fraction of total assets in the aggregate balance sheet of the intermediary sector :

$$\eta_t = \frac{Equity_t}{Asset_t} \quad (3.1)$$

where $Equity_t$ is the market value of the primary dealer's equity in month t and $Asset_t$ is the total value of assets in month t .

Each month t , the aggregate primary dealer capital ratio is built as :

$$\eta_t = \frac{\sum_i MarketEquity_{i,t}}{\sum_i (MarketEquity_{i,t} + BookDebt_{i,t})} \quad (3.2)$$

where i is for a NY Fed primary dealer and t is for the month. Book value of debt is equal to total assets minus common equity, using the most recent data available for each firm at the end of the month. The market value of equity is share price times shares outstanding on the last trading day of the month. To compute the equity capital ratio for the intermediary sector, the balance sheet is first aggregated and then the equity capital ratio is calculated, instead of computing the capital ratio first and then aggregating over primary dealers. This gives us a value-weighted (and not an equal-weighted) aggregate equity capital ratio of primary dealers, which makes best economic sense : assigning greater weights to larger intermediaries reflect their importance in the financial markets.

We model a shock to the financial intermediaries' aggregate equity capital ratio in levels u_t as an innovation in the following auto-regressive model :

$$\eta_t = \rho_0 + \rho\eta_{t-1} + u_t \quad (3.3)$$

This innovation is then converted as a growth rate η_t^Δ by dividing by the lagged capital ratio :

$$\eta_t^\Delta = \frac{u_t}{\eta_{t-1}} \quad (3.4)$$

This is our key risk factor in the following cross-sectional asset pricing tests¹. This factor is estimated at the quarterly and monthly frequencies in He et al. (2017) for the period 1970-2012 and is showed to price the cross-section of assets in many financial markets, including equities, US government and corporate bonds, foreign sovereign bonds, options, credit default swaps, commodities and foreign exchange, so this is a good candidate for a pricing factor of hedge funds, which are by definition sophisticated investment vehicles trading across a large spectrum of assets.

Fig. 3.1 plots the financial intermediaries factor over the sample period January 1990-August 2016. Intermediary capital falls during recessions, with sudden drops and rebounds during the 2008 financial crisis and the 1998 LTCM collapse, representing shocks that affects the whole hedge fund industry. Consistent with the notion of dry-out in financial intermediaries' capital, the financial intermediaries' factor exhibits spikes.

In addition to the financial intermediaries' risk factor, this paper uses various factors shown by Fung and Hsieh (2004) to be important for the hedge fund performance measurement. These are the three trend-following

1. The historical time series data for the primary dealers' aggregate equity capital ratio factor are available on Asaf Manela's website : <http://apps.olin.wustl.edu/faculty/manela/data.html>

FIGURE 3.1 – Primary dealers’ aggregate equity capital ratio returns

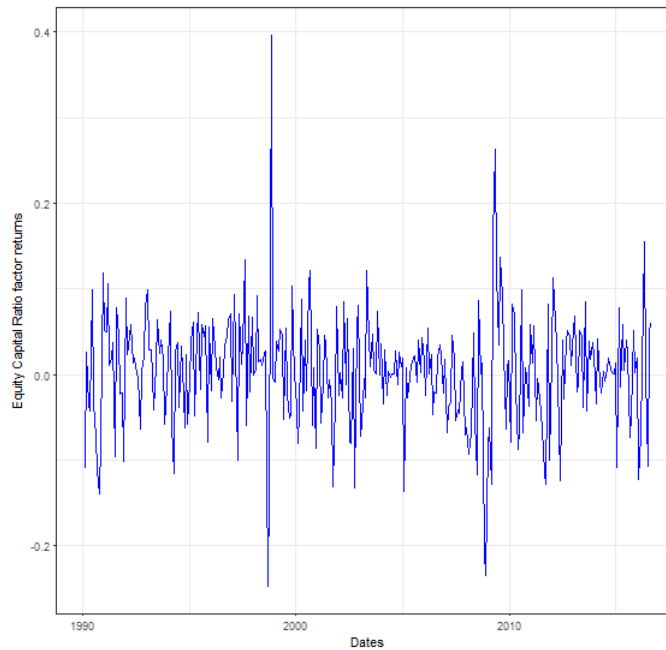


TABLE 3.3 – Factors’ correlations

This table present the correlation coefficients of the Fung and Hsieh hedge fund factors and the financial intermediaries’ risk factor, as measured by shocks to primary dealers’ aggregate equity capital ratio. PTFSBD, PTFSFX and PTFSKOM are trend-following factors for bonds, foreign-exchanges and commodities respectively. SP500 is the return on the S&P 500 index. Size is the difference of returns between the Russell 2000 and the S&P 500. Bond is the change in the 10 years’ treasury yield and credit-spread is the change in the Moody’s Baa yield minus the 10 years’ treasury yield. Finally, FI is the financial intermediaries’ risk factor η_t^Δ .

	PTFSBD	PTFSFX	PTFSKOM	SP500	Size	Bond	Credit spread	FI
PTFSBD	1	0.29	0.19	-0.24	0.02	-0.06	0.2	-0.33
PTFSFX		1	0.35	-0.2	-0.13	-0.09	0.14	-0.15
PTFSKOM			1	-0.17	-0.07	-0.07	0.12	-0.19
SP500				1	0.12	-0.04	-0.07	0.02
Size					1	0.07	-0.04	0.13
Bond						1	-0.55	0.11
Credit-spread							1	-0.15
FI								1

factors of Fung and Hsieh (2001), namely PTFSBD for bonds, PTFSX for currencies and PTFSKOM for commodities, two equity risk factors, the return of the S&P 500 and the difference of returns between the Russell 2000 and the S&P 500, and two bond-oriented factors, the change in the 10 years treasury yield and the change in the Moody’s Baa yield minus the 10 years treasury yield.² Put together, these seven factors form the Fung and Hsieh seven factor model. Table 3.3 presents the pairwise time-series correlation of these factors and the financial

2. The trend-following factors are freely available at <http://faculty.fuqua.duke.edu/dah7/DataLibrary/TF-FAC.xls>

intermediaries factor. The factor most correlated with financial intermediaries' risk is the bond trend-following factor, with a correlation of -0.33. This negative correlation suggests that deteriorations in financial intermediaries' balance sheet capacities is contemporaneously correlated with bond trend-following opportunities, which is consistent with limits-to-arbitrage views of momentum on financial assets, as in Asness et al. (2013). Interestingly, the correlation with the S&P 500 is extremely low, at 0.02. For example, the financial intermediaries risk factor reaches its lowest value of -24.67% during August 1998 and its second lowest value of -23.42% in November 2008 while the S&P 500 gained 6.24% and 0.78% respectively. Said differently, nothing in market returns would indicate they experience severe financial intermediaries' capital shocks during the sample period.

TABLE 3.4 – Basic statistics of the risk factors

This table provides summary statistics for each hedge fund risk factor for the period January 1994 - February 2015. This includes the mean in % (μ), standard deviation in % (σ), kurtosis, skewness and the Sharpe Ratio. FI stands for the financial intermediaries' risk factor η_t^Δ .

	μ	σ	skewness	kurtosis	SR
PTFSBD	-1.36	15.35	1.34	5.38	-0.09
PTFSFX	-0.62	19.59	1.37	5.55	-0.03
PTFSCOM	-0.27	14.36	1.09	4.63	-0.02
S&P 500	0.66	4.28	-0.69	4.18	0.15
Size	0.08	3.28	0.03	7.89	0.24
Bond	-0.12	7.3	-0.027	5.86	-0.02
Credit Spread	0.33	20.97	1.19	12.81	0.02
FI	0.34	6.83	0.39	8.18	0.05

Table 3.4 presents the summary statistics for our risk factors over the sample period January 1994-February 2015. The financial intermediaries risk factor exhibits a positive mean return of 34.26 bps with a volatility of 6.834. It also presents a strong kurtosis of 8.1766 which indicates its propensity to match the thick-tailed return distributions found in the hedge fund industry. However, its skewness is positive, which stands in contrast with most hedge fund strategies. It is the second most leptokurtic factor after the credit-spread. This means that financial intermediaries' risk will not be able to explain the negative skewness found in many hedge fund strategies' returns, but in conjunction with other risk factors, it could explain the distribution of hedge funds' returns.

3.3 Hedge fund returns and financial intermediaries risk

In this section, we study systematically the empirical relation between the cross-section of hedge fund strategy index returns and changes in the equity capital ratio of primary dealers. Investment strategies vary greatly across the hedge fund industry. The degree to which hedge fund returns are exposed to the risk induced by changes in the equity capital ratio of primary dealers might depend on the characteristics of each hedge fund strategy. Hedge fund strategies that are more dependent on prime brokerage short term funding or dealing with a great amount of over-the-counter and derivatives securities should be more exposed to the risk induced by changes in the aggregate balance-sheet of major financial counterparties. Such cross-sectional heterogeneities in exposures to changes in aggregate primary dealers' equity capital ratio may be responsible for systematic differences in hedge fund expected returns, indicating that changes in financial intermediaries' risk is priced in the cross-section of hedge funds. Furthermore, and more importantly, if financial intermediaries' risk is priced, it should predict

Intercept	0.56	0.5016
t_{NW}	(21.641)***	(8.9068)***
t_{GMM}	(20.35)***	(10.092)***
λ_{η}	1.317	1.154
t_{NW}	(19.745)***	(2.5006)**
t_{GMM}	(18.9)***	(2.7327)**
λ_{PTFSBD}		0.75
t_{NW}		(0.1035)
t_{GMM}		(0.1181)
λ_{PTFSFX}		-0.82
t_{NW}		(-0.1063)
t_{GMM}		(-0.0966)
$\lambda_{PTFSCOM}$		-0.79
t_{NW}		(-0.0925)
t_{GMM}		(-0.0885)
λ_{SP500}		0.64
t_{NW}		(0.2606)
t_{GMM}		(0.2684)
λ_{Size}		-0.38
t_{NW}		(-0.3898)
t_{GMM}		(-0.4676)
λ_{Bond}		74.9
t_{NW}		(1.0108)
t_{GMM}		(1.3636)
λ_{Credit}		0.49
t_{NW}		(0.8944)
t_{GMM}		(1.1528)
R^2	70.7	57.55
MAPE	0.0877	1.809
nb indices	24	
nb months	320	

TABLE 3.5 – Fama-McBeth regressions for hedge fund indices

Risk prices estimates for the financial intermediaries' risk and Fung and Hsieh seven factors. The financial intermediaries' risk is defined as the ratio of total market equity to total market assets (book debt and market equity) of primary dealer holding companies. Risk prices are the mean slopes of monthly cross-sectional regressions of hedge fund indices' returns on exposures to each factor, estimated with equations (3.6) et (3.8). These exposures are estimated in a first-stage time-series regression as in equations (3.5) et (3.7). The monthly sample is 01/1990-08/2016. R^2 is the adjusted coefficient of determination in percentage. Generalized-methods-of-moments t_{GMM} and Newey-West t_{NW} t-statistics in parantheses adjust for cross-asset correlation in the residuals and for estimation error of the time-series betas. The mean absolute pricing error $MAPE = \frac{1}{24} \sum_{i=1}^{24} |\hat{y}_i - y_i|$ measures the average magnitude of the pricing errors in percentage.

future hedge fund returns.

We first characterize the relation between financial intermediaries' risk and hedge fund returns at the index level. Then, we link cross-sectional differences in exposures to changes in aggregate primary dealers' equity capital ratio to differences in expected returns.

3.3.1 Hedge fund index returns and financial intermediaries risk

Table 3.5 presents results for Fama and McBeth (1973) two-stage regressions of hedge fund index average returns on financial intermediaries' risk exposures. For each hedge fund index, we estimate exposure from time-series regressions of indices returns R_t^i on our intermediary capital risk factor η_t^Δ :

$$R_t^i = \alpha^i + \beta^i \eta_t^\Delta + \epsilon_t^i \quad (3.5)$$

where R_t^i is the return of fund i in month t , α^i is the intercept of the regression, β^i measures the exposure to the risk factor, η_t^Δ is the realization in month t of financial intermediaries' risk and ϵ_t^i is the residual of fund i in month t . We then run a cross-sectional regression of average indice returns on the estimated regression coefficients for the financial intermediaries' risk factor in order to estimate the risk price λ_η :

$$\hat{E}[R_t^i] = \gamma + \lambda_\eta \hat{\beta}_\eta^i + \nu \quad (3.6)$$

where $\hat{E}[R_t^i]$ is the average return of fund i , γ is the intercept, λ_η is the risk slope coefficient, $\hat{\beta}_\eta^i$ is fund i 's estimated exposure to financial intermediaries' risk and ν is the residual. We also repeat the two-stage procedure with the Fung and Hsieh (2004) seven factors in addition to the financial intermediaries' risk factor :

$$R_t^i = \alpha^i + \beta^i \eta_t^\Delta + \sum_{k=1}^7 \beta_{FH,k}^i R_t^k + \epsilon_t^i \quad (3.7)$$

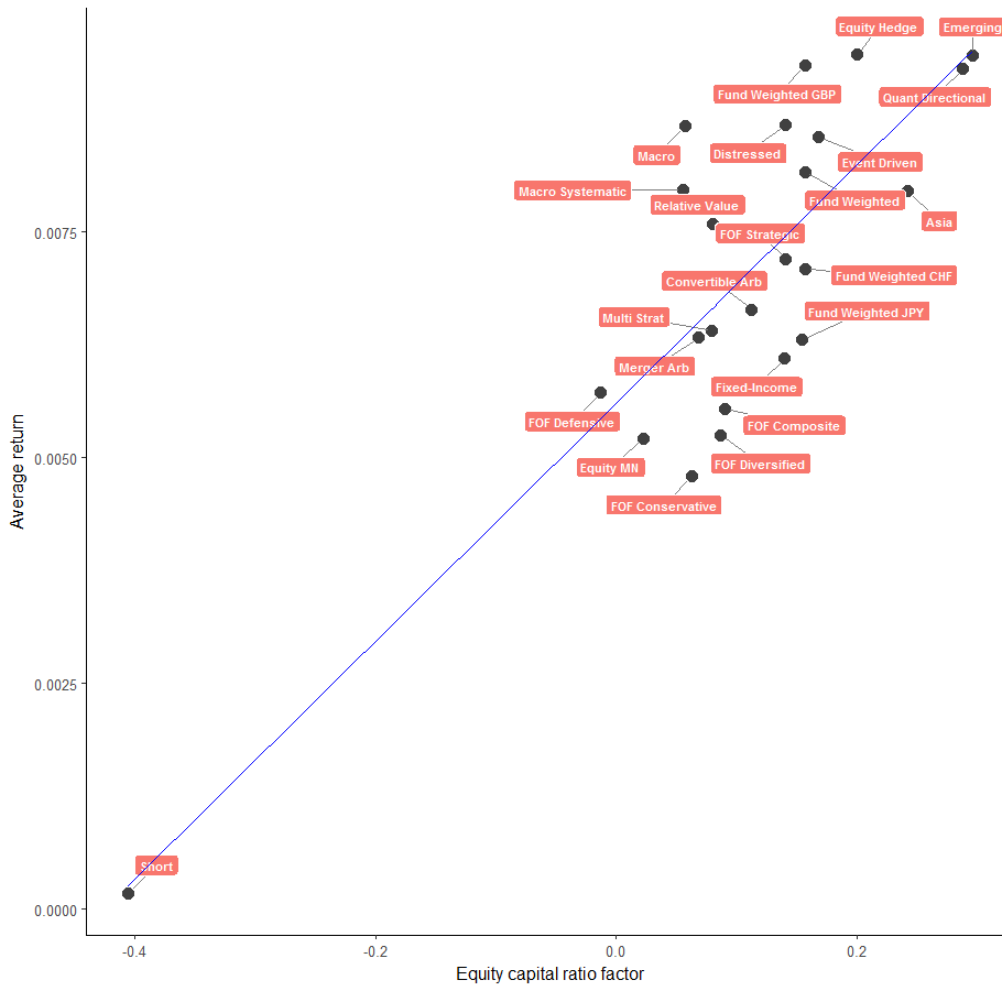
where $\sum_{k=1}^7 \beta_{FH,k}^i R_t^k$ is the part of fund's i return explained by Fung and Hsieh risk factors in month t .

$$\hat{E}[R_t^i] = \gamma + \lambda_\eta \hat{\beta}_\eta^i + \sum_{k=1}^7 \lambda_{\beta,k} \hat{\beta}_{FH,k}^i + \nu \quad (3.8)$$

Results show that financial intermediaries' risk is priced in the cross-section of hedge fund indices. The univariate Fama and McBeth two-stage regression exhibits an intercept coefficient of 0.56% monthly. This intercept is relatively low, showing that a large part of hedge fund index mean returns is explained by factor, but it is highly statistically significant at the 1% level both with Hansen's (1982) generalized method of moments and Newey and West (1987) standard errors. The risk price for changes in aggregate primary dealers' equity capital ratio is 1.317% and is highly statistically significant with t-statistics of 19.74 with Newey-West standard errors and 18.9 with the GMM procedure. This positive slope for financial intermediaries' risk exposures indicates that a 1% increase in exposure of a hedge fund strategy to changes in the equity capital ratio of primary dealers increases the expected return of this strategy of 15.804% annually. The adjusted R-squared is 70.7%, indicating that the large majority of the dispersion in hedge fund strategies expected return can be explained by a single factor,

FIGURE 3.2 – Fama McBeth regression on hedge fund indices

We plot the results of the cross-sectional regression of the average hedge fund indices' returns on financial intermediaries' risk beta. The sample goes from 01/1990 to 08/2016.



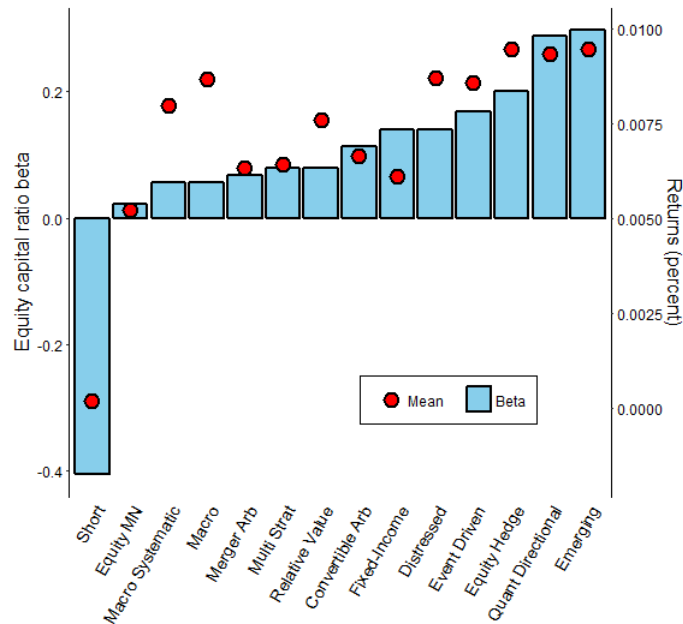
the exposure to financial intermediaries risk. There is a low mean absolute pricing error of 0.0877%, showing the precision of our results.

The multivariate Fama and McBeth regression in Table 3.5 gives a statistically significant intercept of 0.5016% per month, which is a bit lower than for the univariate cross-sectional regression. The slope for the financial intermediaries risk exposure is positive with a coefficient of 1.15% and statistically significant at the 5% level. All the other risk factors are statistically non-significant, indicating an absence of pricing ability in the standard Fung and Hsieh seven factors model for hedge fund strategies. The inclusion of the additional set of factors decrease the adjusted R-square to 57.55%, which shows that adding these risk factors decrease the ability to explain variations in expected hedge fund strategies' returns. The mean absolute pricing error of 1.809% is far

higher than for the univariate model, showing that the addition of the seven factors has actually decreased the precision of our pricing model.

Figure 3.2 plots the relation of hedge fund index average returns on financial intermediaries' beta. We see that Dedicated-Short, the least exposed strategy to financial intermediaries risk, has the lowest mean return while the most exposed strategy, Emerging Markets, has the highest return. This figure clearly depicts the existence of a risk-return trade off among hedge fund strategies, highlighting the importance of limits-to-arbitrage and intermediaries in hedge fund returns. We see in Figure 3 that the strategy Dedicated Short Bias has both the lowest return and financial intermediaries' risk exposure while the three best performing indices (Equity Hedge, Quant Directional and Emerging Markets) have the three highest financial intermediaries' risk loadings.

FIGURE 3.3 – Hedge fund indices : financial intermediaries' risk beta and mean return
 Mean hedge fund indices return and financial intermediaries' risk beta. The financial intermediaries' risk beta is calculated using a regression of monthly indices returns on the unexpected shocks on the equity capital ratio of primary dealers factor only. The analysis goes from 01/1990 to 08/2016.



In summary, our results show that financial intermediaries' risk prices the cross-section of hedge fund strategies returns. Degrees of exposures to changes in the aggregate equity capital ratio of primary dealers explain observed dispersion in the strategies' mean return. The Fung and Hsieh seven factors do not explain variations in expected returns, emphasizing the importance of financial intermediaries' risk in hedge fund returns. This finding challenges the conventional wisdom that hedge fund strategies' returns are replicable passively as in Hasandhozic and Lo (2007). The usual argument says that changes in hedge fund strategy returns are attributable to changes in exposures to tradable risk factors such as the S&P 500 or the size factor, implying that a large portion of these returns can be replicated using passive investment strategies in these factors. However, our results show that the majority of the dispersion in strategies' expected returns comes from differences in exposure to financial

intermediaries risk, which is a non-investable risk factor. A reason often invoked in the difficulty to replicate hedge fund strategies is that these strategies shift exposures to the risk factors as in Cao et al. (2013). We show that this explanation is incomplete because the main source of differences in expected returns is difference in exposure to financial intermediaries' risk. This result is in line with limits-to-arbitrage arguments as in Shleifer and Vishny (1997) : hedge fund strategies exhibiting higher expected return are more exposed to risk because they need to finance their positions from prime brokers and involve dealers in their trading of over-the-counter and derivatives securities. This induces frequent small positive returns and occasional large drawdowns. These large drawdowns are a feature found in the dry-outs of aggregate financial intermediaries' capital.

3.3.2 The cross-section of individual financial intermediaries risk exposures

We showed that differences in exposure to financial intermediaries' risk explain differences in hedge fund strategies expected return, we now want to investigate if the relation holds for individual hedge funds. More particularly, does cross-sectional difference in financial intermediaries risk exposure within a hedge fund strategy explains the dispersion of expected return? To answer this question, we follow a simple approach and sort individual hedge fund returns into decile portfolios, based on their financial intermediaries risk exposures.

Table 3.6 reports the results when we sort funds into decile portfolios. The resulting financial intermediaries risk beta ranges from an average of -0.1763 for decile 1 to an average of 0.6634 for decile 10.

We find that, for the whole sample of individual hedge funds, as the average financial intermediaries' risk beta increases from the bottom to the top decile, the expected portfolio return is almost monotonically increasing. This indicates a global relationship between individual hedge fund returns and financial intermediaries' risk exposure. The difference in average return is economically meaningful : while the bottom decile portfolio has an average expected return of 0.6887% per month, the top decile portfolio has a monthly return of 0.8202%, which means an average difference in expected return of 13.15 bps per month, or 1.578% yearly. This correlation between financial intermediaries' risk beta and return might show that this risk exposure prices the cross-section of individual hedge funds.

However, this difference in average expected return varies greatly from a strategy to another. While the strategies Convertible-Arbitrage, Dedicated-Short, Emerging Markets, Long-Short Equity and Options all have a positive difference in average expected return between their bottom and top deciles portfolios, the strategies Equity Market-Neutral, Event-Driven, Fixed-Income, Macro and Multi-Strategies exhibit a negative average difference in expected returns. This means that, while at the level of the whole sample of individual hedge funds, there is a positive relation between expected return and financial intermediaries' risk exposure, for half of the strategies this relation does not seem to hold within-style. The first explanation that might fit this fact is that hedge fund strategies exhibit structural differences, explaining that there are differences in risk premia for financial intermediaries' risk exposures. However, it is highly unlikely that hedge fund investors in one strategy ask for a different risk compensation compared with investors in another strategy : He et al (2017) show that financial intermediaries risk commands a virtually similar risk premium from a large spectrum of assets. Another potential explanation is that there is not enough difference in exposures at the intra-style level to correctly capture the pricing effect of financial intermediaries' risk, showing some negative relationships between portfolio exposure and average expected returns for some strategies.

	Low	2	3	4	5	6	7	8	9	High	High-Low	
All	beta returns	-0.1763	-0.0164	0.0208	0.0572	0.0951	0.1379	0.1901	0.2584	0.37	0.6634	0.8397
Convertible-Arbitrage	beta returns	0.6887	0.5357	0.6018	0.6816	0.6366	0.636	0.7425	0.8101	0.8379	0.8202	0.1315
Dedicated-Short	beta returns	-0.1855	-0.0324	-0.0064	0.0144	0.0325	0.0685	0.1026	0.1358	0.2054	0.3569	0.6424
Emerging-Markets	beta returns	-0.1975	0.0441	0.6519	0.6334	0.5819	0.4861	0.7512	0.3264	0.6552	0.4324	0.6299
Equity Market-Neutral	beta returns	-0.826	-0.6104	-0.529	-0.4847	-0.4533	-0.3171	-0.2549	-0.1783	-0.0319	0.1442	0.9702
Event-Driven	beta returns	-0.3415	1.076	0.3794	-0.3931	0.2609	-0.259	-0.0729	0.4108	0.4852	0.6248	0.9663
Fixed-Income	beta returns	-0.634	0.569	0.1098	0.1499	0.1973	0.2519	0.325	0.4235	0.5609	0.7918	0.85552
Long-Short Equity	beta returns	0.3807	0.5099	0.2765	0.3916	0.6966	0.8098	0.7908	0.8067	0.7739	0.6834	0.3027
Macro	beta returns	-0.1593	-0.0737	-0.0331	-0.0148	0.0044	0.0219	0.0429	0.0782	0.1222	0.3496	0.5089
Multi-Strategies	beta returns	0.5347	0.4814	0.3794	0.3511	0.6102	0.7122	0.5034	0.6759	0.7255	0.3115	-0.2232
Options	beta returns	-0.0982	0.0081	0.035	0.0613	0.0832	0.1141	0.1586	0.1992	0.2587	0.4927	0.5909
	beta returns	1.2151	0.5934	0.6799	0.7067	0.8239	0.7089	0.8962	0.7409	0.8558	1.1269	-0.0882
	beta returns	-0.1441	-0.0352	-0.011	0.002	0.0162	0.0385	0.0673	0.0983	0.1489	0.3114	0.4555
	beta returns	0.3334	0.6035	0.7528	0.6246	0.5384	0.6111	0.8565	0.2942	0.5695	0.1557	-0.1777
	beta returns	-0.1307	0.0067	0.0559	0.1008	0.1441	0.1919	0.2485	0.3236	0.4359	0.7127	0.8434
	beta returns	0.8606	0.5787	0.7409	0.7313	0.793	0.8689	0.938	0.8794	0.9288	0.0682	-0.7924
	beta returns	-0.3216	-0.0916	-0.0334	-0.0052	0.0178	0.0491	0.092	0.1419	0.2518	0.5328	0.8544
	beta returns	0.903	0.6354	0.4986	0.3677	0.5082	0.6532	0.5821	0.5027	0.6122	0.7008	-0.2022
	beta returns	-0.1392	-0.0096	0.0172	0.0445	0.068	0.0987	0.1365	0.1844	0.2586	0.4742	0.6134
	beta returns	0.7589	0.5685	0.6092	0.5663	0.6278	0.4254	0.4828	0.5148	0.6025	0.06064	-0.1525
	beta returns	-0.2104	-0.1504	-0.0861	-0.0588	-0.0104	0.0373	0.0639	0.0993	0.1569	0.2146	0.425
	beta returns	0.8508	0.4732	1.2547	0.5667	0.476	1.0511	0.9659	0.778	1.2969	1.1014	0.2506

TABLE 3.6 – Decile portfolios of hedge funds sorted by financial intermediaries' risk

This table reports properties of equal-weighted decile portfolios of individual hedge funds. Portfolios are formed in ranking each fund according to its financial intermediaries' risk beta, computed using the following univariate regression $R_t^i = \alpha^i + \beta^i \eta_t^\Delta + \epsilon_t^i$ where R_t^i is the return of fund i in month t , α^i is the intercept of the regression, β^i measures the exposure to the risk factor, η_t^Δ is the realization in month t of financial intermediaries' risk and ϵ_t^i is the residual of fund i in month t . The sample period is January 1994 - February 2015. For each decile portfolio, we report the average financial intermediaries' risk exposure and return.

Another way to look at the relation between individual funds' financial intermediaries' risk exposures is through a parametric regression approach. More specifically, we want to know if financial intermediaries risk is priced in the cross-section of individual hedge fund returns. Indeed, if a risk factor is priced, then the excess return generated by exposure to that factor is an equilibrium compensation for a non-diversifiable source of risk that the individual hedge fund is taking. If the risk factor is not priced, it means it can be considered as a benchmark in a performance attribution model, without implying an exposure to a systematic source of risk. The answer to this question of the price of risk is important from the point of view of efficient allocation of capital in the hedge fund industry. Intuitively, financial intermediaries' risk can be thought as a systemic risk in the sense it reflects the ability of hedge funds to fund their positions and find counterparties to execute their trades. It also drives prices of other financial assets, as showed in He et al. (2017), and can be interpreted as a stochastic discount factor for the financial sector as in He and Krishnamurthy (2013).

As in the previous section on hedge fund index returns, we can rigorously test for the presence of a price for financial intermediaries risk in individual hedge fund returns using a Fama and McBeth (1973) approach. We use a sequential approach, estimating in a first-stage time-series regressions individual hedge fund exposures to financial intermediaries risk and then estimating the cross-sectionnal price of risk for mean hedge fund returns. Table 3.7 summaries Fama-McBeth λ_γ for individual hedge funds.

We find that, for the whole sample of individual hedge funds, there is a positive price of risk of 0.39% per month, statistically significant at the 5% risk level for both Newey-West standard-errors with a t-statistic of 2.342 and for a general method-of-moments (GMM) procedure, with a t-statistic of 2.3354. This implies that there is a global price of financial intermediaries risk in individual hedge fund returns of 4.68% annually and that we can truly consider this risk factor as a non-diversifiable systemic source of risk for hedge funds. When we look at the results for strategies' sub-sample of individual hedge funds, only the convertible arbitrage strategy yields a positive and statistically significant at the 5% risk level price of risk with an estimate of 1.05% per month. Other subsamples do not give statistically significant risk estimates. Two strategies, Event-Driven and Multi-Strategy, give negative adjusted r-squared, meaning that the explanatory power of the financial intermediaries' risk factor is virtually null, because it is inferior to its coefficient of penalization. It seems that strategies subsamples do not exhibit enough variation in financial intermediaries' risk exposures to get meaningful relationships.

To summarize our results, we can say that the financial intermediaries risk factor prices the cross-section of hedge fund returns. Indeed, there is a strong pricing power for the factor's exposures at the index level and for the whole cross-section of individual hedge funds. However, only the Convertible-arbitrage strategy exhibits statistically significant positive pricing and one strategy, Macro, exhibits statistically significant negative pricing, showing a lack of intra-style financial intermediaries' risk pricing. This fact can be explained by a lack of differences in financial intermediaries' risk exposures at the intra-style level, while there is a strong cross-sectional difference inter-style.

	all	convertible-arbitrage	dedicated short	emerging	macro	equity MN	event-driven	fixed-income	LS equity	multi-strat	options
Intercept	0.64	0.37	0.37	0.44	0.62	0.56	0.84	0.57	0.71	0.58	0.85
t_{NW}	(23.938)***	(6.6347)	(4.2328)	(6.7228)***	(11.9234)***	(15.0679)***	(8.6421)***	(12.8538)***	(11.1422)	(10.411)***	(10.7344)***
t_{GMM}	(23.78)***	(5.3062)	(4.8097)	(6.6467)***	(11.997)***	(15.301)***	(8.7231)***	(12.876)***	(10.985)	(9.8887)***	(12.639)***
λ_{ij}	0.39	1.05	0.54	0.61	-0.33	-0.99	0.02	-0.74	0.5	0	1.12
t_{NW}	(2.342)**	(3.414)**	(1.4793)	(-1.1417)	(2.9499)**	(-1.9084)*	(0.0413)	(-1.4601)	(1.5408)	(0.0156)	(1.6406)
t_{GMM}	(2.3354)**	(2.8894)**	(1.5852)	(-1.1469)	(2.9343)**	(-1.6252)	(0.0422)	(-1.4183)	(1.5369)	(0.0159)	(1.8178)*
R^2	1.153	8.99	2.998	2.339	0.29	6.444	-0.001	2.381	23.46	-0.001	3.499
nb funds	5338	237	48	742	379	237	245	419	595	32	2404

TABLE 3.7 – Fama-McBeth for individual hedge funds

Risk price estimates for the financial intermediaries' risk factor, defined as the ratio of total market equity to total market assets (book debt and market equity) of primary dealer holding companies. Risk prices are the mean slopes of monthly cross-sectional regressions of hedge fund indices' returns on exposures to the financial intermediaries' risk factor as in Eq (3.6). These exposures are estimated in a first-stage time-series regression as in Eq (3.5). The monthly sample is 01/1994-02/2015. R^2 is the adjusted coefficient of determination in percentage. Generalized methods-of-moments t_{GMM} and Newey-West t_{NW} t-statistics in parentheses adjust for cross-asset correlation in the residuals and for estimation error of the time-series betas.

3.4 Does financial intermediaries risk exposures predict hedge fund returns ?

Most studies focus on the risk-return characteristics of hedge funds by estimating risk-adjusted returns using multifactor models or by exploring the impact of risk factors on returns. However, the most important question in assessing hedge fund performance is to know if exposure to a particular risk factor will predict future returns. In this section, we investigate the performance of financial intermediaries risk factor beta in predicting the cross-sectional variation in individual hedge fund returns though both parametric and non-parametric tests.

3.4.1 Methodology

We rely in this section on Bali et al. (2011), who provide a methodology to assess if a risk factor's betas predict the cross-sectional variation in monthly individual hedge fund returns. This framework is based on both parametric and non-parametric tests.

First and foremost, the parametric test procedure implies cross-sectional regressions to assess the predictive power of factors betas over one-month ahead hedge fund returns. We first derive univariate monthly time-series estimates of financial intermediaries' risk betas calculated over a rolling-window and second we use Fama and McBeth regressions of one-month ahead hedge fund returns on the betas. Hence, we first regress over the period $[t - 23, t]$ to get the coefficients at date t for the whole cross-section of individual hedge funds and then we regress the cross-section of returns at date $t + 1$ over these coefficients obtained for date t . We repeat this procedure in rolling the window forward and then compute the average and t-statistic for the slope second-stage slope coefficient. If the average of the slope of these Fama-McBeth regressions indicates statistical significance, we can conclude that financial intermediaries risk betas predict future hedge fund returns.

In the first stage, univariate monthly financial intermediaries risk factor betas are estimated for each fund from univariate time series regressions of individual fund returns on the factor over a 24-month rolling-window period. Two-years provide sufficient observations to estimate the financial intermediaries' factor exposure, while allowing for time-variation and without losing too many years in the beginning of the sample. In the second stage, the cross-section of one-month ahead individual fund returns are regressed on the fund's univariate financial intermediaries risk betas each month for the period January 1996-February 2015. Precisely, we start with the monthly returns from January 1994 to December 1995 to estimate financial intermediaries' risk betas for each fund in the sample and then we use rolling regressions with a fixed estimation window of 24 months to get the time-series of first-stage betas :

$$R_t^i = \alpha_t^i + \beta_t^i \cdot \eta_t^\Delta + \epsilon_t^i \quad (3.9)$$

where R_t^i is the excess return on fund i in month t and η_t^Δ is the financial intermediaries' risk factor in month t . α_t^i and β_t^i are the intercept of the regression and the financial intermediaries risk beta for fund i in month t . This is the same equation as in Eq. (3.5), but for a period of 24 months and it will be estimated in a rolling-window fashion.

Then, in the second stage, starting from January 1996, we use Fama and McBeth cross-sectional regressions of one-month ahead individual hedge fund returns on the financial intermediaries' risk betas :

$$R_{t+1}^i = \omega_t + \lambda_t \cdot \tilde{\beta}_t^i + \epsilon_{t+1}^i \quad (3.10)$$

where R_{t+1}^i is the excess return on fund i in month $t + 1$ and $\tilde{\beta}_t^i$ is the financial intermediaries' risk beta for fund i in month t estimated using Eq. (3.9). ω_t and λ_t are, respectively, the monthly intercepts and slope coefficients from the Fama and McBeth regressions. We roll the estimation procedure over the sample, keeping a fixed estimation window of 24 months.

Second, the non-parametric test procedure involves a portfolio analysis. Quintile portfolios will be formed every month by sorting individual hedge funds according to their factor betas over a fixed 24-months estimation window and rolling one-month ahead returns are observed in each quintile to investigate if there is a significant difference in the future return of the high beta quintile with respect to the low beta quintile. We sort hedge fund returns at date $t + 1$ over their coefficients at date t , computed for the period $[t - 23, t]$. We roll the procedure over the period and compute the average and t-statistic of the quintile portfolios.

3.4.2 Findings

Table 3.8 panel (a) presents the time-series average intercept and slope coefficients from Eq. 10 over the sample period January 1996 to February 2015, using as independent variable the univariate financial intermediaries risk betas estimated with a 24-month rolling-window period. The corresponding t-statistics are reported in parentheses. As a robustness check, we also estimated the factor betas using a fixed 36-month rolling-window period³. We obtain a positive and statistically significant at the 1% risk level relation between the financial intermediaries' risk betas and future returns of individual hedge funds. Specifically, for the whole sample of individual hedge funds, we find the average slope coefficients to be 0.89% with a t-statistic of 2.325, meaning that financial intermediaries' risk factor exposures successfully predict one-month ahead individual hedge fund returns. This is an important results because Bali et al. (2011) showed that many traditional hedge fund factors can be correlated with in-sample performance but fail to predict future hedge fund returns. There is a strong implication of predictive power because it implies that the considered factor is really a non-diversifiable systemic risk factor and not only a benchmark factor. Investor whose portfolio has a 1% bigger loading on financial intermediaries' risk will get compensated by a future higher expected return of 10.68% annually, which is economically significant.

To provide some insight if the pricing of financial intermediaries' risk is an inter or intra style effect, Table 8 also reports the regression coefficients of the cross-sectional regressions ran for the strategies sub-sample of individual hedge funds. The results show that there is a positive and statistically significant, at the 10% risk level, risk slope for financial intermediaries risk for Emerging Markets and Long-Short Equity, with risk slopes of 0.85% for a t-statistic of 1.695 and 0.78% for a t-statistic of 1.9058 respectively. Risk-slopes are insignificant for other investment styles. No style exhibits a negative risk slope for financial intermediaries' risk. To summarize, the results in Table 8 give a mixed view. For investment styles such as Convertible-Arbitrage and Dedicated-Short the effect of financial intermediaries' risk seems to be inter-style, with no significant risk slope for future returns observed intra-style, while others such as Emerging-Markets exhibit both inter and intra-style financial intermediaries' risk pricing. This difference might be induced by lower intra-style variability in exposures to financial intermediaries' risk for some strategies such as Dedicated-Short.

3. We do not report results from the 36-month rolling-window estimates to save space.

TABLE 3.8 – One-month ahead individual hedge funds’ returns predictability with financial intermediaries’ risk betas

	all	convertible-arbitrage	dedicated short	emerging	macro	equity MN	event-driven	fixed-income	LS equity	multi-strat
Intercept	0.58 (6.4883)***	0.45 (3.4144)***	0.43 (1.3733)	0.52 (2.8793)***	0.59 (6.0915)***	0.55 (6.9657)***	0.45 (3.4144)***	0.47 (6.7893)***	0.67 (5.208)***	0.64 (9.0073)***
λ_t	0.89 (2.325)***	0.4 (0.5934)	0.39 (0.4448)	0.85 (1.695)*	0.41 (0.9177)	0.44 (0.4366)	0.4 (0.5493)	0.97 (0.1859)	0.78 (1.9058)*	0.19 (0.3842)

(a) Fama-McBeth cross-sectional regressions of one-month ahead individual hedge fund returns on financial intermediaries’ beta

	all	convertible-arbitrage	dedicated short	emerging	macro	equity MN	event-driven	fixed-income	LS equity	multi-strat
Low β	0.47 (5.971)***	0.46 (3.3021)***	-0.44 (-0.7885)	0.5 (2.2487)***	0.64 (4.3958)***	0.78 (2.1081)***	0.46 (3.3021)***	0.47 (4.9971)***	0.47 (5.9751)***	0.62 (8.3828)***
2 β	0.56 (7.7097)***	0.37 (2.458)***	-0.01 (-0.0029)	0.64 (3.7566)***	0.49 (4.9621)***	0.34 (3.4269)***	0.37 (2.458)***	0.61 (10.2273)***	0.62 (7.963)***	0.6 (7.345)***
3 β	0.66 (5.7348)***	0.57 (4.7923)***	-0.52 (-1.3233)	0.68 (2.7084)***	0.48 (4.7378)***	0.58 (7.9152)***	0.57 (4.7923)***	0.66 (8.7233)***	0.66 (5.7365)***	0.53 (6.876)***
4 β	0.82 (4.653)***	0.59 (4.9355)***	-0.01 (-0.0349)	0.91 (2.6774)***	0.72 (4.6889)***	0.59 (9.5994)***	0.59 (4.9355)***	0.82 (7.777)***	0.82 (4.6529)***	0.73 (6.6641)***
High β	1.02 (3.438)***	0.68 (3.054)***	0.36 (1.5799)	1.29 (2.6803)***	0.7 (3.5)***	0.7 (5.4114)***	0.68 (3.0539)***	0.45 (3.4054)***	1.02 (3.4328)***	0.86 (4.3769)***
High β - Low β	0.54 (1.9657)**	0.22 (1.1207)	0.79 (1.3761)	0.79 (1.9525)*	0.06 (0.2286)	-0.08 (-0.1923)	0.22 (1.1207)	-0.02 (-0.4675)	0.55 (1.6494)	0.24 (1.2652)

(b) Quintile portfolios of hedge fund one-month ahead returns sorted by financial intermediaries’ beta

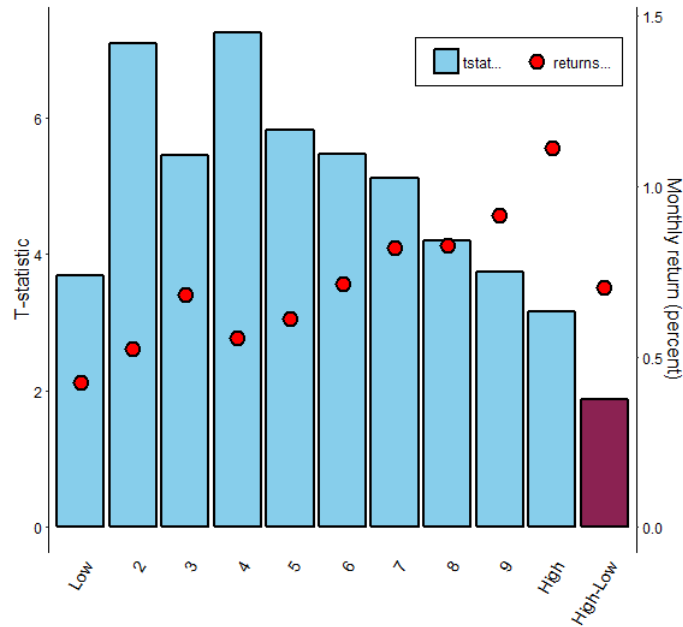
Panel (a) presents results for Fama and McBeth cross-sectional regressions of one-month ahead returns on past 24-month financial intermediaries’ risk exposures. Results include the average regressions’ intercepts and risk slopes λ_t as estimated in Eq (3.10).

Panel (b) presents quintile portfolios formed every month by sorting individual hedge funds on their 24-month financial intermediaries’ risk exposure β from 01/1996 to 01/2015. Quintile 1 is the portfolio of hedge funds with the lowest β and quintile 5 is the portfolio of hedge funds with the highest β . For each quintile portfolio, we report the average next-month return and its t-statistic.

We then look at the results for the quintile portfolios. Quintile portfolios are formed every month from January 1996 to February 2015 by sorting hedge funds based on their past 24-month β_t^i , where quintile Low contains the hedge funds having the lowest β_t^i and quintile High contains the hedge funds with the highest β_t^i . Table 8 panel (b) reports the average β^i over the period and the average next-month returns for the whole sample of individual hedge as well as for strategies sub-samples. T-statistics are reported between parantheses. The whole sample financial intermediaries' risk exposures goes from a negative exposure of -0.1372 for quintile Low to a positive beta of 0.5591 for quintile High, implying a difference of 0.6963 between the lowest exposed quintile and the highest exposed to financial intermediaries' risk quintile. Moving from quintile 1 to quintile 5, the one-month ahead average return increases monotonically. The high-financial-intermediaries'-risk-loading portfolio has the highest average monthly one-month ahead return of 1.02% per month and the low-financial-intermediaries'-risk-loading portfolio has the lowest average future return of 0.47% per month. This yields a yearly high-minus-low portfolio difference in future expected return of 6.48%, statistically significant at the 5% risk level with a t-statistic of 1.9657. The performance of the portfolio spread suggests that high intermediaries' risk-loading hedge funds outperform low intermediaries' risk-loading funds in the future, which is consistent with the interpretation of an expected return premium to holding a non-diversifiable risk. Figure 3.4 shows the results of rolling-window one-month ahead average returns for decile portfolios. We notice a pattern of quasi-monotonous increase in future expected return as we go from the bottom decile to the decile with funds having the highest loading on financial intermediaries' risk.

FIGURE 3.4 – One-month ahead returns for decile portfolio sorted according to financial intermediaries' risk betas

Mean hedge fund indices return and financial intermediaries' risk beta. The financial intermediaries' risk beta is calculated using a regression of monthly indices returns on the financial intermediaries' risk factor only. The analysis goes from 01/1990 to 08/2016.



At the intra-style level, results in Table 3.8 show that only Emerging Markets exhibit a positive and statistically significant, at the 10% risk level, one-month ahead return spread of 0.78% per month, giving evidence

of intra-style financial intermediaries' risk pricing. For other investment styles, return spreads are insignificant, giving no evidence of intra-style risk pricing. Only two investment styles, Equity Market Neutral and Fixed Income, give negative but insignificant return spreads of -0.07% and -0.06% per month respectively. So there is no evidence of negative predictive power for financial intermediaries' risk but also no evidence intra-style of a positive relation between one month ahead returns and financial intermediaries' risk exposures. Once again, as in the previous sections, this result is consistent with strong inter-style variability in exposure to financial exposure but only a weak difference intra-style.

A few more comments can be made here. First, if the rolling one-month-ahead Fama and McBeth cross-sectional regression enables us to estimate a compensation for bearing financial intermediaries' risk, its parametric form can limit its application. The portfolio analysis gives a simple way of gauging the economic importance of financial intermediaries' risk in the cross-section of individual hedge fund returns. The monthly spread of 0.54% is economically important and emphasizes significant differences in the cross-section of funds' returns. An important point here is that this portfolio cannot be replicated in practice because some funds are closed to new investors and cannot be invested in. Furthermore, even for funds that are open to new investors, they may not provide entering points for investors every month but at a lower frequency, typically quarterly. In addition, we cannot rebalance hedge funds monthly as redemption notices are generally made at a quarterly or lower frequency and new investments in hedge funds are subject to lock-up periods, typically around one-year (Aragon, 2007). The final impediment to the replication of this high-minus-low portfolio is the impossibility to short hedge funds. However, such approach is interesting to gauge the magnitude and statistical significance of the difference in future performance of hedge funds loading more on financial intermediaries' risk.

In summary, our results show that financial intermediaries' risk predict future individual hedge fund expected returns and that its impact on funds' returns is economically large. This predictive power comes mainly from inter-style differences in financial intermediaries' risk exposures, with only one strategy, Emerging Markets, exhibiting intra-style pricing for both the parametric and non-parametric frameworks. Portfolio results for one-month ahead returns of hedge funds' portfolio sorted according to their financial intermediaries' risk exposures are robust to changes in the choice of portfolios, with quintile or decile portfolios yielding similar results.

3.5 Financial intermediaries risk and hedge fund risk-adjusted returns

The previous sections introduce the main results about the impact of financial intermediaries' risk on the cross-section of hedge fund returns. In what follows, the paper provides additional analysis and discussion to highlight the significance of the results. In particular, we will focus on the link between risk-adjusted returns, as proxied by Fung and Hsieh seven-factors alphas and hedge funds' financial intermediaries' risk exposures. We want to know if our new factor, shocks to aggregate primary dealers' equity capital ratio, can explain cross-sectional differences in risk-adjusted returns, hence reducing the size of previously documented "anomalies" in hedge fund pricing.

3.5.1 Hedge fund indices' risk-adjusted returns and financial intermediaries risk

Does differences in the financial intermediaries' risk factor explain the observed differences in hedge fund indices' outperformance noticed by Fung and Hsieh (2004)? In other words, does our result, that differences hedge fund indices' expected returns are explained by differences in exposure to financial intermediaries risk, is in fact spurious and driven by other hedge fund systematic risk factors? A way of assessing the robustness of our past results is to look at hedge fund risk-adjusted returns with respect to the popular Fung and Hsieh seven-factor

model. Table 3.9 presents results for Fama and McBeth (1973) cross-sectional regressions of these risk-adjusted returns on financial intermediaries' risk exposures. For each hedge fund indice, we estimate exposures from time-series regressions as in Eq (3.5). We get the Fung and Hsieh risk-adjusted returns α_{FH}^i in running the regressions :

$$R_t^i = \alpha_{FH}^i + \sum_{k=1}^7 \beta_{FH,k}^i F_t^k + \epsilon_{FH,t}^i \quad (3.11)$$

where R_t^i is the excess return on fund i in month t and $\sum_{k=1}^7 \beta_{FH,k}^i F_t^k$ is the part of return explained by Fung and Hsieh risk factors in month t . α_{FH}^i is the Fung and Hsieh seven-factor alpha for fund i . We then run a cross-sectional regression of indices' risk-adjusted returns on the estimated time-series financial intermediaries' risk betas :

$$\hat{\alpha}_{FH}^i = \gamma + \lambda_\eta \hat{\beta}_\eta^i + \nu^i \quad (3.12)$$

where $\hat{\alpha}_{FH}^i$ is the the Fung and Hsieh seven-factor alpha for fund i estimated over the past 24 months, γ is the intercept and λ_η is the risk slope for financial intermediaries' risk.

Intercept	0.44
t_{NW}	(13.835)***
t_{GMM}	(15.708)***
λ_η	0.63
t_{NW}	(3.369)***
t_{GMM}	(4.5769)***
R^2	31.04
nb indices	24
nb months	320

TABLE 3.9 – Fama-McBeth 7-factors alphas on financial intermediaries' risk betas for hedge funds' indices

Hedge fund risk-adjusted returns (alphas) explained by exposure to the financial intermediaries' risk, defined as the ratio of total market equity to total market assets (book debt and market equity) of primary dealer holding companies. Portion of explained alphas is the mean slopes of monthly cross-sectional regressions of hedge fund indices' Fung and Hsieh 7-factors alphas on exposures to the financial intermediaries' risk factor. These exposures and alphas are estimated in first-stage time-series regressions. The monthly sample is 01/1990-08/2016. R^2 is the adjusted coefficient of determination in percentage. Generalized method of moments t_{GMM} and Newey-West t_{NW} t-statistics in parentheses adjust for cross-asset correlation in the residuals and for estimation error of the time-series betas.

Table 3.9 presents results for the cross-sectional regression. There is strong evidence of financial intermediaries' risk pricing in the cross-section of hedge fund indices' risk-adjusted returns. Results exhibit a positive intercept of 0.44% per month and a positive monthly risk slope of 0.63%. The risk price is statistically significant at the 1% level with t-statistics of 3.369 and 4.5769 respectively for Newey-West and GMM estimation procedures. As measured with the adjusted coefficient of determination, 31.04% of hedge fund indices' variation

in risk-adjusted returns is explained by differences in exposures to financial intermediaries' risk.

Our results show that inter-style differences in alpha, measured with respect to the Fung and Hsieh seven-factor model, is linked to different exposures to financial intermediaries' risk. A strong part of previously thought "anomalies" or "outperformance" in hedge fund pricing at the strategy level is in fact compensation for bearing undiversifiable systematic risk. This view is consistent with Jurek and Stafford (2015) who show that hedge fund indices exhibit strong alphas but these returns are compensation for bearing downside market risk. This paper offers an identification of the source of this downside market risk, highlighting the importance of changes in aggregate primary dealers' equity capital ratio as a risk exposure in hedge fund strategies.

3.5.2 Financial intermediaries risk-sorted portfolios of individual hedge funds

The previous subsection investigates the relationship between Fung and Hsieh seven-factor alpha and financial intermediaries' risk at the investment style level. This subsection investigates the pricing of financial intermediaries' risk with risk-adjusted returns using portfolios of individual hedge funds while allowing for time-variation in financial intermediaries' risk loadings. Specifically, we form 5 and 10 portfolios of hedge funds every month, with equal number of funds in each portfolio, using two-year rolling financial intermediaries' risk factor loadings. Funds are kept in the portfolios for one month. The financial intermediaries' risk beta is computed using a simple regression of the funds' monthly return on the financial intermediaries' risk factor. In any given month, we only include funds having no missing observations. 24-months provide sufficient observations to accurately estimate financial intermediaries' betas without losing too much observations in the beginning of the sample. Portfolio formation therefore begins January 1996 and ends February 2015, giving 231 monthly observations. The portfolio approach is convenient because it enables us to compare the financial intermediaries' risk with Fung and Hsieh risk factors. Such comparison is simply made by regressing the monthly individual hedge fund returns in the financial intermediaries' beta portfolios on the seven Fung and Hsieh factors. The average intercept of these regressions is the Fung and Hsieh alpha.

Figure 3.5 plots the alpha of each financial intermediaries' risk-loading decile portfolio risk-adjusted returns (points) along with the respective t-statistics (in bars). The figure shows that the high financial intermediaries' risk loading portfolio has the highest risk-adjusted monthly return of 1.25% while the low-financial intermediaries' risk portfolio has a lower average monthly risk-adjusted return of 1.01%. The rest of portfolio risk-adjusted returns are generally increasing with financial intermediaries' risk loading : it is decreasing for the three lowest portfolios then linearly increasing. The figure also includes the high-minus-low portfolio, whose monthly alpha is 0.24% with a t-statistic of 2.367. The performance of this portfolio spread indicates that high financial intermediaries-loading funds outperform low financial intermediaries-loading funds, consistent with the interpretation of an expected return premium to holding financial intermediaries' risk. The fact that there is an annual spread in risk-adjusted returns of 2.88% between the highest and lowest decile portfolios suggests that the difference in returns found in previous sections cannot be explained by other commonly used hedge fund risk factors.

FIGURE 3.5 – Risk-adjusted returns of financial intermediaries’ risk-beta sorted portfolios of individual hedge funds

Each month hedge funds are sorted into 10 equally weighted portfolios according to historical primary dealers’ aggregate equity capital ratio’s beta. This financial intermediaries’ risk beta is calculated using an univariate of monthly portfolio returns during the 24 months prior to portfolio formation. Portfolio returns begin January 1996 and end February 2015. Monthly portfolio alphas are calculated using regression of portfolio returns on the Fung and Hsieh 7-factors. The figure also displays the alpha of the high-minus low financial intermediaries’ risk-beta portfolio.

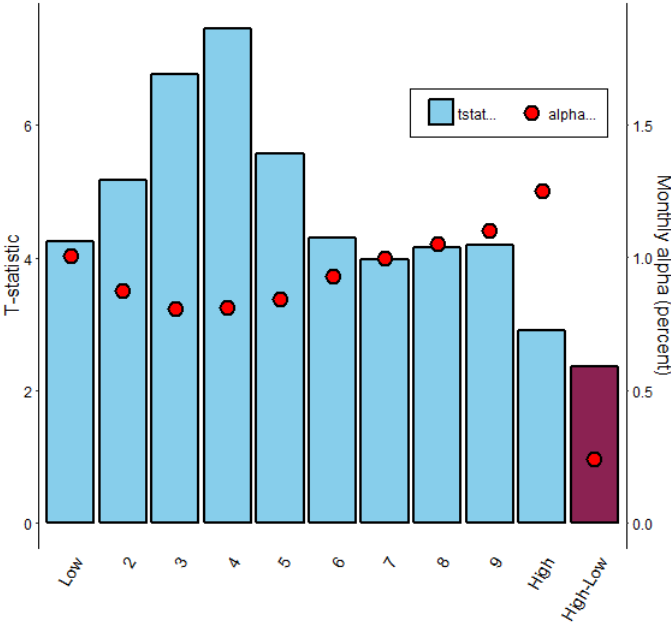


TABLE 3.10 – Rolling-window relation between risk-adjusted returns and financial intermediaries' risk exposure

	all	convertible-arbitrage	dedicated short	emerging	macro	equity MN	event-driven	fixed-income	LS equity	multi-strat
Intercept	0.91 (29.08)***	0.76 (24.3241)***	0.25 (6.1856)***	0.96 (22.2345)***	0.8 (32.2951)***	0.73 (25.9543)***	0.77 (24.7624)***	0.75 (35.1967)***	0.93 (16.1425)***	0.64 (9.0146)***
λ_η	0.44 (4.3713)***	0.61 (3.1233)***	0.81 (4.18091)***	0.87 (6.3952)***	-0.7 (-0.416)	0.27 (1.5365)	0.98 (7.2749)***	-0.71 (-3.7496)***	0.65 (4.4764)***	0.16 (0.3371)

(a) Rolling-window Fama-McBeth cross-sectional regressions of individual hedge fund Fung and Hsieh 7 factors alphas on financial intermediaries' risk betas

	all	convertible-arbitrage	dedicated short	emerging	macro	equity MN	event-driven	fixed-income	LS equity	multi-strat
Low β_η	0.91 (24.74)***	0.67 (12.2314)***	0.35 (2.6942)***	0.11 (21.97)***	0.98 (13.3805)***	0.8 (19.0969)***	0.84 (30.1817)***	0.82 (19.3765)***	1.07 (18.9967)***	0.92 (33.07)***
2 β_η	0.81 (33.78)***	0.52 (10.1543)***	0.13 (1.3035)***	0.94 (22.8573)***	0.7 (24.32)***	0.61 (29.554)***	0.72 (30.0895)***	0.76 (29.1638)***	1.03 (21.77)***	0.77 (30.26)***
3 β_η	0.88 (24.85)***	0.69 (22.5)***	-0.3 (-3.3688)***	0.76 (18.5174)***	0.97 (31.8515)***	0.67 (30.271)***	0.77 (27.7936)***	0.79 (36.0255)***	1.07 (19.2207)***	0.72 (30.1)***
4 β_η	1 (20.78)***	0.71 (23.14)***	-0.06 (-0.7572)	0.79 (21.28)***	1.23 (26.1841)***	0.8 (22.7421)***	0.85 (24.1556)***	0.72 (29.1535)***	1.11 (18.5998)***	0.89 (25.54)***
High β_η	1.17 (16.8)***	0.9 (26.77)***	0.46 (8.3726)***	1.69 (17.7377)***	0.8 (14.1566)***	0.89 (21.3343)***	1.05 (19.6018)***	0.58 (15.8874)***	0.12 (13.7997)***	0.96 (17.97)***
High β_η - Low β_η	0.26 (3.7861)***	0.22 (3.6441)***	0.11 (0.7494)	0.61 (6.836)***	-0.17 (-2.16)***	0.09 (1.5094)	0.21 (4.6462)***	-0.24 (-4.6982)***	0.11 (1.3046)	0.04 (0.8783)

(b) Rolling-window quintile portfolios of hedge funds Fung and Hsieh's 7-factors alphas sorted by financial intermediaries' risk beta

Panel (a) presents cross-sectional estimates of hedge fund Fung and Hsieh 7 factors' alpha on financial intermediaries' risk beta, defined as the ratio of total market equity to total market assets (book debt and market equity) of primary dealer holding companies. λ_η is the mean slope of monthly cross-sectional regression of hedge fund indices' returns on exposures to the financial intermediaries' risk factor. The exposures are estimated in a first-stage time-series regression (a regression with the Fung and Hsieh 7 factors for the alpha and separately a single factor model for the financial intermediaries' risk beta). The monthly sample is 01/1994-02/2015.

Panel (b) presents quintile portfolios formed every month by sorting individual hedge funds on their past 24-month financial intermediaries' risk exposure. The sample goes from 01/1996 to 01/2015. Quintile 1 is the portfolio of hedge funds with the lowest β_η and quintile 5 is the portfolio of hedge funds with the highest β_η . For each quintile portfolio, we report the average 24-month Fung and Hsieh 7 factors' alpha.

The results for the quintile portfolios are reported in Table 3.10 Panel (b). They indicate that, over the period January 1996- February 2015, there is a monthly risk-adjusted return spread for the highest quintile portfolio minus the lowest quintile portfolio of 0.26% with an associated t-statistic of 3.7861. This result indicates that, whether we take quintile or decile portfolios, there is an economically significant risk-adjusted return spread between funds that are the most exposed to financial intermediaries' risk and funds that are the least exposed. This clearly shows the robustness of the pricing power of financial intermediaries' risk for hedge funds.

To get more information about the intra-style pricing power of financial intermediaries' risk with respect to inter-style, Table 3.10 Panel (b) reports the performance, measured by risk-adjusted returns, of sorted financial intermediaries loading quintile portfolios for each investment style. Results show that three investment styles, Convertible-Arbitrage, Emerging-Markets and Event-Driven, present evidence of intra-style pricing power for the financial intermediaries' risk factor, with high-minus-low quintile monthly risk-adjusted return spreads of 0.22%, 0.61% and 0.21% respectively, each statistically significant at the 1% risk level. However, two strategies, Global Macro and Fixed-Income Arbitrage, presents statistically significant negative pricing power for the financial intermediaries' risk factor, with risk-adjusted return spreads of -0.17% and -0.24% per month respectively. This negative pricing for two strategies is a puzzle in the sense that there is a positive inter-style relationship between risk-adjusted returns and exposures to financial intermediaries' risk, and evidence of intra-style pricing for three strategies. Furthermore, asset pricing theory tells us that investors should earn a premium to compensate systematic risk bearing and not pay a premium for it.

In summary, our results show the robustness of the pricing of hedge funds expected returns by financial intermediaries' risk exposures. The decile of the highest exposed individual hedge funds outperforms in a risk-adjusted fashion the decile of the lowest exposed funds by 8.4% annually, which is economically significant. Results are robust to moving from decile portfolios to quintiles. There is evidence of intra-style pricing for three strategies, but two other exhibit statistically significant negative pricing power, which is puzzling. A potential explanation for this results is the omission of another unknown potential risk-factor in the risk-adjusted returns, giving rise to the negative pricing relationship.

3.5.3 Fama and McBeth cross-sectional pricing for individual hedge funds

In this section, we conduct parametric tests to assess the pricing power of financial intermediaries' betas over risk-adjusted individual hedge fund returns. These parametric tests are used as a robustness check to confirm of infirm results obtained with non parametric tests. In the first stage, starting from January 1996, we estimate time-series of univariate monthly financial intermediaries' risk betas over a fixed 24-month window with the following regression :

$$R_t^i = \alpha_t^i + \beta_t^i \cdot \eta_t^\Delta + \epsilon_t^i \quad (3.13)$$

where R_t^i is the return on fund i in month t and η_t^Δ is the financial intermediaries' risk factor in month t . α_t^i and β_t^i are the intercept of the regression and the financial intermediaries' risk beta for fund i in month t . We get the risk-adjusted returns with the following regression over the same fixed 24-month window :

$$R_t^i = \alpha_{FH,t}^i + \sum_{k=1}^7 \beta_{FH,k,t}^i F_t^k + \epsilon_{FH,t}^i \quad (3.14)$$

where R_t^i is the return on fund i in month t and $\sum_{k=1}^7 \beta_{FH,k}^i F_t^k$ is the part of return explained by Fung and Hsieh risk factors in month t for fund i . α_{FH}^i is the Fung and Hsieh seven-factor alpha for fund i in month t . Then, in the second stage, we use Fama and McBeth cross-sectional regressions of individual hedge fund seven-factor risk-adjusted returns on the financial intermediaries' risk betas :

$$\alpha_{FH,t}^i = \omega_t^i + \lambda_t \cdot \beta_t^i + \epsilon_{t+1}^i \quad (3.15)$$

where $\alpha_{FH,t}^i$ is the Fung and Hsieh seven-factor alpha of fund i in month t , computed using a fixed estimation window of 24 months, ω_t^i and λ_t are respectively the intercept of the regression and the risk slope for fund i in month t .

Table 3.10 Panel (a) presents the time-series average intercept and slope coefficients from Eq 15 over the sample period January 1996-February 2015. The corresponding t-statistics are presented in parentheses. Results show an overall cross-sectional risk price for financial intermediaries' betas of 0.44% with an associated t-statistic 4.3713. This result confirms that individual risk-adjusted results are related to financial intermediaries risk exposures. When we look at the intra-style Fama and McBeth average coefficients, we find that 5 out of the 9 strategies exhibit a positive and statistically significant relationship between Fung and Hsieh seven-factor alphas and loadings on financial intermediaries risk : Convertible Arbitrage, Dedicated Short, Emerging Markets, Event-Driven and Long-Short Equity with respective coefficients of 0.61%, 0.81%, 0.87%, 0.98% and 0.65%. One strategy, Fixed-Income Arbitrage, exhibits a negative and statistically significant relation with a -0.71% estimate and an associated t-statistic of -3.7496. This negative price of risk deepens the puzzle of the negative risk-adjusted return spread found in the last section for this strategy.

To sum up our results, there is a positive price of risk for individual hedge funds in the whole sample as well as for five intra-style investment styles. Because the explained variable is Fung and Hsieh seven-factor risk-adjusted return, this relationship is robust to inclusion of popular hedge fund risk factors. There is an unexplained negative intra-style price of risk for the Fixed-Income Arbitrage strategy.

3.6 Long-run performance

A common stylized fact of hedge fund returns is their serial-correlation, with Getmansky et al. (2004) showing significant serial-correlation up to order two for monthly hedge fund returns. This statistical property is at the center of debate in the academic literature about the hedge fund industry. Indeed, it could impact the reliability of the reported returns in the Lipper TASS database because the voluntary nature of fund's reporting to commercial databases means that serial-correlation may imply return "smoothing". The idea here is that a fund has discretion in its reporting of returns, resulting in returns that are smoothed over a few months, and hence giving rise to artificial serial-correlation that reduces the measured volatility. Such smoothing suggests that measuring a fund's performance over a long period could be more accurate than just one-month ahead. To study this potential effect, Table 3.11 reports long-run returns of the financial-intermediaries' risk-loading portfolios of Table 3.11. Specifically, the table uses 3, 6, 9 and 12 months future returns computed for non-overlapping intervals. For example, to calculate three-month holding portfolio monthly returns, portfolio are only rebalanced at the beginning of January, April, July and October of each year. Results indicate that the performance of the financial intermediaries' risk sorted portfolios does not vary significantly with changes in rebalancing frequency, showing evidence of the robustness of the predictive power of financial intermediaries' risk for hedge fund returns. The quintile high-minus-low future return spread varies over 5.3028-6.576% per year, which is comparable to the

6.48% annual expected return obtained using monthly rebalancing. However, the spreads are only statistically significant at the 10% risk level for the 3-month rebalancing frequency and 20% for the lower portfolio rebalancing frequencies.

		Low	2	3	4	High	High-Low
3 months	returns	0.4798 (6.4071) ^{***}	0.5371 (7.3087) ^{***}	0.6655 (5.7026) ^{***}	0.7964 (4.4608) ^{***}	1.0279 (3.4979) ^{***}	0.548 (1.9562) [*]
6 months	returns	0.5525 (8.1701) ^{***}	0.5246 (7.2238) ^{***}	0.643 (5.3367) ^{***}	0.7775 (4.3239) ^{***}	1.0029 (3.3891) ^{***}	0.4504 (1.5742)
9 months	returns	0.5378 (6.8891) ^{***}	0.5413 (7.0564) ^{***}	0.6403 (5.5343) ^{***}	0.8085 (4.6094) ^{***}	0.9797 (3.3903) ^{***}	0.4419 (1.6138)
1 year	returns	0.55 (7.8142) ^{***}	0.533 (6.8531) ^{***}	0.6638 (5.8135) ^{***}	0.7831 (4.4166) ^{***}	0.993 (3.4048) ^{***}	0.443 (1.5989)

TABLE 3.11 – Long run performance

Each month hedge funds are sorted in 5 equally weighted portfolios according to historical financial intermediaries' risk beta. The financial intermediaries' risk beta is computed in averaging portfolio constituents' estimates from regressions of monthly fund returns on the financial intermediaries' risk factor, using the 24 months prior to portfolio formation. Portfolio returns begin January 1996, using funds having no missing observations during the prior years. The table reports the average monthly return (in percent) for the quintile portfolios, as well as the high-minus-low portfolio for holding periods of 3, 6, 9 and 12 months. The portfolio uses non-overlapping returns, for example, the three-month holding period sorts individual hedge funds in the beginning of January, April, July and October. T-statistics are between parentheses. The analysis uses the TASS individual hedge fund database for the period January 1994 to February 2015.

From a practical point of view, lower-frequencies portfolios seem more investable because they relax key assumptions such as the absence of restrictions in investment entry points and notice periods for exits. The persistence of performance implies a strong predictive power for financial intermediaries' risk. This point is of particular interest for hedge fund investors and funds of hedge funds because it shows that a higher or lower loading on financial intermediaries' risk will influence the investment's expected return over a sufficiently long period to cover the lockup period.

3.7 Conclusion

In this paper, we analyse the relation between financial intermediaries' risk exposures and the cross-sectional risk and return profile of individual hedge funds. Our empirical results give new findings in the hedge fund literature.

First, many hedge fund investment styles are significantly exposed to financial intermediaries' risk, where financial intermediaries' risk is proxied by unexpected changes in the aggregate equity capital ratio of primary dealers. This exposure explains a large fraction of hedge fund expected returns and risk-adjusted performance measures at the index level.

Second, at the individual level, hedge fund returns sorted with respect to their financial intermediaries' risk exposure imply a significant variation in expected return of 1.518% annually. A high loading on financial in-

intermediaries' risk leads to a greater expected return. The analysis is corroborated by a two-stage Fama and McBeth cross-sectional regression, which gives a significant positive slope of about 0.39% monthly for financial intermediaries' risk exposure. Such a premium explains an economically significant fraction of the variation in expected return as a compensation for exposure to financial intermediaries' risk.

Third, the central finding of this paper is that exposure to financial intermediaries' risk predicts future expected return over the sample period January 1994- February 2015. Two separate tests have been conducted to determine the significance of factor loadings on future hedge fund returns : parametric Fama and McBeth cross-sectional regressions and non-parametric portfolio tests that sort individual hedge funds into quintiles based on their past financial intermediaries' risk betas. The two tests provide clear results of a positive and significant relation between financial intermediaries' risk beta and future hedge fund returns. These results are corroborated by evidence that financial intermediaries' risk beta predict longer-run hedge fund performance.

Finally, hedge fund risk-adjusted returns, defined as the intercept in a regression of individual time-series returns over the Fung and Hsieh seven factors, are also related to exposures to financial intermediaries risk. At the index level, more than 31% of in-sample risk-adjusted returns variation. At the individual fund level, two tests have been conducted, a rolling-window non-parametric portfolio test and a rolling-window parametric Fama and McBeth cross-sectional regression test. Both indicate that risk-adjusted returns are statistically and economically significantly explained by exposures to financial intermediaries' risk. This is an indication that the previous results cannot be ruled out once we introduce common hedge fund factors, and that previously documented "anomalies" in hedge fund pricing are in fact at least partly compensation for bearing a nondiversifiable source of risk, unexpected changes in the aggregate primary dealers' equity capital ratio. These findings are important for hedge fund investors, because risk-adjusted performance measures ignoring financial intermediaries exposures will in fact underestimate funds' risk.

The results of this paper have several implications. First, they emphasize the robustness of He et al. (2017) intermediary asset pricing approach in extending the set of financial assets to hedge funds. Second, from a risk management point of view, this study gives a new tool for evaluating the counterparty risk a hedge fund is exposed to. Third, it enables better asset-allocation processes for funds-of-funds because it allows investors to structure investment products that load on financial intermediaries' risk accordingly to their preferences. Finally, it highlights the crucial role played by financial intermediaries in the hedge fund industry, confirming King and Maier's (2009) view that prime brokers should be the main target of financial regulations in the hedge fund industry.

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3.8 Appendix A : Financial intermediaries’ risk and liquidity risk

Due to their role as marginal buyers in global financial markets, shocks to the equity capital ratio of primary dealers can lead to liquidity spirals : Brunnermeier and Pedersen (2008) show that funding liquidity determines market liquidity. Therefore, is financial intermediaries risks only a proxy for market liquidity risk ? This question is important because Sadka (2010) demonstrates that exposure to liquidity risk is an important determinant of the cross-section of hedge fund returns. It might be that changes in primary dealers’ balance sheets affect hedge funds only through their impact on market liquidity, via a liquidity spiral mechanism similar to Brunnermeier and Pedersen (2008). In this section, we investigate if changes in market liquidity exposures explain the relation between hedge fund return and financial intermediaries’ risk exposure.

To look at the robustness of our past results in presence of market liquidity risk, we use Pastor and Staumbaugh’s (2003) traded liquidity factor. This is the value-weighted return on the high minus low portfolio from a sort of individual stocks according to their historical liquidity betas. We use this factor rather than those developed by Sadka (2010) because it has a longer time series and is an investable portfolio, so it theoretically enables hedge fund replication.

We first analyze the impact of introducing liquidity risk on our results at the index level. Then we look at its impact on the relation between financial intermediaries’ risk and individual hedge fund risk-adjusted returns.

3.8.1 Financial intermediaries’ risk, liquidity risk and index returns

Does financial intermediaries’ risk is a proxy for market liquidity risk ? In order to answer this question, we first investigate the correlation between these two sources of risk. For the period January 1994 - February 2015

for which we have market liquidity data, the correlation between financial intermediaries' risk and liquidity risk is low, at 0.04. Therefore, it seems implausible that financial intermediaries' risk only captures market liquidity effects.

To assess the impact of controlling for market liquidity in the pricing of financial intermediaries' risk, we run two types of Fama and McBeth (1973) two-stage regressions of hedge fund index returns. In the first type, for each hedge fund index i , we estimate exposures from time series regressions of indices returns R_t^i :

$$R_t^i = \alpha^i + \beta^i \eta_t^\Delta + \sum_{k=1}^7 \beta_{FH,k}^i R_t^k + \beta_{Liq}^i Liq_t + \epsilon_t^i \quad (3.16)$$

where R_t^i is the return of fund i in month t , α^i is the intercept of the regression, β^i measures the exposure to the financial intermediaries' risk factor η_t^Δ , $\sum_{k=1}^7 \beta_{FH,k}^i F_t^k$ is the part of fund's i return explained by Fung and Hsieh risk factors in month t , β_{Liq}^i is the exposure to the liquidity factor Liq_t and ϵ_t^i is the residual of fund i in month t . We then run a cross-sectional regression of average index returns on the estimated coefficients :

$$\hat{E}[R_t^i] = \gamma + \lambda_\eta \hat{\beta}_\eta^i + \sum_{k=1}^7 \lambda_{\beta,k} \hat{\beta}_{FH,k}^i + \lambda_{Liq} \hat{\beta}_{Liq}^i + \nu^i \quad (3.17)$$

where $\hat{E}[R_t^i]$ is the average return of fund i , γ is the intercept, λ_η is the risk slope coefficient, $\hat{\beta}_\eta^i$ is fund i 's estimated exposure to financial intermediaries' risk, $\lambda_{\beta,k}$ is the risk price of factor k , λ_{Liq} is the risk price of liquidity and ν is the residual.

The second type is a Fama and McBeth regression of the indices' risk-adjusted returns on financial intermediaries' risk exposure. The risk-adjusted returns are obtained in regression indices' returns on the Fung and Hsieh seven factors plus the liquidity factor :

$$R_t^i = \alpha_{Liq}^i + \sum_{k=1}^7 \beta_{FH,k}^i F_t^k + \beta_{Liq}^i Liq_t + \epsilon_{FH,t}^i \quad (3.18)$$

where R_t^i is the excess return on fund i in month t , $\sum_{k=1}^7 \beta_{FH,k}^i F_t^k$ is the part of return explained by Fung and Hsieh risk factors in month t and β_{Liq}^i is the exposure to the liquidity factor. α_{Liq}^i is the Fung and Hsieh plus liquidity alpha for fund i . We get the exposure of indices' on financial intermediaries' risk with the univariate regressions as in Eq 5. We then run a cross-sectional regression of indices' risk-adjusted returns on the estimated time-series financial intermediaries' risk betas :

$$\hat{\alpha}_{Liq}^i = \gamma + \lambda_\eta \hat{\beta}_\eta^i + \nu^i \quad (3.19)$$

Table 3.12 presents results for the two cross-sectional regressions with liquidity risk. The multivariate Fama and McBeth regression gives a statistically significant intercept of 0.58%, which is a bit bigger than for the univariate cross-sectional regression in Table 3.5 (0.56%) and for the multivariate cross-section regression with financial intermediaries' risk and Fung and Hsieh seven factors (0.5016%). This means that adding liquidity risk

to the Fung and Hsieh seven factors and the financial intermediaries' risk actually increases the unexplained part of expected returns. We still have a positive and statistically significant risk price for financial intermediaries' risk with a coefficient of 1.317 with associated t-statistics of 3.01 for Newey-West standard errors and 1.99 for generalized method-of-moments. This positive risk price shows the robustness of financial intermediaries risk with respect to liquidity risk. The cross-sectional regression gives a negative risk price for liquidity risk, which is counter-intuitive. However, this coefficient is only statistically significant for Newey-West t-statistic but is insignificant with generalized method-of-moments' one. No other coefficient is statistically significant, highlighting the pricing power of financial intermediaries' risk over hedge funds at the style level.

Overall, when we compare these results with those obtained without taking into account market liquidity, we find that financial intermediaries' risk explain hedge fund return. For expected returns, the price of liquidity risk exposure is negative and non statistically significant. When we look at the Fama and McBeth regressions for risk-adjusted returns, the fact including market liquidity in the set of risk-factors strongly reduces the amount of cross-sectional variation explained by financial intermediaries' risk but it does not cancel its positive and statistically significant risk price.

The second cross-sectional regression presents results for risk-adjusted returns computed for Fung and Hsieh seven factors and liquidity risk. The idea here is to look if "anomalies" in pricing can be explained by financial intermediaries risk, even after taking into account liquidity risk, which can be a proxy for the ease of implementing investment strategies, and is therefore a limits-to-arbitrage factor. The results in Table 3.12 show strong evidence of financial intermediaries' risk pricing in the cross-section of hedge fund indices' risk-adjusted returns, even after taking into account liquidity risk. There is a positive and statistically significant intercept of 0.43%, which is similar to the 0.44% obtained without liquidity risk. The risk price is positive and statistically significant at the 1% level.

To summarize, our results for hedge fund indices are robust to the inclusion of liquidity risk. Pricing of the financial intermediaries' risk at the inter-style level is not due to variations in liquidity risk exposures, and financial intermediaries' risk is not a proxy for market liquidity risk at the index level.

3.8.2 Individual hedge fund pricing

The previous subsection investigates the robustness of financial intermediaries' risk pricing power when we include liquidity risk at the index level. This subsection looks at the pricing of financial intermediaries' risk with risk-adjusted returns taking into account liquidity risk for individual hedge funds.

Individual hedge fund portfolios

We first begin our analysis using portfolios of individual in a dynamic framework. We form monthly quintile portfolios of hedge funds sorted according to their past two years rolling financial intermediaries' risk exposure, estimated with a univariate regression of funds' monthly returns on the financial intermediaries' risk factor. For a given month, we only select funds having no missing observation. The portfolio formation process begins in January 1996 and ends in February 2015. We get the risk-adjusted returns by regressing hedge funds' returns on the Fung and Hsieh seven factors and the Pastor and Stambaugh (2003) liquidity factor.

Results for the quintile portfolios presented in Table 3.13 panel (b) show that, over the period January 1996-February 2015 there is a monthly risk-adjusted return spread for the highest quintile portfolio minus the lowest quintile portfolio of 0.14%. However, with an associated t-statistic of 1.7623, this spread is only statistically

significant at the 10% percent level. Furthermore, the relationship is not strictly monotonous. At the individual level, there is no strong evidence of financial intermediaries' pricing for individual funds' risk-adjusted returns taking into account liquidity risk.

At the intra-style level, two strategies exhibit positive and strongly statistically significant risk price for financial intermediaries' risk : Convertible arbitrage, Emerging Markets and Event-Driven with spreads of 0.15% and 0.44% and associated t-statistics of 2.2728 and 4.2258 respectively. Two other strategies, Macro and Fixed Income, present negative risk prices of -0.23% and -0.24% with associated t-statistics -2.5741 and -4.3968 respectively.

Even if the inclusion of liquidity risk to compute risk-adjusted returns decreases the magnitude of the high-minus-low quintile spreads and henceforth its statistical significance, there is still a positive and weakly statistically significant risk-adjusted returns' spread for the global high-minus-low portfolio.

Fama and McBeth cross-sectional regressions

If the non-parametric approach shows only a weak robustness in the relation between risk-adjusted returns and financial intermediaries' risk at the individual level when we take into account liquidity risk, it might be that there is still evidence of pricing with a parametric approach. Here, we repeat the parametric tests done in section 3.5. To do so, we first estimate time-series of univariate monthly financial intermediaries' risk betas over fixed 24-month window with regression (3.13). We then get risk-adjusted returns as in equation (3.14) but we add liquidity risk. Finally, we use Fama and McBeth cross-sectional regressions of individual hedge fund Fung and Hsieh seven factors and liquidity risk on risk-adjusted returns on the financial intermediaries' risk betas estimated in (3.16).

Table 3.13 panel (a) present the time-series average intercept and risk prices over the period January 1996 - February 2015. The overall risk price for financial intermediaries' beta 0.29% per month and is statistically significant with an associated t-statistic of 2.3679. This results underline that, even if the quintile portfolios do not exhibit a statistically significant positive risk-adjusted spread, there is evidence of pricing of financial intermediaries' risk in the cross-section of individual risk-adjusted returns when liquidity risk is taken into account. The intra-styles coefficients show positive pricing for four strategies : Convertible Arbitrage, Dedicated-Short, Emerging Markets and Event-Driven with risk prices of 0.51%, 0.74%, 0.62% and 0.53% with associated t-statistics of 2.3652, 3.5915, 3.6769 and 4.5694 respectively. Only the Fixed Income investment style presents evidence of statistically significant negative pricing.

When we compare these results to those without taking into account liquidity risk in Table 3.10, we notice that including market liquidity risk in the definition of risk-adjusted returns decreases the financial intermediaries' risk price from 0.44% to 0.29% but this price of risk is still statistically significant.

	$E[R_i]$	α_i
Intercept	0.58	0.43
t_{NW}	(10.01)***	(14.65)***
t_{GMM}	(10.13)***	(14.96)***
λ_η	2.98	0.4
t_{NW}	(3.01)***	(2.58)**
t_{GMM}	(1.99)**	(2.74)***
λ_{PTFSBD}	5.3	
t_{NW}	(0.91)	
t_{GMM}	(0.62)	
λ_{PTFSFX}	1.29	
t_{NW}	(0.2)	
t_{GMM}	(0.16)	
$\lambda_{PTFSCOM}$	-4.07	
t_{NW}	(-0.66)	
t_{GMM}	(-0.42)	
λ_{SP500}	0.83	
t_{NW}	(0.38)	
t_{GMM}	(0.37)	
λ_{Size}	1.49	
t_{NW}	(1.49)	
t_{GMM}	(0.59)	
λ_{Bond}	64.27	
t_{NW}	(1.39)	
t_{GMM}	(1.33)	
λ_{Credit}	1.17	
t_{NW}	(0.27)	
t_{GMM}	(0.32)	
$\lambda_{Liquidity}$	-5.79	
t_{NW}	(-2.41)**	
t_{GMM}	(-1.03)	
R^2	63.37	12.96
MAPE	1.9	0.19
nb indices		24
nb months		312

TABLE 3.12 – **Fama-McBeth regressions for hedge fund indices**

Risk prices estimates for financial intermediaries' risk, proxied by the primary dealers' aggregate equity capital ratio (ECR) and Fung and Hsieh seven factors plus liquidity risk. The ECR is defined as the ratio of total market equity to total market assets (book debt and market equity) of primary dealer holding companies. Risk prices are the mean slopes of monthly cross-sectional regressions of hedge fund indices' returns on exposures to each factor, estimated with equations (3.6) et (3.8). These exposures are estimated in a first-stage time-series regression as in equations (3.5) et (3.7). The monthly sample is 01/1990-12/2015. R^2 is the adjusted coefficient of determination in percentage. Generalized- methods-of-moments t_{GMM} and Newey-West t_{NW} t-statistics in parentheses adjust for cross-asset correlation in the residuals and for estimation error of the time-series betas. The mean absolute pricing error $MAPE = \frac{1}{24} \sum_{i=1}^{24} |\hat{y}_i - y_i|$ measures the average magnitude of the pricing errors in percentage.

TABLE 3.13 – Rolling-window relation between risk-adjusted returns and financial intermediaries’ risk exposure

	all	convertible-arbitrage	dedicated short	emerging	macro	equity MN	event-driven	fixed-income	LS equity	multi-strat
Intercept	0.89 (26.7174)***	0.71 (23.3084)***	0.23 (5.5896)***	0.97 (18.6384)***	0.78 (31.6474)***	0.71 (23.7021)***	0.72 (30.3729)***	0.74 (34.2028)***	0.91 (15.9216)***	0.78 (28.6306)***
λ_η	0.29 (2.3679)***	0.51 (2.3652)***	0.74 (3.5915)***	0.62 (3.6769)***	-0.17 (-0.9259)	0.23 (1.2441)	0.53 (4.5694)***	-0.74 (-3.651)***	0.51 (3.3253)***	0.38 (2.6318)

(a) **Rolling-window Fama-McBeth cross-sectional regressions of individual hedge fund Fung and Hsieh 7 factors alphas on financial intermediaries’ risk betas**

	all	convertible-arbitrage	dedicated short	emerging	macro	equity MN	event-driven	fixed-income	LS equity	multi-strat
Low β_η	0.92 (24.3399)***	0.65 (12.6767)***	0.39 (2.8606)***	1.13 (20.9097)***	1 (17.9669)***	0.78 (13.0357)***	0.8 (30.4909)***	0.81 (17.7747)***	1.06 (18.1028)***	0.9 (30.1052)***
2 β_η	0.79 (31.8769)***	0.51 (10.6292)***	0.21 (1.8283)*	0.88 (20.6764)***	0.68 (26.7712)***	0.58 (21.5374)***	0.67 (28.0928)***	0.76 (28.1641)***	1 (20.3743)***	0.75 (28.5895)***
3 β_η	0.84 (22.4037)***	0.67 (21.176)***	-0.27 (-2.8464)***	0.89 (15.9572)***	0.75 (29.3513)***	0.66 (30.2589)***	0.71 (25.4156)***	0.79 (35.4884)***	1.02 (17.4652)***	0.69 (27.52)***
4 β_η	0.96 (18.0518)***	0.65 (19.094)***	-0.08 (-1.04)	1.09 (16.8458)***	0.78 (20.743)***	0.78 (24.6471)***	0.74 (22.7668)***	0.71 (27.0017)***	1.04 (16.026)***	0.84 (22.8884)***
High β_η	1.06 (13.0796)***	0.80 (13.729)***	0.45 (8.0087)***	1.57 (14.8365)***	0.77 (12.6112)***	0.86 (18.7943)***	0.86 (18.8275)***	0.57 (16.1244)***	1.04 (10.9127)***	0.86 (15.2508)***
High β_η - Low β_η	0.14 (1.7623)*	0.15 (2.2728)***	0.06 (0.3414)	0.44 (4.2258)***	-0.23 (-2.5741)***	0.08 (1.3142)	0.06 (1.5515)	-0.24 (-4.3968)***	-0.02 (-0.1747)	-0.01 (-0.2782)

(b) **Rolling-window quintile portfolios of hedge funds Fung and Hsieh’s 7-factors alphas sorted by financial intermediaries’ risk beta**

Panel (a) presents cross-sectional estimates of hedge fund Fung and Hsieh 7 factors’ alpha plus liquidity risk on the financial intermediaries’ risk beta. Financial intermediaries’ risk is defined as the ratio of total market equity to total market assets (book debt and market equity) of primary dealer holding companies. λ_η is the mean slope of monthly cross-sectional regression of hedge fund indices’ returns on exposures to the financial intermediaries’ risk factor. The exposures are estimated in a first-stage time-series regression (a regression with the Fung and Hsieh 7 factors plus liquidity risk for the alpha and separately a single factor model for the financial intermediaries’ risk beta). The monthly sample is 01/1996-02/2015.

Panel (b) presents quintile portfolios formed every month by sorting individual hedge funds on their past 24-month financial intermediaries’ risk exposure. The sample goes from 01/1996 to 01/2015. Quintile 1 is the portfolio of hedge funds with the lowest β_η and quintile 5 is the portfolio of hedge funds with the highest β_η . For each quintile portfolio, we report the average 24-month Fung and Hsieh 7 factors plus liquidity risk alpha.

To summarize, there is evidence of pricing for the whole sample of individual risk adjusted returns taking into account liquidity risk, showing the robustness of our past results. Of the five strategies identified as having a positive risk price without taking into account liquidity risk, only Long Short Equity do not exhibit statistically positive slopes in the cross-sectional regressions after the inclusion of liquidity. The only strategy presenting negative pricing was the only one having negative pricing without including liquidity risk. When we include liquidity risk in the set of risk factors, we decrease the magnitude of the effect of financial intermediaries risk without canceling it. It seems as if financial intermediaries risk encompasses market liquidity risk in a more global risk factor.

3.9 Appendix B : Financial intermediaries' risk and emerging markets

Do our results are driven by the existence of another omitted risk factor that is partially correlated with financial intermediaries' risk? To answer this question, after the examination of the interaction between liquidity and financial intermediaries' risk, we look at emerging market risk. Caglayan and Ulutas (2014) show that hedge funds are exposed to emerging markets and therefore it might be useful to include it as a risk factor. To control for emerging markets' risk, we use the MSCI Emerging Market index monthly returns as a supplementary risk factor.

We first analyze the impact of introducing emerging markets' risk on our results for indices. We then investigate its potential relevance for the relation between financial intermediaries' risk and individual hedge fund risk-adjusted returns.

3.9.1 Financial intermediaries' risk, emerging markets and index returns

In this subsection, we want to investigate if the inter-style pricing of financial intermediaries' risk is robust to taking into account emerging market risk. We first look at the correlation between the two factors. For the period January 1994 - February 2015, we have a strong correlation of 0.55. Over the period, they present similar monthly average of 0.35% for financial intermediaries' risk and 0.38% for emerging markets. Similarly, they present close volatilities of 6.77% and 6.7%. However, the two factors differ strongly over kurtosis, with financial intermediaries' risk having a high kurtosis of 8.22 while the emerging market risk factor has a relatively lower kurtosis of 4.92.

Does the introduction of this highly correlated factor invalidates our previous results? To check this, we run two Fama and McBeth (1973) two-stage regressions. These regressions are the same as in the Appendix A, with the difference that we change the liquidity factor to be our emerging market factor.

Table 3.14 shows the results for both Fama and McBeth regressions with emerging market risk. The multivariate Fama and McBeth regression of average returns on Fung and Hsieh seven factors augmented with emerging market risk gives a positive and statistically significant price of financial intermediaries risk. This slope is of 4.16% with associated Newey-West and generalized method-of-moments of 2.3866 and 2.0967 respectively. The only other statistically significantly priced factor with generalized method-of-moments t-statistics is the emerging market risk factor. With Newey-West standard errors, the only statistically significant factor is the financial intermediaries' risk, showing its importance. Furthermore, it is important to note its economic significance : it has a 4.16% monthly risk price whereas the emerging market risk factor only has a 0.14% coefficient, and both factors have similar averages and standard deviations and are therefore comparable.

Results for the second cross-sectional regression of risk-adjusted return with respect to exposure on financial intermediaries' risk exposure show again that financial intermediaries' risk is priced. There is a positive and sta-

tistically significant slope of 0.46%. The intercept is exactly the same as those for risk-adjusted returns estimated with Fung and Hsieh seven factors returns.

As a summary, our results show that the pricing of financial intermediaries' risk at the index level is robust to the inclusion of emerging market risk, a popular risk factor in the hedge fund literature.

3.9.2 Individual hedge fund pricing with emerging markets factor

While our results are robust at the inter-style level, does our financial intermediaries' risk factor price risk-adjusted returns at the individual hedge fund level when we take into account emerging markets' risk? This subsection will answer this question using both parametric and non-parametric tests.

Individual hedge fund portfolios

Our non-parametric test consist of forming monthly quintile portfolios of hedge funds sorted with respect to their past two years rolling financial intermediaries' risk beta. This exposure is computed using a univariate regression of a fund's monthly returns on the financial intermediaries' risk factor, excluding funds having missing observations over the window of 24 months. We then get the risk -adjusted returns with regressions of individual funds' returns on the Fung and Hsieh seven factors and the emerging factor. We repeat the procedure for the period January 1996 to February 2015.

Table 3.15 panel (b) shows the results for the quintile portfolios' risk-adjusted returns. For the whole sample of individual funds, there is a negative but statistically non significant spread of -0.02% per month. Interestingly, the only strategy having a positive and strongly statistically significant intra-style risk price for financial intermediaries' risk is Emerging Markets. While we could suspect that this strategy is the most exposed to the emerging markets' risk factor, it is the one having its risk-adjusted returns explained the best by financial intermediaries' risk exposure. Four strategies exhibit now negative and statistically significant risk-adjusted returns spreads : Dedicated Short, Global Macro, Fixed Income and Multi-Strategy.

Globally, our results for individual hedge funds' risk-adjusted portfolio returns show a lack of robustness when we include emerging market risk, a factor highly correlated with financial intermediaries' risk, as a risk control. Including this risk factor, which is both correlated with the equity market risk factor and financial intermediaries' risk, mechanically decreases the price of risk of financial intermediaries exposures.

Fama and MacBeth cross-sectional regressions

To test the pricing of financial intermediaries' risk at the individual level for risk-adjusted returns taking into account emerging markets' risk, we first compute time-series of univariate financial intermediaries' risk exposures over a fixed two-year window with regression (3.13). Next, we estimate risk-adjusted returns as in equation (3.14) but we add emerging markets' risk as a supplementary factor. We finally get the time-series of cross-sectional estimates using Fama and McBeth regressions of the risk-adjusted returns on the factors' exposures.

Time-series' average estimates and their t-statistics over the period January 1996 - February 2015 are presented in Table 3.15 panel (a). Globally, there is no evidence of pricing with an average slope coefficient of -0.01% with an associated t-statistic of -1.3384. Two strategies, Emerging Markets and Event-Driven, show a positive

and statistically significant risk price while two other strategies, Global Macro and Fixed-Income, exhibit negative average slopes for financial intermediaries' risk.

	$E[R_i]$	α_i
Intercept	0.52	0.44
t_{NW}	(10.1594)***	(15.5666)***
t_{GMM}	(10.01)***	(15.932)***
λ_η	4.16	0.46
t_{NW}	(2.3866)**	(3.0679)***
t_{GMM}	(2.0967)**	(3.2367)***
λ_{PTFSBD}	4.42	
t_{NW}	(0.6857)	
t_{GMM}	(0.6381)	
λ_{PTFSFX}	2.75	
t_{NW}	(0.4426)	
t_{GMM}	(0.2679)	
$\lambda_{PTFSCOM}$	-3.16	
t_{NW}	(-0.5584)	
t_{GMM}	(-0.5238)	
λ_{SP500}	-2.05	
t_{NW}	(-0.6809)	
t_{GMM}	(-0.1102)	
λ_{Size}	0.74	
t_{NW}	(0.6043)	
t_{GMM}	(0.2935)	
λ_{Bond}	3.87	
t_{NW}	(0.0568)	
t_{GMM}	(0.2978)	
λ_{Credit}	0.86	
t_{NW}	(0.1545)	
t_{GMM}	(0.1282)	
$\lambda_{Emerging}$	0.14	
t_{NW}	(0.672)	
t_{GMM}	(2.696)**	
R^2	62.58	17.84
MAPE	0.39	0.18
nb indices		24
nb months		312

TABLE 3.14 – **Fama-McBeth regressions for hedge fund indices with emerging markets' risk**

Risk prices estimates for the financial intermediaries' risk factor and Fung and Hsieh seven factors plus emerging markets' risk. The financial intermediaries' risk factor is defined as the ratio of total market equity to total market assets (book debt and market equity) of primary dealer holding companies. Risk prices are the mean slopes of monthly cross-sectional regressions of hedge fund indices' returns on exposures to each factor, estimated with equations (3.6) et (3.8). These exposures are estimated in a first-stage time-series regression as in equations (3.5) et (3.7). The monthly sample is 01/1994-02/2015. R^2 is the adjusted coefficient of determination in percentage. Generalized- methods-of-moments t_{GMM} and Newey-West t_{NW} t-statistics in parentheses adjust for cross-asset correlation in the residuals and for estimation error of the time-series betas. The mean absolute pricing error $MAPE = \frac{1}{24} \sum_{i=1}^{24} |\hat{y}_i - y_i|$ measures the average magnitude of the pricing errors in percentage.

TABLE 3.15 – Rolling-window relation between risk-adjusted returns and financial intermediaries' risk exposure

	all	convertible-arbitrage	dedicated short	emerging	macro	equity MN	event-driven	fixed-income	LS equity	multi-strat
Intercept	0.82 (26.5461)***	0.74 (23.8885)***	0.25 (5.87)***	0.75 (19.0896)***	0.72 (30.8429)***	0.7 (24.0998)***	0.72 (30.37)***	0.74 (34.2)***	0.81 (14.76)***	0.75 (28.8097)***
λ_η	-0.01 (-1.3384)	0 (0.0157)	0.18 (1.0792)	0.37 (3.3349)***	-0.58 (-3.9987)***	-0.18 (-0.9357)	0.53 (4.5694)***	-1.16 (-5.8641)***	0.1857 (1.296)	0.02 (0.2436)

(a) **Rolling-window Fama-McBeth cross-sectional regressions of individual hedge fund Fung and Hsieh 7 factors alphas on financial intermediaries' risk betas**

	all	convertible-arbitrage	dedicated short	emerging	macro	equity MN	event-driven	fixed-income	LS equity	multi-strat
Low β_η	0.86 (24.4092)***	0.65 (11.8238)***	0.69 (6.2463)***	0.91 (21.2245)***	0.96 (19.1841)***	0.79 (13.3056)***	0.8 (30.4909)***	0.84 (19.9414)***	0.98 (17.8877)***	0.88 (30.2593)***
2 β_η	0.74 (30.7352)***	0.48 (9.3209)***	0.46 (5.0171)***	0.77 (20.2154)***	0.67 (27.9119)***	0.58 (21.6107)***	0.68 (29.0927)***	0.75 (28.2073)***	0.91 (19.5341)***	0.72 (27.0893)***
3 β_η	0.76 (21.5413)***	0.63 (19.9724)***	-0.15 (-1.7797)*	0.71 (15.1086)***	0.69 (24.5787)***	0.65 (29.3896)***	0.71 (25.4156)***	0.77 (34.9879)***	0.9 (16.1594)***	0.63 (25.2226)***
4 β_η	0.83 (17.2709)***	0.61 (19.2811)***	0 (0.0375)	0.85 (16.6121)***	0.65 (24.0086)***	0.75 (16.7046)***	0.74 (22.7668)***	0.68 (27.5934)***	0.88 (14.9421)***	0.76 (21.3276)***
High β_η	0.84 (14.353)***	0.74 (17.4634)***	-0.28 (7.2836)***	1.157 (14.1795)***	0.57 (17.4479)***	0.8 (11.2082)***	0.86 (18.8275)***	0.5 (13.4878)***	0.84 (11.346)***	0.74 (14.9675)***
High β_η - Low β_η	-0.02 (-0.3612)	0.09 (1.7666)*	-0.28 (-2.2022)**	0.24 (3.095)***	-0.39 (-5.349)***	0.01 (0.2039)	0.05 (1.5515)	-0.34 (-6.1208)***	-0.13 (-1.87)*	-0.14 (-2.8776)***

(b) **Rolling-window quintile portfolios of hedge funds Fung and Hsieh's 7-factors alphas sorted by financial intermediaries' risk beta**

Panel (a) presents cross-sectional estimates of hedge fund Fung and Hsieh 7 factors plus emerging markets' risk alpha on the financial intermediaries' risk beta. Financial intermediaries' risk is defined as the ratio of total market equity to total market assets (book debt and market equity) of primary dealer holding companies. λ_η is the mean slope of monthly cross-sectional regression of hedge fund indices' returns on exposures to the financial intermediaries' risk factor. The exposures are estimated in a first-stage time-series regression (a regression with the Fung and Hsieh 7 factors plus emerging markets' risk for the alpha and separately a single factor model for the financial intermediaries' risk beta). The monthly sample is 01/1996-02/2015.

Panel (b) presents quintile portfolios formed every month by sorting individual hedge funds on their past 24-month financial intermediaries' risk exposure. The sample goes from 01/1996 to 01/2015. Quintile 1 is the portfolio of hedge funds with the lowest β_η and quintile 5 is the portfolio of hedge funds with the highest β_η . For each quintile portfolio, we report the average 24-month Fung and Hsieh 7 factors plus emerging market risk alpha.

Conclusion

Mes travaux de thèse s'intéressent à la mesure de la performance des *hedge funds*. Ces derniers ont connu une forte croissance de leurs actifs sous gestion ces dernières décennies et étaient considérés comme étant très peu corrélés avec les classes d'actifs traditionnelles avant la crise financière de 2008. Celle-ci a révélé qu'une grande partie de ce que les investisseurs considéraient auparavant comme de l'*alpha*, c'est-à-dire de la performance absolue, était en réalité un ensemble d'expositions à des facteurs de risques "exotiques", différents de ceux traditionnellement employés par les investisseurs. Les outils de mesure de performance étaient inadaptés et/ou incomplets, et cette thèse s'efforce d'apporter sa pierre à l'édifice d'une meilleure compréhension des rendements de ces véhicules d'investissement alternatifs, source de controverses parmi les investisseurs. Le fait même que ces derniers aient été surpris par les larges pertes de leurs portefeuilles de *hedge funds* lors de la crise de 2008 démontre l'intérêt de ces travaux tant pour les gérants d'actifs que pour les investisseurs individuels. La prise de conscience du caractère volatil des rendements des *hedge funds* a conduit au développement de solutions passives cherchant à les répliquer. Les rendements décevants de ces réplifications mettent en exergue la nécessité de comprendre les sources de la performance et du risque des *hedge funds* en identifiant notamment les facteurs de risques systématiques auxquels leurs stratégies d'investissement complexes les exposent.

Le premier chapitre démontre, au moyen de méthodes paramétriques et non-paramétriques, qu'une partie non-négligeable de la surperformance des *hedge funds* par rapport aux modèles à facteurs provient de biais statistiques engendrés par la présence d'autocorrélation dans les rendements des *hedge funds*. Bien que ce phénomène statistique soit documenté depuis longtemps dans cette industrie, aucune étude n'avait à ma connaissance quantifié l'impact engendré sur les mesures de performance absolues. En réduisant la surperformance des *hedge funds*, la prise en compte de l'autocorrélation montre bien que les *hedge funds* sont mieux expliqués par les modèles à facteurs existants que précédemment envisagé. Le fait que l'autocorrélation diminue également les mesures des expositions aux facteurs appuie ce point et ouvre la voie à une meilleure attribution de la performance des fonds. Ce premier chapitre a été co-écrit avec mes superviseurs de thèse Gaëlle Le Fol et Serge Darolles.

Après avoir démontré l'impact de l'autocorrélation dans les rendements des *hedge funds* sur la mesure de la performance, le deuxième chapitre s'intéresse à ses sources. En effet, la littérature avance deux grandes hypothèses pour expliquer les niveaux anormalement élevés de l'autocorrélation dans les rendements des *hedge funds* par rapport aux classes d'actifs plus classiques : la présence d'illiquidité dans le portefeuille d'actifs sous-jacents ou le lissage intentionnel de la part du gérant du fonds. Connaître la nature de l'autocorrélation des rendements d'un fonds est ainsi intéressant, car dans le premier cas cela signale un facteur de risque de liquidité omis dans l'analyse de performance tandis que dans le second l'investisseur fait face à un risque opérationnel. La méthodologie empirique de ce chapitre part d'une intuition simple : si l'autocorrélation provient de l'illiquidité du portefeuille sous-jacent, alors les fonds ayant des rendements plus autocorrélés devraient avoir de plus fortes expositions au risque de liquidité. Cette intuition n'est cependant pas validée sur le plan empirique, avec une

relation non-linéaire entre autocorrélation et risque de crédit et une absence de prime de risque associée, contredisant les prémisses d'articles académiques récents tels que Kruttli, Patton et Ramadorai (2015).

Ce chapitre a des implications directes pour les investisseurs *hedge funds*. Il démontre que l'autocorrélation dans les rendements des *hedge funds* provient en grande partie du lissage et non principalement de l'illiquidité du portefeuille sous-jacent, ce qui indique que les conflits d'agence entre gérants de fonds et investisseurs sont beaucoup plus prononcés que ce qui a pu être envisagé auparavant. Ce chapitre appelle à un plus grand contrôle du comportement des gérants de *hedge funds* de la part des investisseurs et des régulateurs. Ce deuxième chapitre a également été co-écrit avec mes superviseurs de thèse Gaëlle Le Fol et Serge Darolles.

Toujours en conservant une approche de mesure de performance et des risques, le troisième chapitre s'interroge sur le risque posé par l'interaction fréquente des *hedge funds* avec des intermédiaires financiers. Ce chapitre part également d'une idée simple, selon laquelle quelle que soit la nature de la stratégie employée par un *hedge fund*, elle va se retrouver confrontée à un risque plus ou moins fort de "limite à l'arbitrage" tel que théorisé par Shleifer et Vishny (1997). Il teste donc l'existence d'une prime de risque de capital des intermédiaires financiers dans la coupe transversale des rendements des *hedge funds*. Les résultats empiriques sont unanimes et démontrent l'existence d'une telle prime de risque, expliquant une portion significative de la variation des rendements des *hedge funds* en coupe transversale. Ils montrent les difficultés que doivent surmonter les produits cherchant à répliquer les rendements des *hedge funds* du fait du caractère non "investissable" de cette prime de risque : il n'existe pas de produit permettant de s'exposer directement sur ce risque de capital des intermédiaires financiers.

Pour résumer, mes travaux de thèse s'attachent à démystifier les *hedge funds* et la source de leurs rendements. Une telle entreprise me semble d'autant plus importante que cette classe d'actifs fait l'objet d'un fort débat, avec un scepticisme de plus en plus marqué vis-à-vis de ce type d'investissement malgré l'augmentation des actifs gérés. Ainsi, mes travaux cherchent désormais à expliquer les déterminants des flux de capitaux des investisseurs et la distribution des actifs sous gestion au sein de l'industrie des *hedge funds*.

Résumé

Les hedge funds ont connu une croissance rapide de leurs actifs sous gestion. Cependant, leur mauvaise performance durant la crise financière de 2008 et ces dernières années a remis en question le caractère absolu de leurs rendements.

Mes travaux de thèse visent à expliciter les sources de la performance mesurée des hedge funds.

Le premier chapitre démontre un lien positif entre le degré d'autocorrélation dans les rendements des hedge funds et leur surperformance. Conformément à l'hypothèse d'un biais dans les estimateurs, les fonds les plus autocorrélés ont également les plus faibles expositions mesurées aux facteurs de risques

Le chapitre deux montre que l'autocorrélation dans les rendements des hedge funds ne provient que très partiellement de problèmes de liquidité, et donc que le lissage des rendements par les gérants de fonds est très prégnant.

Enfin, le troisième chapitre met en évidence que le risque de capital sur les intermédiaires financiers est un nouveau facteur de risque expliquant fortement la coupe transversale des rendements des hedge funds. Une partie de l'alpha provient en fait d'une prime de risque pour l'exposition à ce facteur.

Mots Clés

Hedge funds, mesure de performance, liquidité, modèles à facteurs, autocorrélation, économétrie, prime de risque, limites à l'arbitrage

Abstract

The hedge fund industry experienced a fast growth of its assets under management. However, its poor performance during the 2008 financial crisis and the recent years questioned the absolute character of hedge fund returns.

My thesis work aims to explicit the sources of the measured performance of hedge funds.

The first chapter demonstrates a positive link between the magnitude of serial correlation in hedge funds returns and their outperformance. In accordance with the hypothesis of a bias in the estimates, the most serially correlated funds also have the lowest measured risk exposures.

The second chapter shows that serial correlation in hedge fund returns comes only really partially from liquidity issues, and so returns smoothing by fund managers is pervasive.

Finally, the third chapter highlights that the risk on the capital of financial intermediaries is a new risk factor strongly explaining the cross-section of hedge fund returns. A portion of the alpha comes in fact from a risk premia for bearing an exposure to this factor.

Keywords

Hedge funds, performance measurement, liquidity, multiple factors models, serial-correlation, econometrics, risk premium, limits to arbitrage

