Three essays on informational feedback from stock prices to corporate decisions

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Abstract

In my doctoral thesis, I investigate the information feedback from stock prices to managers' decisions. More specifically, I study whether and how managers learn new information from stock prices to guide their corporate decisions. My doctoral thesis includes three essays focusing on this topic. The first essay studies the relationship between stock market informational efficiency and real economy efficiency at firm-level. In the first essay, I find that when stock prices reflect a greater amount of information that managers care about, corporate decisions made by managers become more efficient. The second essay studies whether managers seek to learn short sellers' information from stock prices and use it in corporate decisions. In the second essay, I overcome the empirical difficulties by exploiting a unique institutional feature in Hong Kong stock market that only stocks included in an official list are allowed for short sales. I find that that non-shortable firms' managers learn short sellers' information on external conditions from shortable peers' stock prices and use it in their corporate decisions. The third essay studies the real effects of long-term option trading. I find that long-term option trading stimulates the production of long-term information, which managers can use to guide their long-term investment decisions.

Résumé

Ce travail doctoral étudie l'effet « retour » de l'information financière liée aux prix des actions sur les décisions des dirigeants d'entreprise. Plus précisément, j'étudie si et comment les gestionnaires apprennent effectivement de nouvelles informations contenues dans les prix des actions pour guider leurs décisions d'entreprise. Cette thèse est composée de trois essais, abordant chacun un aspect différent de ce même sujet. Le premier essai étudie le lien entre l'efficacité informationnelle du marché d'actions et le niveau d'efficacité économique réelle de l'entreprise. Dans le premier essai, je montre que lorsque les prix des actions agrègent une quantité d'informations utile plus grande, les décisions d'entreprise prises par les gestionnaires devraient être encore plus efficaces. Le deuxième essai étudie si les gestionnaires cherchent à apprendre les informations utilisées par les vendeurs à découvert. L'étude des prix des actions en présence de vendeurs à découvert est-il utile pour les décisions de l'entreprise ? Dans le deuxième essai, j'ai surmonté les difficultés empiriques en exploitant une caractéristique institutionnelle du le marché des actions de Hong Kong. Je constate que les gestionnaires des entreprises « non-shortable » peuvent tirer profit des informations des vendeurs à découvert sur les conditions économiques sectorielles par l'intermédiaire des prix des actions d'autres entreprises « shortable » dans la même industrie et qu'ils les utilisent dans leurs décisions d'entreprise. Le troisième essai étudie les effets réels de la négociation d'options à long terme. Dans le troisième essai, je constate que l'introduction d'une catégorie spécifique d'options à long terme stimule la production d'informations privées à long terme et donc entraîne une augmentation de l'informativité des prix sur les fondamentaux à long terme des entreprises. Par conséquent, les dirigeants peuvent extraire davantage d'informations du prix de l'action pour guider leurs décisions d'investissement à long terme.

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To my parents.

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Résumé en Français

La recherche en Finance est fondée sur le paradigme souvent accepté que les prix des actions sont des signaux utiles pour l'allocation des ressources. Ils contribuent à des décisions efficaces de production et d'investissement (Fama et Miller, 1972). Dans un article récent, Bond, Edmans et Goldstein (2012) soutiennent que les dirigeants d'entreprise peuvent se servir utilement des informations contenues dans les prix des actions lorsqu'ils prennent des décisions managériales. Il en est ainsi parce que les prix des actions agrégent de très nombreuses informations provenant de divers investisseurs ; les prix peuvent alors incorporer des informations qui sont nouvelles pour les gestionnaires. La littérature a apporté un certain nombre de preuves empiriques allant dans le sens de l'hypothèse d'un apprentissage de la part des gestionnaires : ceux-ci saisissant les informations contenues dans prix de l'action et les utilisent pour prendre des décisions d'investissement (Chen, Goldstein et Jiang, 2007), les décisions de fusion et d'acquisition (Luo, 2005), et les décisions de placement de trésorerie (Fresard, 2012). Par conséquent, étudier comment l'information est agrégée dans les prix des actions et comment elle est transmise aux dirigeants peut aider à comprendre et à identifier le rôle joué par les prix des actions dans l'activité économique réelle.

Ce travail doctoral étudie l'effet « retour » de l'information financière liée aux prix des actions sur les décisions des dirigeants d'entreprise. Plus précisément, j'étudie si et comment les gestionnaires apprennent effectivement des nouvelles informations contenues dans les prix des actions pour guider leurs décisions d'entreprise. Ma thèse de doctorat est composée de trois essais, chacun abordant un aspect différent de ce même sujet.

Le premier essai est intitulé « L'informativité des prix et la sous-optimalité des choix managériaux dans l'entreprise » ("Stock price informativeness and managerial inefficiency").

Cet essai étudie le lien entre l'efficacité informationnelle du marché d'actions et le niveau d'efficacité économique réelle de l'entreprise.

L'idée généralement admise est que l'efficience du marché d'actions favorise l'efficacité de l'économie réelle. Cette thèse a été validée empiriquement au niveau des secteurs industriel par Durnev, Morck et Yeung (2004) et au niveau des pays par Wurgler (2000). On peut donc s'attendre à ce que, au niveau de l'entreprise, lorsque les prix de l'action agrègent une plus grande quantité d'informations, l'efficacité économique de l'entreprise devrait etre plus elevée. Cela n'est vrai que si on peut montrer que les prix des actions influent sur les décisions réelles des gestionnaires au niveau individuel de chaque entreprise. Les résultats des études récentes montrent effectivement que les gestionnaires tiennent compte de l'information spécifique contenue dans les prix des actions lorsqu'ils prennent des décisions d'entreprise. Il existe donc un mécanisme qui fait que le marché des actions peut affecter activement l'activité économique réelle à partir du rôle informationnel des prix des actions. Par conséquent, je pose l'hypothèse que lorsque les prix des actions agrègent une quantité d'informations utile plus grande, les décisions d'entreprise prises par les gestionnaires devraient être encore plus efficaces.

Dans le premier essai, j'examine empiriquement le lien entre l'informativité des prix et l'inefficience managériale. Ma principale mesure de l'informativité des prix est la probabilité de négociation informée (probability of informed trading, PIN), qui est dérivée d'un modèle de microstructure de marché développé par Easley et al. (1996). La mesure PIN est calculée comme étant le rapport entre les flux d'ordres informés estimés et les flux d'ordres totaux sur le marché. Ainsi, un PIN plus élevé indique que les prix de l'action contiennent relativement plus d'informations de sources privées et sont donc plus informatifs.

Un des principaux défis est de savoir comment quantifier l'inefficience managériale dans la prise de décisions d'entreprise. Dans le premier essai, je mesure le degré d'inefficacité managériale par la sous-évaluation de l'entreprise. Ce déficit correspond à une sous-optimalité des choix de l'entreprise. L'inefficience managériale est calculeé comme l'écart entre la valeur réelle des entreprises observée sur le marché et leur valeur « frontière », qui est la valeur maximale hypothétique des entreprises en l'absence de problème d'inefficience managériale. L'intuition est que si les gestionnaires répondent aux opportunités de croissance des entreprises en prenant les décisions optimales, leurs entreprises devraient atteindre la valeur-frontière. Sinon, l'inefficacité managériale dans la prise de décisions d'entreprise se traduit par des résultats sous-optimaux. Autrement dit, la valeur de l'entreprise est inférieure à la valeur frontière. Par conséquent, les pertes de la valeur de l'entreprise mesurent le degré d'inefficience managériale.

Dans le premier essai, en utilisant un échantillon d'entreprises aux États-Unis pour la période 1993-2010, je constate une relation négative entre la mesure PIN et les pertes de valeur de l'entreprise. Mes résultats montrent qu'une augmentation interquartile de la mesure PIN est associée à une diminution des pertes de la valeur de l'entreprise de 0,045, ce qui équivaut à une amélioration moyenne de 2,28% de la valeur de l'entreprise. En outre, j'étudie la relation entre la mesure PIN et la performance opérationnelle des entreprises. Les résultats indiquent que la mesure PIN est aussi négativement liée à la sous-performance opérationnelle des entreprises. Ces résultats concordent avec l'hypothèse selon laquelle l'informativité des prix peut réduire l'inefficience managériale dans la prise de décisions d'entreprise. Je montre également que la relation négative entre la mesure PIN et les pertes de valeur managériale reste inchangée lorsque on contrôle les problèmes d'endogénéité potentielle, ou lorsque j'utilise des mesures alternatives de l'informativité des prix et de l'inefficience managériale. En procédant à divers tests de robustesse, nous confirmons que l'informativité des prix de l’action contribue à réduire l'inefficience managériale.

Les mécanismes théoriques de cette relation sont ensuite explorés. Bond, Edmans et Goldstein (2012) discutent des effets réels des prix de l’action sur des décisions d'entreprise. Ils soutiennent que les prix de l'action peuvent influer sur les décisions réelles des gestionnaires par deux voies différentes : l'hypothèse de l'apprentissage (learning hypothesis) et l'hypothèse de contractualisation (contracting hypothesis). L'hypothèse de l'apprentissage suppose que les gestionnaires ne disposent pas d'information parfaite pour les décisions d'entreprise, alors que les investisseurs peuvent avoir des informations supplémentaires utiles aux gestionnaires. Donc, les gestionnaires apprennent des informations nouvelles auprès des investisseurs par l'intermédiaire des prix de l’action et les utilisent pour guider les décisions de l'entreprise. Dans ce cas, les prix de l'action influent sur les décisions d'entreprise en révélant des informations nouvelles aux gestionnaires ignorées jusqu’alors par eux. Deuxièmement, l'hypothèse de contractualisation suppose que les gestionnaires se soucient des prix de l'action parce que leur rémunération est contractuellement associée au prix de l'action de l’entreprise, qui reflète leurs décisions passées. L'augmentation de l'informativité des prix accroit les incitations des gestionnaires à prendre des décisions qui améliorent la valeur de l'entreprise et conduisent à un moindre degré d'inefficacité managériale. Dans ce cas, les prix de l'action influent sur des décisions d'entreprise en reflétant l'information sur les décisions passées des gestionnaires.

En examinant la variation en coupe transversale de l'effet de la mesure PIN sur les pertes de valeur de l'entreprise, il est montré que l'effet négatif de la mesure PIN sur les déficits de valeur est plus prononcé pour les entreprises dont le résultat opérationnel est plus volatil et les dépenses de R&D plus intenses. Cette constatation est compatible avec l'hypothèse de l'apprentissage. Les tests menés conduisent également à des résultats empiriques compatibles avec l'hypothèse de contractualisation : l'effet de la mesure PIN sur les déficits de la valeur de l'entreprise est plus grand lorsque la sensibilité de la rémunération à la performance est plus élevée et lorsque les entreprises n’adoptent pas de mesures anti offre publique d'achat. Par conséquent, les résultats globaux suggèrent que l'effet négatif de l'informativité des prix de l'action sur l'inefficience managériale s'explique à la fois par l'hypothèse de l'apprentissage et par l'hypothèse de contractualisation.

Le premier essai contribue à la littérature de deux façons. Premièrement, des études antérieures ont apporté des preuves empiriques sur le lien entre l'efficacité informationnelle du marché d'actions et l'efficacité des choix économiques réels au niveau des secteurs industriels et au niveau des pays. Cet essai contribue à cette littérature en proposant un résultat empirique au niveau de l'entreprise. En outre, la méthodologie empirique mise en oeuvre peut être utilisée dans des recherches futures qui étudient le lien entre l'efficacité informationnelle du marché d'actions et l'optimalité réelle des choix économiques au niveau de l'entreprise. Deuxièmement, cet essai contribue à la littérature croissante sur l'hypothèse d'apprentissage en mettant en évidence l'intérêt pour les dirigeants d'utiliser l'information pertinente dans les prix des actions. Cet essai fournit des preuves directes pour l'argument selon lequel rechercher les informations dans les prix des actions améliore l'efficacité des décisions de l'entreprise.

Le deuxième essai est intitulé « Les dirigeants peuvent-il apprendre des vendeurs à découvert sur les marchés boursiers ? » ("Do managers learn from short sellers?"). Cet essai étudie si les gestionnaires cherchent à apprendre des informations utilisées par les vendeurs à découvert. L'étude des prix des actions en présence de vendeurs à découvert est-elle utile pour les décisions de l'entreprise ?

Bien qu'un grand nombre d'études démontrent que les gestionnaires appréhendent les informations utiles contenues dans prix de l'action, peu d'attention a été accordée à la source privée d'où provient cette information pertinente : qui possède l'information inconnue *ex ante* aux gestionnaires et qui intervient en bourse sur la base de cette information ? Dans le deuxième essai, j'essaie de combler cette lacune en examinant si les gestionnaires cherchent à apprendre des informations des vendeurs à découvert par l'intermédiaire des prix de l'action et les utilisent pour les décisions de l'entreprise.

Dans la littérature financière, les vendeurs à découvert sont souvent considérés comme des investisseurs sophistiqués ayant des informations privées. Les résultats des études récentes montrent que les vendeurs à découvert peuvent avoir des informations privées qui sont inconnues *ex ante* des gestionnaires. Par conséquent, lorsque les vendeurs à découvert sont actifs sur le marché, les prix des actions sont susceptibles d'intégrer l'information des vendeurs à découvert qui sont inconnues *ex ante* des gestionnaires. Ces gestionnaires peuvent donc être incités à apprendre des informations des vendeurs à découvert par l'intermédiaire des prix des actions et utiliser ces informations pour les décisions de l'entreprise.

Il est difficile d'identifier empiriquement si les gestionnaires apprennent des informations des vendeurs à découvert en regardant les prix des actions pour deux raisons. Premièrement, il n'existe pas de proxy empirique pour mesurer l'information contenue dans les prix de l'action provenant des vendeurs à découvert. Deuxièmement, les activités des vendeurs à découvert peuvent affecter simultanément le prix de l'action et les décisions de l'entreprise par d'autres voies.

Dans le deuxième essai, j'ai surmonté ces difficultés empiriques en exploitant une caractéristique institutionnelle unique du marché des actions de Hong Kong. La règlementation impose que seules les actions incluses dans une liste officielle spécifique sont admises pour les ventes à découvert. À l'aide de cette caractéristique institutionnelle, j'étudie si les gestionnaires apprennent des vendeurs à découvert en examinant si les choix d'investissement des entreprises qui ne sont pas autorisées pour les ventes à découvert (“entreprises non-shortable”) sont influencés par les prix des actions d'autres entreprises du même secteur qui sont admises à la vente à découvert (“entreprises shortable”). Cette stratégie empirique me permet d'identifier les informations des vendeurs à découvert et de distinguer les effets de l’activité des vendeurs à découvert sur les décisions d'entreprise causées par d'autres voies. Je pose l'hypothèse que les gestionnaires des entreprises « non-shortable » peuvent tirer profit des informations des vendeurs à découvert sur les conditions économiques sectorielles par l'intermédiaire des prix des actions d'autres entreprises « shortable » dans la même industrie et les utilisent dans leurs décisions d'entreprise. Par conséquent, il s’agit de vérifier si les décisions d'investissement des entreprises « non-shortable » sont sensibles au prix de l’action d'autres entreprises « shortable » qui sont dans la même industrie.

En utilisant un échantillon d'entreprises de Hong Kong pour la période 2002-2013, je constate que l'investissement des entreprises « non-shortable » est positivement et significativement lié aux prix des actions des autres entreprises « shortable » qui sont dans la même industrie celle-ci étant définie par le code SIC à deux chiffres. Cependant aucune relation n'est trouvée entre l'investissement des entreprises « non-shortable » et les prix des actions des autres entreprises qui sont également « non-shortable » dans la même industrie. Ces résultats suggèrent que les gestionnaires des entreprises « non-shortable » font attention aux prix des actions des entreprises « shortable » qui peuvent agréger les informations des vendeurs à découvert.

En termes d'importance économique, une diminution d'un écart type dans le prix de l’action des entreprises shortable est associée à une baisse de 10% du niveau d'investissement des entreprises non-shortable qui sont dans la même industrie. D'autres analyses confirment que les résultats obtenus ne sont pas déterminés par des caractéristiques de l'entreprise autres que l'autorisation de vente à découvert. Mes résultats sont aussi robustes à d'autres définitions du périmètre de l'industrie et à d'autres tests supplémentaires.

En outre, les résultats montrent également que la sensibilité de l'investissement des entreprises « non-shortable » aux prix des actions des autres entreprises « shortable » qui sont dans la même industrie, est plus prononcée dans les situations où les gestionnaires des entreprises « non-shortable » sont plus susceptibles d'apprendre une information pertinente des vendeurs à découvert par l'intermédiaire des prix des actions.

Conformément à cette prédiction, les analyses en coupe transversale montrent que l'investissement des entreprises « non-shortable » devient plus sensible aux prix des actions d'autres entreprises « shortable » qui sont dans la même industrie (1) lorsque les prix de l’action de leurs propres entreprises agrégent une faible quantité d'informations négatives et donc les gestionnaires sont davantage incité à apprendre des informations des vendeurs à découvert; (2) lorsque l'environnement d'information de leurs entreprises est plus faible (par exemple, moindre couverture des analystes financiers) et donc les gestionnaires sont moins susceptibles d'obtenir des informations négatives provenant d'autres sources; et (3) lorsque l'information négative est plus utile pour les décisions d'investissement des entreprises. Les résultats globaux sont compatibles avec l’hypothèse que les gestionnaires des entreprises « non-shortable » peuvent apprendre des informations des vendeurs à découvert par l'intermédiaire des prix des actions d'autres entreprises « shortable » qui sont dans la même industrie et les utilisent dans les décisions d'investissement.

Le deuxième essai contribue à la littérature de plusieurs façons. Premièrement, il contribue à une littérature récente sur l'effet d'apprentissage des gestionnaires en identifiant une source spécifique d'information apprise par les dirigeants via les prix des actions. Mes résultats suggèrent que les gestionnaires capturent les informations provenant des vendeurs à découvert par l'intermédiaire des prix de l'action et les utilisent dans les décisions d'investissement des entreprises. Deuxièmement, cet essai contribue également aux études sur l'avantage informationnel des vendeurs à découvert. Un grand nombre d'études a montré que les vendeurs à découvert ont accès à des informations privées qui sont peu connues des gestionnaires. Le deuxième essai suggère que les vendeurs à découvert possèdent des informations sur les conditions extérieures et l'environnement économique qui sont inconnues ou mal appréhendées par les dirigeants. Troisièmement, cet essai contribue à la littérature qui étudie les effets réels des activités de vente à découvert sur les décisions de l'entreprise. Les études antérieures portent généralement sur les effets des activités de vente à découvert sur les contraintes de financement des entreprises ou sur les incitations des gestionnaires. Cet essai diffère en montrant que les activités de vente à découvert peuvent affecter les décisions de l'entreprise par la voie de l'information, c'est-à-dire en transmettant les informations des vendeurs à découvert aux dirigeants par l'intermédiaire des prix des actions.

Le troisième essai est intitulé « Les effets réels de la négociation d'options à long terme » ("The real effects of long-term option trading"). Cet essai étudie si l'existence et la négociation d'options à long terme stimule la production d'informations spécifiquement à long terme que les dirigeants peuvent utiliser pour guider les décisions d'investissement à long terme.

Les résultats des études récentes ont montré que les gestionnaires peuvent tirer une information utile contenue dans les prix des actions et les utilisent pour guider leurs décisions. La raison vient de l'énorme quantité d'information collectée auprès des investisseurs qui est agrégée dans les prix des actions qui sont donc informés sur les fondamentaux de l'entreprise. Le rôle allocatif des prix des actions dépend de l'information recueillie et analysée par les investisseurs. Mais, en raison du coût élevé du traitement et de la collecte des informations privées à long terme et en raison de leur aversion au risque, les investisseurs sont plus susceptibles de recueillir des informations à court terme que des informations à long terme. Par conséquent, les prix des actions intègreront plus d'informations à court terme et moins d'informations à long terme, ce qui entraînera une réduction de l'informativité des prix sur les fondamentaux à long terme des entreprises. Donc, lorsque les gestionnaires prennent des décisions à long terme, le rôle informatif et allocatif des prix de l'action pourrait être plus limité.

Le troisième essai étudie si l'introduction d'options à long terme peut résoudre ce problème. Plus précisément, j'étudie si l'introduction d'une catégorie spécifique d'options à long terme stimule la production d'informations privées à long terme et donc entraîne une augmentation de l'informativité des prix sur les fondamentaux à long terme des entreprises. Si tel est le cas, les dirigeants peuvent extraire davantage d'informations du prix de l'action pour guider leurs décisions d'investissement à long terme.

Pour ce faire, j'étudie les options appelées "Long-term Equity AnticiPation Securities" (LEAPS). Semblables aux options régulières, les LEAPS sont des options standardisées de style américain cotées au Chicago Board Options Exchange (CBOE). Mais, contrairement aux options régulières qui expirent avec une maturité de moins d'un an, les LEAPS ont une durée d'échéance maximale de trois ans.

Des études antérieures ont montré que l'introduction d'options peut modifier les incitations des investisseurs à recueillir des informations privées et donc affecte l'efficacité informationnelle des prix de l'action sous-jacents. Cao (1999) montre que l'introduction d'actifs dérivés améliore les opportunités de négociation des investisseurs et augmente les incitations des investisseurs à recueillir des informations privées sur les actifs sous-jacents. Par conséquent, l'introduction d'actifs dérivés augmente la quantité d'informations recueillies et conduit à des prix plus informatifs des actifs sous-jacents. En outre, parce que l'effet de levier offert par les options réduit le coût des transactions pour les investisseurs informés, la négociation d'options peut augmenter l'efficience informationnelle des prix de l'action en stimulant la négociation informée. On pose l'hypothèse que la négociation de LEAPS stimule la production d'informations à long terme, et que les gestionnaires peuvent les utiliser pour guider les décisions d'investissement des entreprises à long terme.

Pour tester cette hypothèse, je mesure l'investissement des entreprises à long terme par l'investissement en recherche et développement (R&D). En utilisant un échantillon d'entreprises aux États-Unis pour la période 1999-2009, je montre que la sensibilité de l'investissement en R&D aux prix de l'action est plus élevée pour les entreprises avec LEAPS comparée aux autres entreprises. En termes d'importance économique, la sensibilité de l'investissement en R&D aux prix de l'action augmentera d'environ 80%, lorsqu'une entreprise dispose de LEAPS sur le marché de son action. Ce résultat est robuste pour divers sous-échantillons, y compris le sous-échantillon d'entreprises contrôlées pour la taille et le sous-échantillon d'entreprises ayant des dépenses de R&D non nulles. En outre, ce résultat maintenu après contrôle du biais de sélection potentielle et après contrôle pour d'autres sources d'informations concurrentes. De plus, je montre que l'effet de la négociation de LEAPS sur la sensibilité de l'investissement en R&D aux prix de l'action est plus prononcé dans les situations où la négociation de LEAPS sont plus susceptibles d'augmenter les incitations des investisseurs à recueillir des informations privées à long terme.

D'autres analyses complémentaires montrent que la négociation de LEAPS aide les gestionnaires à investir plus efficacement dans la R&D en atténuant le problème du sous-investissement. En outre, l'investissement en R&D induit par la négociation de LEAPS a un effet positif sur la performance opérationnelle et la croissance futures des entreprises. Les résultats globaux suggèrent que la négociation d'options à long terme peut avoir des effets réels en renforçant le rôle allocatif des prix de l'action.

Le troisième essai contribue à la littérature en étudiant empiriquement les effets réels de la négociation d'options à long terme. Mes résultats suggèrent que la négociation de dérivés peut affecter les décisions de l'entreprise par la voie de l'information, c'est-à-dire que la négociation de dérivés stimule la production d'informations qui sont nouvelles pour les gestionnaires et affecte les décisions de l'entreprise par un mécanisme d'apprentissage managérial.

Au total, la thèse présentée met en lumière le rôle allocatif des prix des actions en analysant la voie par laquelle les prix des actions révèlent des informations utile pour guider les décisions de l'entreprise. Ces travaux pourraient ouvrir sur de futures recherches. Nous identifions deux séries d'interrogations.

Tout d'abord, l'effet de retour d'information suppose que les prix des actions reflètent efficacement les informations fournies par les participants du marché. Donc les variations des prix des action révèlent des informations sur les chocs fondamentaux. Cependant, les variations des prix des actions pourraient être causées par des chocs non fondamentaux, par exemple, une pression sur les prix causée par les flux provenant de fonds communs de placement ou de gérants de portefeuille, ou encore une pression globale provenant du sentiment du marché. Par conséquent, les prix des actions pourraient être contaminés par un bruit. Il est important de comprendre comment le bruit qui affecte les prix observés des actions impacte la rétroaction de l'information des prix des actions vers les décisions de l'entreprise. Est-ce que les gestionnaires peuvent filtrer le bruit dans les prix de l'action lorsqu'ils utilisent les prix de l'action comme source d'information ? Sinon, est-ce que les gestionnaires sont trompés par le bruit dans les prix de l'action ? Si tel est la cas, le bruit dans les prix de l'action se transmet à l'activité économique réelle. Quelles en sont alors les conséquences ?

Par ailleurs, il est possible que les décisions de l'entreprises influent sur les incitations des investisseurs à recueillir de l'information privée et donc sur le niveau d'informativité des prix des actions. Par conséquent, le rôle informationnel des prix des actions pourrait être affecté (ou déterminé) par les décisions de l'entreprise, en particulier les décisions prises par les dirigeants en réponse aux nouvelles informations sur les prix des actions. Dans ce cas, si les gestionnaires ne sont pas disposés à changer les décisions de l'entreprise en réponse à l'information reflétée dans les prix des actions, les investisseurs sont moins susceptibles de recueillir de l'information privée qui soit utile aux gestionnaires. Cela conduit à un rôle allocatif plus limité des prix des actions. Il serait donc intéressant d'étudier comment l'informativité des prix des actions varie avec la volonté des gestionnaires d'apprendre des informations contenues dans les prix de l'action.

Introduction

A long standing view in finance research is that stock prices provide accurate signals for resource allocation, leading to efficient production and investment decisions (Fama and Miller, 1972). In a recent paper, Bond, Edmans and Goldstein (2012) argue that managers can learn information from stock prices when making corporate decisions. This is because stock prices aggregate many pieces of information from diverse investors, they may incorporate some information that is new to managers. Extant literature has documented empirical evidence that managers learn information from stock prices and use it to make investment decisions (Chen, Goldstein and Jiang, 2007), merger and acquisition decisions (Luo, 2005), and cash saving decisions (Fresard, 2012). Therefore, studying how information is aggregated into stock prices and further transmitted to managers can give a better understanding of the allocational role played by stock prices in real economic activates.

In my doctoral thesis, I investigate the information feedback from stock prices to managers' decisions. More specifically, I study whether and how managers learn new information from stock prices to guide their corporate decisions. My doctoral thesis includes three essays focusing on this topic.

The first essay is titled "**Stock Price Informativeness and Managerial Inefficiency**". This essay studies the relationship between stock market informational efficiency and real economy efficiency at firm-level.

It is widely believed that stock market efficiency promotes real economy efficiency. Empirical evidence of this view has been shown at industry level by Durnev, Morck and Yeung (2004) and at country level by Wurgler (2000). Thus, one may expect that, at firm level, when stock prices aggregate a greater amount of information, firms' real activities should become more efficient. This can occur only if stock prices affect managers' real decisions. Recent studies find that managers take into account the specific information contained in stock prices when they are making corporate decisions, hence stock market has an active role in affecting real economic activities through the informational role of stock prices. Therefore, I hypothesize that when stock prices reflect a greater amount of information that managers care about, corporate decisions made by managers should be more efficient.

In essay one, I investigate this prediction by empirically examine the relationship between stock price informativeness and managerial inefficiency. My main proxy for price informativeness is the probability of informed trading (PIN), which is derived from a market microstructure model developed by Easley et al. (1996). The PIN measure is computed as the ratio of estimated informed order flows to total order flows. Thus, higher PIN indicates that stock prices contain relatively more information from private sources and hence are more informative.

One main challenge is how to quantify managerial inefficiency in making corporate decisions. In essay one, I measure the degree of managerial inefficiency by firm value shortfalls. The firm value shortfalls are calculated as the deviation of firms' actual value from their frontier value, which is firms' hypothetical maximum value absent of managerial inefficiency problem. The intuition is that if managers respond to firms' growth opportunities by making efficient corporate decisions, their firms should reach the frontier value. Otherwise, managerial inefficiency in making corporate decisions will translate into sub-optimal outcomes. That is, firm value falling below the frontier value. Therefore, firm value shortfalls can be seen as a proxy for the level of managerial inefficiency.

In essay one, using a large sample of U.S. public firms over the period from 1993 to 2010, I find a negative relationship between PIN and firm value shortfalls. My results show that an interquartile increase in PIN is associated with a decrease in firm value shortfalls by 0.045, which is equivalent to an average improvement of 2.28% in firm value. In addition, I investigate the relationship between PIN and firms' operating performance. The results indicate that PIN is also negatively related to operating profitability shortfalls. These results are compatible with the expectation that price informativeness can reduce managerial inefficiency in making corporate decisions. Further analyses show that the negative relationship between PIN and firm value shortfalls is unchanged when I control for potential endogeneity issues, use alternative measures of both price informativeness and managerial inefficiency, and perform a variety of robustness tests. The overall evidence suggests that stock price informativeness affects managerial inefficiency.

I further explore possible explanations for this relationship. Bond, Edmans and Goldstein (2012) discuss the real effects of stock prices on managers' corporate decisions. They argue that stock prices can affect managers' real decisions through two different channels: learning hypothesis and contracting hypothesis. First, learning hypothesis assumes that managers do not possess perfect decision-relevant information while investors may have some incremental information that is useful to managers. Hence, managers learn new information from investors via stock prices and use it to guide corporate decisions. In this case, stock prices affect managers' corporate decisions by revealing information that is new to managers. Second, contracting hypothesis argues that managers care about stock prices because their contracts are tied to firms' stock prices, which reflect information about their past decisions. More informative stock prices increase managers' incentives to make value-enhancing decisions and lead to a lower level of managerial inefficiency. In this case, stock prices influence corporate decisions by reflecting information about managers' past decisions.

By examining the cross-sectional variation on the effect of PIN on firm value shortfalls, I show that the negative effect of PIN on firm value shortfalls is stronger for firms with more volatile operating income and more intensive R&D expenditures. This finding is consistent with learning hypothesis. Moreover, I also find empirical evidence consistent with contracting hypothesis: the effect of PIN on firm value shortfalls is greater when pay-for-performance sensitivity is higher and when firms adopt less takeover defenses. Therefore, the overall evidence suggests that the negative effect of stock price informativeness on managerial inefficiency appears to stem from the channels of learning hypothesis and contracting hypothesis.

Essay one contributes to the literature in two ways. First, prior studies have shown empirical evidence on the connection between stock market efficiency and real economy efficiency at industry level and country level. This essay contributes to this literature by providing evidence at firm level. Moreover, my empirical framework in this essay can be used in future studies that focus on firm level connection between stock market efficiency and real economic efficiency. Second, this essay adds to the growing literature on learning hypothesis by directly examining the real consequence of managerial learning. This essay provides direct evidence for the argument that managerial learning enhances the efficiency of corporate decisions.

The second essay is titled "**Do Managers Learn from Short Sellers?**". This essay studies whether managers seek to learn short sellers' information from stock prices and use it in corporate decisions.

While a large number of studies provide evidence that managers learn useful information from stock prices, little attention has been paid to the source of this information: who has the information that is *ex ante* unknown to managers and trade on it? In essay two, I try to fill this gap by examining whether managers seek to learn short sellers' information from stock prices and use it in corporate decisions.

Short sellers are often believed to be sophisticated investors with private information in finance literature. Recent studies argue that short sellers may have private information that is *ex ante* unknown to managers. Hence, when short sellers are active in the market, stock prices are likely to incorporate information from short sellers that is *ex ante* unknown to managers, thus managers may have incentives to learn short sellers' information from stock prices and use such information to make corporate decisions.

To empirically identify whether managers learn short sellers' information from stock prices is challenging due to two reasons. First, there is no natural empirical proxy for the information incorporated in stock prices from short sellers. Second, short selling activities can affect stock prices and managers' decisions simultaneously through channels other than the information channel.

In essay two, I overcome the empirical difficulties by exploiting a special institutional feature in Hong Kong stock market that only stocks included in an official list are allowed for short sales. Using this institutional feature, I study whether managers learn from short sellers by examining whether non-shortable firms' investment is influenced by the stock prices of their shortable peer firms in the same industry. This empirical strategy allows me to identify short sellers' information and to separate the effects of short selling activities on corporate decisions due to other channels. I hypothesize that non-shortable firms' managers can learn short sellers' information on external conditions from shortable peers' stock prices and use it in their corporate decisions. Hence, non-shortable firms' investment decisions are sensitive to their shortable peers' stock prices.

Using a sample of firms listed in Hong Kong market from 2002 to 2013, I find that non-shortable firms' investment is positively and significantly related to the stock prices of their shortable peers in the same two-digit SIC industry. However, such a relationship is not found between non-shortable firms' investment and the stock prices of their peers that are also non-shortable. These findings suggest that non-shortable firms' managers pay attention to the stock prices of shortable peers that may aggregate information from short sellers. In terms of economic significance, a one standard deviation decrease in the average stock prices of shortable peers is related to a decrease in non-shortable firms' average investment level by around 10%. Further analyses confirm that my findings are not driven by shortable peers' firm characteristics other than short-sale eligibility. This relationship is also robust to alternative peer definitions and to a variety of additional tests.

In addition, my hypothesis also predicts that non-shortable firms' investment sensitivity to shortable peers' stock prices becomes stronger in situations where non-shortable firms' managers are more likely to learn short sellers' information from stock prices. Consistent with this prediction, the cross-sectional analyses show that non-shortable firms' investment becomes more sensitive to shortable peers' stock prices (1) when their own firms' stock prices incorporate a smaller amount of negative information and therefore managers are more motivated to learn from shortable peers' stock prices; (2) when the information environment of these firms is poorer (e.g., lower analyst coverage) and thus their managers are less likely to obtain negative information from other sources; and (3) when negative information is more valuable for investment decisions. The overall evidence is consistent with my hypothesis that non-shortable firms' managers learn short sellers' information from shortable peers' stock prices and use it in investment decisions.

Essay two contributes to the literature in several ways. First, it contributes to a recent literature on managerial learning by identifying a specific source of information learned by managers from stock prices. My findings suggest that managers learn short sellers' information from stock prices and use it in corporate investment decisions. Second, this essay also relates to the studies on the information advantage of short sellers. A large body of literature has shown that short sellers have access to private information that is known to managers. Essay two suggests that short sellers possess information on external conditions that is *ex ante* unknown to managers. Third, this essay contributes to the literature that studies the real effects of short selling activities on corporate decisions. Prior studies typically focus on the effects of short selling activities on firms' financing constraints or managers' incentives. This essay differs by showing that short selling activities can affect corporate decisions through an information channel, that is, short selling affects corporate decisions by transmitting short sellers' information to managers via stock prices.

The third essay is titled "**The Real Effects of Long-term Option Trading**". This essay investigates whether long-term option trading stimulates the production of long-term information, which managers can use to guide their long-term investment decisions.

Recent studies have shown that managers can learn information from stock prices to guide their corporate decisions. This happens because stock prices aggregate many pieces of information from investors and hence are informative about firms' fundamentals. Therefore, the allocational role of stock prices depends on the information acquired by investors. However, due to the high cost to trade on long-term private information or risk aversion, investors are more likely to collect short-term information than long-term information. Consequently, stock prices will incorporate more short-term information and less long-term information, leading to reduced stock price informativeness about firms' long-run fundamentals. Therefore, when managers are making long-term corporate decisions, the allocational role played by stock prices might be limited.

In essay three, I investigate whether introducing long-term options can resolve this problem. More specifically, I study whether long-term option trading stimulates the production of long-term private information and thus leads to an increase in stock price informativeness about firms' long-term fundamentals. Therefore, managers can learn more information from stock prices to guide their long-term investment decisions.

To do so, I look at the Long-term Equity AnticiPation Securities (LEAPS). Similar to regular options, LEAPS are standardized American-style options listed in CBOE. However, different from regular options that usually expire in less than one year, LEAPS have a time to maturity that is up to three years.

Prior studies have shown that introducing options can alter investors' incentives to acquire private information and hence affects the informational efficiency of underlying stock prices. Cao (1999) argues that the introduction of derivative assets improves the trading opportunities of investors and hence increases investors' incentives to acquire private information about underlying assets. Consequently, the introduction of derivative assets increases the amount of information collected and leads to more informative prices of the underlying assets. In addition, because the leverage afforded by options lowers the transaction cost for informed investors, option trading can increase the informational efficiency of stock prices by stimulating informed trading. Therefore, I hypothesize that LEAPS trading stimulates the production of long-term information, which managers can use to guide their long-term investment decisions.

To test this hypothesis, I use R&D investment as a proxy for long-term investment. Using a large sample of U.S. firms over the period from 1999 to 2009, I show that the sensitivity of R&D investment to stock prices is higher for firms with active LEAPS trading. In terms of economic significance, the R&D investment to stock price sensitivity will increase by around 80%, if a firm has active LEAPS trading in the market. This result is robust to various subsamples, including the subsample of firms matched on size and the subsample of firms with non-zero R&D expenditure. Moreover, this result holds after controlling for the potential selection bias and controlling for other competing information sources. In addition, I show that the effect of LEAPS trading on firms' R&D investment sensitivity to stock prices becomes stronger in situations in which LEAPS trading is more likely to increase investors' incentives to acquire long-term private information.

Further analyses show that active LEAPS trading helps managers make more efficient R&D investment by mitigating the problem of under-investment. Moreover, the R&D investment induced by LEAPS trading has a positive effect on firms' future operating performance and growth. Taken together, these findings suggest that long-term option trading activities can have real effects by enhancing the allocational role of stock prices.

Essay three contributes to the literature by empirically investigating the real effects of long-term option trading. My findings suggest that derivatives trading can affect corporate decisions through an information channel. That is, derivates trading stimulates the production of information that is new to managers and further affects corporate decisions through managerial learning mechanism.

Chapter 1

Stock Price Informativeness and Managerial Inefficiency

1.1 Introduction

A long-standing view in finance research is that stock market efficiency promotes real economy efficiency. Since a key role of stock market is to aggregate information from different sources into stock prices, one may expect that, at firm level, when stock prices aggregate a greater amount of information, firms' real activities should become more efficient.[1] This can occur only if stock prices affect managers' real decisions. Recent studies find that managers take into account the specific information contained in stock prices when they are making corporate decisions, hence stock market has an active role in affecting real economic activities through the informational role of stock prices.[2] Therefore, a priori, when stock prices reflect a greater amount of information that managers care about, corporate decisions made by managers should be more efficient.

In this paper, I investigate this prediction by empirically examining the relationship between stock price informativeness and managerial inefficiency. My main proxy for price informativeness is the probability of informed trading (PIN), which is derived from a market microstructure model developed by Easley et al. (1996). The PIN measure is computed as the

[1] In this paper, I focus on the informational efficiency of stock market. Fama (1970) states that "a market in which prices always 'fully reflect' available information is called 'efficient'".
[2] For example, see Chen, Goldstein and Jiang (2007), Foucault and Fresard (2014), Fresard (2012), and Luo (2005).

ratio of estimated informed order flows to total order flows. Thus, higher PIN indicates that stock prices contain relatively more information from private sources and hence are more informative.

One main challenge in this paper is to quantify managerial inefficiency in making corporate decisions. In my setting, I measure the degree of managerial inefficiency by firm value shortfalls. The firm value shortfalls are calculated as the deviation of firms' actual value from their frontier value, which is firms' hypothetical maximum value absent of managerial inefficiency problem. The intuition is that if managers respond to firms' growth opportunities by making efficient corporate decisions, their firms should reach the frontier value. Hence, managerial inefficiency in making corporate decisions will translate into sub-optimal outcomes. That is, firm value falling below the frontier value. Therefore, firm value shortfalls can be seen as a proxy for the level of managerial inefficiency.[3] In this paper, I follow the methodology used by Edmans, Goldstein and Jiang (2012) to estimate firms' frontier value and further calculate firm value shortfalls.

Using a large sample of U.S. public firms over the period from 1993 to 2010, I find a negative relationship between PIN and firm value shortfalls. My results show that an interquartile increase in PIN is associated with a decrease in firm value shortfalls by 0.045, which is equivalent to an average improvement of 2.28% in firm value. In addition, I investigate the relationship between PIN and firms' operating performance. The results indicate that PIN is also negatively related to operating profitability shortfalls. These results are compatible with the expectation that price informativeness can reduce managerial inefficiency in making corporate decisions. Further analyses show that the negative relationship between PIN and firm value shortfalls is unchanged when I control for potential endogeneity issues, use alternative measures of both price informativeness and managerial inefficiency, and perform a variety of robustness tests. The overall evidence suggests that stock price informativeness affects managerial inefficiency.

[3] Similarly, Habib and Ljungqvist (2005) use firm value shortfalls to proxy for agency cost, which is one source of managerial inefficiency. Edmans, Goldstein and Jiang (2012) argue that the deviation of a firm' actual value from its frontier value is caused by managerial inefficiency or mispricing.

After establishing a relationship between stock price informativeness and managerial inefficiency, I turn to explore possible explanations for this relationship. In a recent paper, Bond, Edmans and Goldstein (2012) discuss the real effects of stock prices on managers' corporate decisions. They argue that stock prices can affect managers' real decisions in two ways, depending on the type of information contained in stock prices.

In the first case, stock prices affect managers' corporate decisions by revealing information that is new to managers. This channel is called learning hypothesis. Learning hypothesis assumes that managers do not possess perfect decision-relevant information while investors may have some incremental information that is useful to managers. Hence, managers learn new information from investors via stock prices and use it to guide corporate decisions. As lack of necessary information may lead to managerial inefficiency in making corporate decisions, informative stock prices overcome this problem by revealing new information to managers and therefore result in efficient corporate decisions.

To test learning hypothesis, I examine whether the effect of stock price informativeness on managerial inefficiency is more prominent when information from stock prices is more valuable and hence managers are more likely to learn from stock prices. Subrahmanyam and Titman (1999) predict that new information from stock prices is more important for firms with greater product demand uncertainty. In addition, Edmans, Jayaraman and Schneemeier (2016) argue that information from stock prices is particularly valuable to managers when firms' production function changes rapidly. Consistent with both predictions, I find that the negative effect of PIN on firm value shortfalls is stronger for firms with more volatile operating income and more intensive R&D expenditures.

In the second case, stock prices influence corporate decisions by reflecting information about managers' past decisions. On the one hand, when managers' compensation is contingent on stock prices, their incentives to make value-enhancing decisions will depend on the extent to which their decisions are reflected in stock prices. On the other hand, when the quality of managers' decisions is poor, informative stock prices send signals about the need to intervene and hence induce corporate governance mechanisms. Thus, more informative stock prices increase managers' incentives to make value-enhancing decisions and lead to a lower level of managerial inefficiency. This channel is called contracting hypothesis.

I investigate the two aspects of contracting hypothesis. First, Holmstrom and Tirole (1993) argue that when stock prices are more informative, firms can design more efficient contracts to increase managers' incentive to engage in value-enhancing activities. In support, I find that PIN enhances the negative effect of pay-for-performance sensitivity on firm value shortfalls. Second, even if managers' compensation is not contingent on stock prices, managers can still be tied to stock prices due to corporate governance mechanisms. When stock prices are informative, mismanagement will result in low stock prices and trigger takeover threats from corporate control market (Edmans, Goldstein and Jiang, 2012). I show that the effect of PIN on firm value shortfalls is greater when firms adopt less takeover defenses.

In summary, the overall evidence suggests that the negative effect of stock price informativeness on managerial inefficiency appears to stem from the channels of learning hypothesis and contracting hypothesis.

This paper mainly contributes to extant literature in two ways. First, prior studies have shown empirical evidence on the connection between stock market efficiency and real economy efficiency at industry level and country level.[4] This paper contributes to this literature by providing evidence at firm level. By employing established measures from prior studies, I present an empirical framework to investigate the connection between stock market (informational) efficiency and real economic efficiency at firm level. Specifically, I show that more informative stock prices facilitate more efficienct corporate decisions and result in a lower level of managerial inefficiency. Moreover, this empirical framework can be used in future

[4] For example, see Durnev, Morck and Yeung (2004) for empirical evidence at industry level and Wurgler (2000) for empirical evidence at country level.

studies that focus on firm-level connection between stock market efficiency and real economic efficiency.

Second, this paper adds to the growing literature on learning hypothesis by directly examining the real consequence of managerial learning. Whereas existing studies, such as Chen, Goldstein and Jiang (2007), Fresard (2012) and so on, show the effect of stock price informativeness on corporate decisions and posit that this effect may enhance the efficiency of corporate decisions, there is a lack of direct evidence.[5] In this respect, this paper differs from prior studies by showing that higher stock price informativeness is related to a lower level of managerial inefficiency through the mechanism of learning hypothesis. As such, this paper provides direct evidence for the argument that managerial learning enhances the efficiency of corporate decisions.

The reminder of this paper is organized as follows. Section 1.2 reviews related literature and develops testing hypotheses. Section 1.3 describes variable measurements and sample construction. Section 1.4 presents main empirical results. Section 1.5 investigates possible explanations for the main finding. Section 1.6 concludes.

1.2 Literature Review and Hypothesis Development

This paper is closely related to a recent literature that analyzes the real effects of stock prices on corporate decisions. In a secondary market where stocks are traded among investors without transferring capital to firms, stock prices can still affect managers' real decisions due to the informational role. As pointed out by Bond, Edmans and Goldstein (2012), there are two channels through which information contained in stock prices affects managers' decisions within

[5] See Fresard (2012).

a framework of rationality, and further linking stock price informativeness to managerial inefficiency.[6]

The first channel is called learning hypothesis. Since stock prices aggregate many pieces of private information from investors, they may incorporate specific information that managers do not have. Hence, learning hypothesis implies that, by observing stock prices, managers can learn new information from stock prices and use it to guide their corporate decisions.[7]

In theory, Dow and Gorton (1997) argue that investors are willing to produce important information about future probability of investment opportunities that managers do not have, and to trade profitably on it. Ultimately, this information is incorporated in stock prices and transmitted to managers via stock prices. In a different way, Subrahmanyam and Titman (1999) argue that through day-to-day activities, investors may obtain serendipitous information that is valuable to managers.

In a recent paper, Bai, Philippon and Savov (2014) build a model to demonstrate how information from stock prices influences managers' investment decisions and firm value. In their model, managers learn information from stock prices to form their expectations on firms' productivity and then choose investment levels to maximize firm value based on their expectations. Thus, firm value increases with the quantity of information available to managers, because information increases managers' ability to optimize their investment decisions in response to firms' growth opportunities.

On the empirical side, Chen, Goldstein and Jiang (2007) find that corporate investments are more sensitive to stock prices when stock prices contain more private information. Their findings

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[6] Bond, Edmans and Goldstein (2012) also provide an explanation based on managers' irrational reaction to stock prices. I do not consider this explanation in this paper for two reasons. First, managers are usually regarded as professional employees with ability to form rational beliefs. Second, stock prices changes caused by irrational investors can be arbitraged away in the long-run.

7 It is plausible to argue that managers can learn new information from stock prices. While managers may have informational advantage on internal firm conditions, stock prices, by aggregating of information from diverse outsider investors, can be particularly informative about external conditions that are necessary for managers to make efficient corporate decisions.

suggest that managers learn information from stock prices and use it to guide corporate investments. Fresard (2012) shows that cash saving decisions are also more sensitive to stock prices when stock prices are more informative. Moreover, Luo (2005) finds that abnormal returns around merger and acquisition announcements predict whether firms consummate the deals later. He interprets this finding as evidence that managers learn information from stock market for merger and acquisition decisions.

The above studies show that stock prices are an important source for managers to gain information for corporate decision making. David, Hopenhayn and Venkateswaran (2014) develop a model linking imperfect information to resource misallocation. They show that when managers decide input factors under limited information about their firms' fundamentals, imperfect information leads to a misallocation of input factors across firms and aggregate productivity loss. However, through the mechanism of learning hypothesis, informative stock prices provide managers useful information to complement their knowledge on firms, and hence overcome the misallocation problem caused by their imperfect information. Therefore, more informative stock prices lead to a lower degree of managerial inefficiency in making corporate decisions and result in higher firm value.

The second channel through which information reflected by stock prices affects managers' decisions is named contracting hypothesis. Contracting hypothesis argues that managers care about stock prices because their contracts are tied to firms' stock prices, which reflect information about their past decisions. On the one hand, when managers' compensation is tied to stock prices, managers' incentives to make value-enhancing decisions depend on the extent to which their decisions are reflected in stock prices. If stock prices are not informative about their decisions, managers are weakly incentivized to make efficient corporate decisions.

Two prominent theoretical studies on this line of research are Holmstrom and Tirole (1993) and Faure-Grimand and Gromb (2004). In the model of Holmstrom and Tirole (1993), when more private information flows into the stock market and makes stock prices more informative, firms can design more efficient managerial contracts that are contingent on firms' future earnings. In addition, Faure-Grimand and Gromb (2004) study the relationship between public trading and activity of insider who can affect firm value. The more informative the stock price is, the more the insider can get rewarded for his value-enhancing activity, if he has to liquidate his stake before the effect of activity is publicly observed. Therefore, informative stock prices increase insider's incentives to take value-enhancing actions.

On the empirical side, Ferreira, Ferreira and Raposo (2011) show that when managers' compensation is tied to stock prices, price informativeness is a more effective substitute for internal governance mechanism such as board independence. Another related study is Fang, Noe and Tice (2009). They find that higher stock liquidity leads to higher firm value by enhancing the incentive effect of managers' pay-for-performance contracts, because higher stock liquidity encourages more informed investors to trade and results in more informative stock prices.

On the other hand, even if managers' compensation is not contingent on stock prices, managers can still be tied to stock prices due to corporate governance mechanisms.[8] Durnev, Morck and Yeung (2004) argue that stock prices convey meaningful signals on the quality of managers' decisions. Thus, when managers' decisions are poor, informative stock prices reveal to financial markets the need to intervene and trigger corporate governance mechanisms. In addition, Ferreira, Ferreira and Raposo (2011) find that price informativeness can substitute for internal monitoring by independent directors more effectively, when firms are more open to corporate control market and are supervised by larger institutional shareholders. In such cases, informative stock prices incentivize managers to make efficient corporate decisions.

In summary, based on the above reasoning, I expect that more informative stock prices would lead to a lower level of managerial inefficiency in making corporate decisions, through learnging hypothesis and/or contracting hypothesis. Therefore, I propose the following hypotheses :

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[8] These corporate governance mechanisms include shareholder activism, institutional investor pressure, corporate control or board independence.

Hypothesis 1: Firms whose stock prices are more informative will have a lower level of managerial inefficiency in making corporate decisions.

Hypothesis 2 (learning hypothesis): More informative stock prices lead to a lower level of managerial inefficiency as managers can learn valuable information from stock prices. This helps managers to make efficient corporate decisions.

Hypothesis 3 (contracting hypothesis): More informative stock prices lead to a lower level of managerial inefficiency as stock prices can reflect information about managers' past decisions. This enhances managers' incentives to make efficient corporate decisions.

1.3 Variable Construction and Sample

1.3.1 Variable Construction

1.3.1.1 Stock Price Informativeness Measure

In this paper, I primarily use the probability of informed trading (PIN) as the measure of stock price informativeness. The PIN measure is derived from a market microstructure model developed by Easley et al. (1996). In their structural model, order flows are from either noise traders who trade for exogenous reasons or informed traders who trade for speculative purposes based on their private information about firms' fundamental value. The trading process is as follows. At the beginning of each day, the probability that a private information event occurs is α. Throughout the day, three types of order flows are initiated in the market with different arrival rates: informed orders from informed traders at the arrival rate of μ, uninformed buy orders from noise traders at the arrival rate of ε_b, and uninformed sell orders from noise traders at the arrival rate of ε_s. Hence, the probability of informed trading for a stock, PIN, is computed as the ratio of expected informed order flows to expected total order flows.

$$\mathrm{PIN} = \frac{\alpha\mu}{\alpha\mu + \varepsilon_b + \varepsilon_s}$$

The estimation of PIN uses the information from intra-day trading process. PIN will be low when there is few fluctuation of daily buy and sell orders for stocks, which are likely to come from uninformed trading. Oppositely, PIN will be high when the order flows for the stocks frequently deviate from their normal order flow level. These "abnormal" order flows are likely to come from investors with private information. Intuitively, as PIN captures the probability of informed trading for stocks, it is a good proxy for the quantity of private information incorporated into stock prices. When the PIN is higher (lower), it means that a larger (smaller) fraction of orders are based on private information, and hence, stock prices contain greater (fewer) amount of private information from investors. Consisitent with this intuition, Vega (2006) finds that stocks with higher PIN will experience smaller post-announcement drift. This finding suggests that when PIN is higher, stock prices contain a greater amount of private information and therefore track firms' fundamentals more closely.

In prior empirical studies, PIN is widely used as a proxy for stock price informativeness. Chen, Goldstein and Jiang (2007) relate PIN to managerial decisions. They find that the sensitivity of firm investment to stock prices increases with PIN, supporting the hypothesis that managers learn private information impounded in stock prices. PIN also seems to be related to corporate governance mechanisms. Ferreira, Ferreira and Raposo (2011) show a negative relationship between PIN and board independence, suggesting that board independence is less demanding when stock price is more informative.

While using PIN measure as the main proxy for stock price informativeness in this paper, I acknowledge that this measure is not perfect. One concern of using PIN as price informativeness measure is that PIN may reflect other factors rather than private information in stock prices, as indicated by Atkas et al. (2007). Hence, I also consider other stock price informativeness measures to corroborate my results. Duarte and Young (2009) develop a methodology to decompose PIN into two components, one related to pure private information in stock prices

(APIN) and another related to illiquidity effects (PSOS). Therefore, I first consider APIN as an alternative measure of price informativeness.

Second, I use price non-synchronicity (or firm-specific stock return variation). Roll (1988) suggests that price non-synchronicity is correlated with the amount of private information incorporated in stock prices. He argues that stock prices change with the arrival of new information from two sources. The first source is the release of public information, while the second is the private information gathered by speculators who trade for profit. Roll (1988) finds that stock price non-synchronicity does not change greatly in response to the exclusion of identifiable information event dates, and hence concludes that firm-specific variation is due to the arrival of private information. A large body of theoretical and empirical studies supports the use of price non-synchronicity as price informativeness measure.[9]

I calculate stock price non-synchronicity by regressing firm i's return on industry j, $r_{i,j,t}$, on market and industry returns, $r_{m,t}$ and $r_{j,t}$:

$$r_{i,j,t} = \alpha_i + \beta_{i,m} r_{m,t} + \beta_{i,j} r_{j,t} + \varepsilon_{i,t}$$

where $r_{m,t}$ is value-weighted market returns from CRSP, and $r_{j,t}$ is value-weighted industry returns defined at three-digit SIC code level, excluding firm i itself. Because CRSP reports a zero return when there is no trading for a stock in a given date, I use weekly returns to avoid this "thin trading problem".[10] Then I obtain R2 from the regression for each firm-year observation and use the logarithm transformation of 1-R2 as the stock price informativeness measure, Ψ.

$$\Psi = \ln\left(\frac{1 - R2}{R2}\right)$$

[9] For example, see Veldkamp (2006) for theoretical studies, and Durnev et al. (2003), Morck , Yeung and Yu (2000), and Durnev, Morck and Yeung (2004) for empirical studies.

[10] The weekly returns are compounded by daily returns from Wednesday to the following Wednesday using close prices (Hou and Moskowitz, 2005).

This price informativeness measure, Ψ, follows the intuition of Roll (1988) that stock returns only comove with market and industry returns in the absence of firm-specific information. Hence, stock prices contain a fewer amount of private information when Ψ is lower.

1.3.1.2 Managerial Inefficiency Measure

To empirically test my hypotheses, I need to measure the economic (in)efficiency of corporate decisions made by managers. In this paper, I use firm value shortfalls from frontier value to measure the degree of managerial inefficiency. The intuition is as follows. If managers respond to firms' growth opportunities by making economically efficient decisions, their firm value should reach the maximum potential level, which is called the frontier value. Otherwise, managerial inefficiency will result in firms' actual value being below the frontier. Therefore, firm value shortfalls, calculated as the difference between firms' actual value and the frontier value, capture the degree of managerial inefficiency.

In prior studies, Habib and Ljungqvist (2005) use a stochastic frontier value approach to estimate firms' frontier value. They argue that the shortfalls of firms' actual value from the frontier are due to agency cost. Edmans, Goldstein and Jiang (2012) employ another form of stochastic frontier analysis method to calculate firms' frontier value and attribute the deviation of actual value from the frontier to manager's mismanagement or mispricing. Their approach is called censored least absolute deviation (CLAD) method. In this paper, I follow the CLAD method used by Edmans, Goldstein and Jiang (2012) to estimate firms' frontier value. The advantage of CLAD method is that it makes no parametric assumption in estimating the frontier value. Hence, it can accommodate many common features in corporate finance data, such as heteroskedasticity, or within-cluster correlation.

Formally, I assume that a firm's frontier value is determined by a set of variables representing firm fundamentals: $Q^* = f(X)$. Since Q^* represents the potential value a firm could reach once its managers make efficient corporate decisions, the X variables should consist of important firm fundamentals that are determined by managers. In this paper, the X variables I choose are firm size, firms' "soft" spending on research and development and advertising and "hard" spending on capital investment, asset tangibility and leverage.

Ideally, the maximum value among peer firms that have the same firm fundamentals (X variables) could be seen as the frontier value. However, as pointed out by Edmans, Goldstein and Jiang (2012), it would be problematic to use the maximum value among peers as frontier value if the X variables do not include all value-relevant firm fundamentals or if there is mispricing in firm value. Hence, an improvement is to set the frontier value to a high percentile, $(1-\alpha)^{\text{th}}$, rather than the maximum among peers. In this paper, I follow the setting of Edmans, Goldstein and Jiang (2012) and use $\alpha = 0.2$. This implies that 80% (20%) of firms are managed below (over) the frontier value. As I describe later, my results are not sensitive to the choice of α within a wide range from 0.1 to 0.5.

After choosing X and α, and observing the actual firm value Q, the frontier value can be estimated by:

$$Q_{i,t} = X_{i,t}\beta + u_{i,t}$$

where Q is firm i's actual value, X is a vector of fundamental variables, and u is the shortfall of firm i's actual value from the frontier and satisfies the condition that $\text{Quantile}_{1-\alpha}(u) = 0$.

To estimate the frontier value, I define industry peer at three-digit SIC code level. Then, for a given α, I estimate $\hat{\beta}$ by the CLAD method for each three-digit SIC industry seperately:

$$\min_{\hat{\beta}\in B} \frac{1}{n}\left\{ \sum_{Q_{i,t} > f(X_{i,t};\hat{\beta})} (1-\alpha)\left|Q_{i,t} - f\left(X_{i,t};\hat{\beta}\right)\right| + \sum_{Q_{i,t} \le f(X_{i,t};\hat{\beta})} \alpha\left|Q_{i,t} - f\left(X_{i,t};\hat{\beta}\right)\right| \right\}$$

$$\text{s.t.}\;\; f\left(X_{i,t};\hat{\beta}\right) \ge 0$$

where $f(X_{i,t}; \hat{\beta})$ is the estimated frontier value. In addition, the non-negativity constraint is achieved by the CLAD method.

Finally, after estimating $\hat{\beta}$, the frontier value is calculated as $Q^* = X\hat{\beta}$ and hence firm value shortfall is calculated as $\text{Shortfall} = Q^* - Q = X\hat{\beta} - Q$. The shortfalls of firms' actual value from the frontier are used as a proxy for managerial inefficiency in making corporate decisions. Intuitively, lower shortfalls mean that firms' actual value is closer to the frontier value, implying a lower degree of managerial inefficiency. In this paper, a firm's frontier value is estimated within its three-digit SIC industry. Hence, I compare a firm's value with its industry peers.[11]

1.3.2 Sample Selection

To construct my sample, I collect data from several sources. My initial sample consists of all U.S. public firms with non-missing accounting data in Compustat between 1993 and 2010.[12] I exclude firms in the financial and banking industries (SIC code 6000-6999) and utility industries (SIC code 4900-4999). I also exclude firms with non-positive book value of total assets and missing data on end of year market value. Then I estimate the frontier value for each firm-year and calculate managerial inefficiency measure as the shortfalls of firms' actual value from the frontier. After these procedures, I obtain PIN data from Stephen Brown and merge my sample with the PIN data for each firm-year. Moreover, I obtain stock return data from the Center for Research in Security Prices (CRSP), institutional ownership data from ThomsonReuters, analyst coverage data from Institutional Brokers Estimates System (I/B/E/S), and managerial compensation data from Compustat Executive Compensation database. Finally, my sample includes 6,268 unique firms and 41,023 firm-year observations.

[11] See Appendix A.1 for more details on the construction of firm value shortfalls.

[12] My sample ends in 2010 because of the availability of PIN data. The PIN data obtained from Stephen Brown's website is from 1993 to 2010. I thank Stephen Brown for making PIN data available.

Table 1.1: Summary Statistics

This table reports number of observations, mean, standard deviation as well as the 25th, 50th and 75th percentiles for the main variables used in empirical analysis. Variable definitions can be found in Appendix A.2. The sample comprises 6,268 unique firms and 41,023 firm-year observations during the period from 1993 to 2010. The sample excludes firms in the financial and banking industries (SIC code 6000-6999) and utility industries (SIC code 4900-4999). The sample also excludes firms with non-positive sales and missing data on end of year market value. Panel A reports the summary statistics for the variables. Panel B reports the correlation matrix for the variables.

Panel A: Summary statistics						
Variable	# of obs	Mean	Std Dev	25%	50%	75%
Q	41023	1.978	1.278	1.129	1.531	2.327
LogAsset	41023	5.370	1.771	4.011	5.288	6.642
R&D	41023	0.629	1.278	0.000	0.023	0.568
Adv	41023	0.058	0.143	0.000	0.000	0.025
Capex	41023	0.273	0.178	0.135	0.228	0.375
Tang	41023	0.356	0.475	0.088	0.177	0.381
Leverage	41023	0.009	0.330	-0.222	0.049	0.260
Shortfalls	41023	0.691	1.133	0.105	0.598	1.277
PIN	41023	0.186	0.096	0.109	0.194	0.259
APIN	11974	0.166	0.071	0.112	0.150	0.203
Ψ	40205	2.060	1.359	1.027	1.949	2.964
Age	41023	16.425	14.188	6.000	12.000	23.000
MktShr	41023	0.042	0.099	0.001	0.005	0.031
HHISIC3	41023	0.180	0.126	0.092	0.140	0.230
Growth	41023	1.195	0.298	1.025	1.115	1.263
Segment	41023	2.117	1.687	1.000	1.000	3.000
Analyst	41023	6.406	7.491	1.000	4.000	9.000
Institution	41023	0.466	0.299	0.194	0.462	0.721
Spread	41023	0.017	0.013	0.008	0.013	0.021
CumRet	41023	0.061	0.820	-0.527	-0.123	0.399

Panel A of Table 1.1 shows the summary statistics for my final sample. The definitions of all variables are presented in Appendix A.2. In my sample, the mean (median) value of PIN is 0.186 (0.194), which is comparable to the result found in other studies (e.g., Brown, Hillegeist and Lo, 2004). To compare my managerial inefficiency measure with other studies, I calculate firms' predicted efficiency level, which is the ratio of firms' actual value to their frontier value. In my sample, the mean (median) predicted efficiency is 76.8% (71.7%). In prior studies, Habib and

Ljungqvist (2005) find that the average predicted efficiency is 83.8% for a sample of firms covered by S&P index. Nguyen and Swanson (2009) find that firms have an average (median) predicted efficiency level of 70% (72%) in their sample. My results are similar to theirs. Finally, to mitigate the effects of extreme outliers in empirical analysis, I winsorize all potentially unbounded variables at 5% and 95% levels in each panel year.

Panel B of Table 1.1 reports the correlation matrix for the variables. The PIN measure is positively correlated with stock price non-synchronicity (Ψ) with a correlation coefficient of 0.347. The high correlation between PIN and price non-synchronicity supports the idea that both measures capture the amount of private information incorporated in stock prices.

Panel B: Correlation matrix

	Shortfalls	PIN	APIN	Ψ	Age	MktShr	HHISIC3	Growth	Segment	Analyst	Institution	Spread	CumRet
Shortfalls	1.000												
PIN	0.030	1.000											
APIN	0.112	0.467	1.000										
Ψ	0.091	0.347	0.490	1.000									
Age	0.001	-0.223	-0.201	-0.177	1.000								
MktShr	-0.084	-0.263	-0.328	-0.242	0.290	1.000							
HHISIC3	-0.062	-0.033	-0.051	-0.012	0.124	0.354	1.000						
Growth	-0.094	0.052	0.002	-0.001	-0.230	-0.046	-0.088	1.000					
Segment	0.041	-0.181	-0.213	-0.194	0.275	0.262	0.145	-0.106	1.000				
Analyst	-0.136	-0.415	-0.527	-0.473	0.224	0.369	-0.027	0.054	0.127	1.000			
Institution	-0.140	-0.315	-0.502	-0.480	0.116	0.264	0.053	-0.039	0.189	0.448	1.000		
Spread	0.138	0.174	0.313	0.309	-0.178	-0.213	-0.066	0.004	-0.134	-0.295	-0.473	1.000	
CumRet	0.106	-0.004	-0.025	-0.035	-0.015	0.001	-0.008	-0.025	0.077	0.005	0.037	0.021	1.000

1.4 Empirical Results

1.4.1 Baseline Specification Tests

To assess whether stock price informativeness affects managerial inefficiency, the managerial inefficiency measure, firm value shortfalls, is regressed on the price informativeness measure, PIN, and a vector of control variables. The baseline specification is as follows:

$$\text{Shortfall}_{i,t} = \delta_i + \eta_t + \beta \text{PIN}_{i,t-1} + \gamma \text{Control}_{i,t} + \varepsilon_{i,t}$$

where $\text{Shortfall}_{i,t}$ is firm i's value shortfall estimated at year t and $\text{PIN}_{i,t-1}$ is the probability of informed trading for firm i at year t-1. In prior studies, a lagged relationship is found between managerial decisions and stock price informativeness (e.g., Chen, Goldstein and Jiang, 2007; Fresard, 2012; and Durnev, Morck and Yeung, 2004). Thus, I regress managerial inefficiency measure at year t on the pre-determined measure of stock price informativeness at year t-1.

To identify the effect of price informativeness on managerial inefficiency, I also include a set of control variables that may affect firm value shortfalls but are unlikely to be determined by managers. Moreover, the X variables are included in all regressions throughout the paper as additional control variables, since the dependent variable is calculated using those variables.[13] Finally, I include both firm-fixed and year-fixed effects in the baseline specification.

Table 1.2 summarizes the regression results for my baseline specification. Column (1) presents the coefficients of a regression of firm value shortfalls on PIN. There is strong evidence of a negative and statistically significant relationship. The estimated coefficient for PIN is -0.1512 and significant at 5% level.

[13] The estimated coefficients for X variables are not tabulated for brevity in this paper.

Table 1.2: Baseline Specification

This table presents coefficient estimates of stock price informativeness on managerial inefficiency. The dependent variable is Shortfalls. The main explanatory variable is PIN. All the variables are defined in the Appendix A.2. The sample period is from 1993 to 2010. The estimations correct the error term structure for heteroskedasticity and within-firm clustering. The t-statistics are in parentheses. ***, ** and * denote statistical significance at the 1%, 5% and 10% level, respectively.

Variable	(1)		(2)		(3)	
PIN	-0.1512	**	-0.2693	***	-0.3024	***
	(-1.98)		(-3.60)		(-4.23)	
Age			-0.0006		0.0023	
			(-0.10)		(0.38)	
MktShr			-0.2106		-0.0777	
			(-1.05)		(-0.36)	
HHISIC3			0.0487		0.0565	
			(0.50)		(0.56)	
Growth			-0.5162	***	-0.4356	***
			(-13.01)		(-11.48)	
Segment			0.0167	***	0.0112	*
			(2.75)		(1.82)	
Analyst			-0.0146	***	-0.0061	***
			(-6.40)		(-2.71)	
Institution			-1.0523	***	-0.8351	***
			(-16.95)		(-14.67)	
Spread					15.5482	***
					(16.20)	
CumRet					0.3514	***
					(38.81)	
Firm FE	Yes		Yes		Yes	
Year FE	Yes		Yes		Yes	
# of obs	41023		41023		41023	
Adj R2	0.108		0.148		0.237	

In Column (2), this result remains qualitatively unchanged after controlling for other factors that may affect firm value shortfalls. The estimated coefficient for PIN is -0.2693, with t-statistics of -3.60. Regarding the control variables, I find that firms with higher growth opportunities tend to have lower shortfalls. Number of segments is positive and significantly related to shortfalls, confirming the diversification discount found in prior literature. Both number of analysts and institutional ownership enter with a negative and significant coefficient, suggesting that analysts and institutional investors play a monitoring role in disciplining managers' decisions. In contracts, I find no statistically significant relationship between firm value shortfalls and firm age, market share, and industry competition.

Furthermore, even if managers make efficient decisions, firms' actual value may still deviate from their frontier value due to market frictions, such as stock mispricing and illiquidity. To mitigate this concern, I control for stock mispricing and illiquidity in Column (3). Baker and Wurgler (2002) argue that because stock mispricing is a transient phenomenon, overvalued stocks will experience negative returns in the future when mispricing is corrected. Following their argument, my proxy for stock mispricing is calculated as cumulative market-adjusted excess returns over a time period of 36 months subsequent to the measurement of firm value shortfalls. In addition, I measure stock illiquidity using bid-ask spread estimated from daily high and low prices (Corwin and Schultz, 2012).

Controlling for market frictions does not change my result. The PIN coefficient is -0.3024 with t-statistics of -4.23. In addition, I find that firms whose stocks earn positive excess returns in next 3 years are undervalued in prior and hence have higher shortfalls. This is consistent with the argument of Baker and Wurgler (2002). The illiquidity measure is positively and significantly related to shortfalls, which is consistent with the finding that higher stock liquidity leads to higher firm value (Fang, Noe and Tice, 2009).

The effect of PIN on managerial inefficiency is economically significant. Using the specification in Column (3), an increase of price informativeness measure PIN from a 25th percentile value of 0.109 to a 75th percentile value of 0.259 will decrease firm value shortfalls by 0.045. Given that the median value of firm value Q in my sample is 1.978, this implies an average improvement of firm value by 2.28%.

In summary, I find that PIN has a statistically and economically significant negative relationship with firm value shortfalls, even after controlling for many variables that may be correlated with shortfalls. This result suggests that managerial inefficiency is lower for firms whose stock prices are more informative.

1.4.2 Operating Performance

If more informative stock prices lead managers to make better decisions and hence result in more efficient real activities, I should expect that stock price informativeness will have a negative effect on shortfalls in not only firm value but also firms' operating performance. In this subsection, I test the latter aspect in my paper.

Specifically, I use two measures of firms' operating profitability instead of Tobin's Q to construct managerial inefficiency proxy.[14] Then I estimate the baseline specification again, using shortfalls in operating profitability as dependent variable. The two operating profitability measures used in this paper are ROA and ROE. ROA (ROE) is calculated as the percentage of operating income before depreciation, interest and taxes to the book value of total assets (total equity).

The results are summarized in Table 1.3. Column (1) and (2) present the results of regressions in which the dependent variables are estimated using ROA as a measure of operating profitability, and Column (3) and (4) illustrate the results that are based on ROE. All estimation results show a negative and statistically significant relationship between operating profitability shortfalls and PIN. These results are compatible with a negative relationship between stock price informativeness and managerial inefficiency.

[14] I remove the non-negativity constraint from the estimation method, when using two operating profitability measures to construct shortfalls.

Table 1.3: Operating Performance

This table presents coefficient estimates of stock price informativeness on managerial inefficiency, as measured by operating profitability shortfalls. In this table, I use two measures of firms' operating profitability instead of Tobin's Q to construct the dependent variable Shortfalls. The two operating profitability measures used here are ROA in Column (1) and (2) and ROE in Column (3) and (4). The main explanatory variable is PIN. All the variables are defined in the Appendix A.2. The sample period is from 1993 to 2010. The estimations correct the error term structure for heteroskedasticity and within-firm clustering. The t-statistics are in parentheses. ***, ** and * denote statistical significance at the 1%, 5% and 10% level, respectively.

	ROA Shortfalls				ROE shortfalls			
Variable	(1)		(2)		(3)		(4)	
PIN	-3.4533	***	-3.2386	***	-7.5644	***	-6.8727	***
	(-4.78)		(-4.56)		(-4.12)		(-3.79)	
Age			0.0081				-0.2448	
			(0.18)				(-1.28)	
MktShr			-4.7122	***			-14.1570	***
			(-3.82)				(-3.07)	
HHISIC3			-0.9130				-3.4827	
			(-0.93)				(-1.33)	
Growth			-2.3861	***			-5.2687	***
			(-5.88)				(-5.28)	
Segment			0.1876	***			0.3442	**
			(3.60)				(2.31)	
Analyst			0.0200				0.0812	
			(1.04)				(1.52)	
Institution			-4.1400	***			-8.2075	***
			(-8.09)				(-5.69)	
Spread			118.5769	***			241.4119	***
			(11.40)				(8.90)	
CumRet			0.4352	***			0.8920	***
			(5.07)				(3.98)	
Firm FE	Yes		Yes		Yes		Yes	
Year FE	Yes		Yes		Yes		Yes	
# of obs	40964		40964		40964		40964	
Adj R2	0.058		0.079		0.049		0.062	

The effect of PIN on shortfalls in operating profitability is also economically significant. Using the specifications in Column (2) and (4), when PIN increases from a 25th percentile value of 0.109 to a 75th percentile value of 0.259, shortfalls in ROA will decrease by approximately 0.49 percentage points, and shortfalls in ROE will decrease by 1.03 percentage points.

Overall, these results provide additional support to Hypothesis 1 that higher stock price informativeness leads managers to make more efficient corporate decisions and results in better operating performance.

1.4.3 Endogeneity Problem

In my baseline specification, I allow for a lagged relationship by regressing managerial inefficiency measure at year t on pre-determined stock price informativeness proxy at year t-1. At first glance, this alleviates the endogeneity concern caused by the contemporaneous reverse causality from managerial inefficiency to stock price informativeness. However, since both firm value shortfalls and PIN are relatively stable across years, an endogeneity problem may still arise from the contemporaneous reverse causality from managerial inefficiency to stock price informativeness.

I begin with two alternative specifications to address this concern. First, I apply the dynamic-panel GMM method of Arellano and Bond (1991), which allows for including lagged dependent variables, firm value shortfalls at year t-1, into the baseline specification as an additional explanatory variable. The results are displayed in Column (1) and (2) of Table 1.4. There is still evidence of a negative relationship between firm value shortfalls and PIN. In Column (2), the estimated coefficient for PIN is -0.2606 and significantly at 1% level.

Table 1.4: Endogeneity Problem

This table presents coefficient estimates of stock price informativeness on managerial inefficiency, after controlling for endogeneity issues. In Column (1) and (2), I include lagged dependent variable as an additional control variable and apply dynamic-panel GMM method of Arellano and Bond (1991) to estimate the coefficient. In Column (3) to (5), I use a first difference approach and regress the change in firm value shortfalls on the change in price informativeness measures as well as the changes in other control variables. In Column (3) and (4), I use PIN to measure price informativeness, while in Column (5) I use stock price non-synchronicity. Finally, in Column (6) and (7), I employ an instrumental variable method to address the potential endogeneity problem. Share turnover at year t-1 is used as an instrumental variable for PIN. All the variables are defined in the Appendix A.2. The sample period is from 1993 to 2010. The estimations correct the error term structure for heteroskedasticity and within-firm clustering. The t-statistics are in parentheses. ***, ** and * denote statistical significance at the 1%, 5% and 10% level, respectively.

	Lagged Shortfalls		First Difference			IV Method	
						PIN	Shortfalls
Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)
PIN	-0.3179 ***	-0.2606 ***	-0.4012 ***	-0.3305 ***			-1.3824 ***
	(-4.09)	(-3.80)	(-6.09)	(-5.53)			(-3.81)
Age		-0.0076 ***		-0.0040	-0.0046 **	0.0004	0.0030
		(-2.69)		(-1.57)	(-2.14)	(1.00)	(0.48)
MktShr		0.1839		0.1756	0.2069	-0.0020	-0.0709
		(0.79)		(0.73)	(0.84)	(-0.20)	(-0.33)
HHISIC3		-0.0238		-0.0633	-0.0815	-0.0015	0.0567
		(-0.21)		(-0.61)	(-0.75)	(-0.22)	(0.56)
Growth		-0.1290 ***		-0.1351 ***	-0.1337 ***	0.0136 ***	-0.4303 ***
		(-2.68)		(-3.15)	(-3.09)	(6.69)	(-11.28)
Segment		0.0012		0.0022	0.0011	-0.0010 **	0.0100
		(0.19)		(0.39)	(0.19)	(-2.41)	(1.61)
Analyst		0.0130 ***		0.0092 ***	0.0091 ***	-0.0012 ***	-0.0085 ***
		(5.17)		(4.07)	(4.02)	(-9.75)	(-3.55)
Institution		-0.7689 ***		-0.8194 ***	-0.8416 ***	-0.0090 **	-0.8541 ***
		(-11.55)		(-13.16)	(-13.17)	(-2.44)	(-14.89)
Spread		11.8789 ***		12.8311 ***	12.8946 ***	-0.4753 ***	14.9726 ***
		(11.33)		(13.72)	(13.59)	(-5.90)	(15.24)
CumRet		0.5349 ***		0.5030 ***	0.5038 ***	0.0030 ***	0.3551 ***
		(45.61)		(47.30)	(46.69)	(5.19)	(38.56)
Lagged Shortfalls	0.3393 ***	0.2659 ***					
	(24.76)	(21.74)					
Ψ					-0.0181 ***		
					(-4.66)		
Turnover						-0.0193 ***	
						(-42.51)	
Firm FE	No	No	No	No	No	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
# of obs	33389	33389	33633	33633	32863		40074
Adj. R2			0.172	0.337	0.338		0.111

Second, I focus on the effect of changes in PIN on changes in firm value shortfalls and with changes in other control variables. The results in Column (3) and (4) show that an increase in PIN is associated with a decrease in firm value shortfalls, confirming a negative relationship between managerial inefficiency and stock price informativeness. In addition, in Column (5) where I use stock price non-synchronicity instead of PIN as the proxy for price informativeness, there is still a negative and significant relationship between change in firm value shortfalls and change in stock price non-synchronicity.

Furthermore, I employ an instrumental variable method to address the potential endogeneity problem. To do so, I need an instrumental variable that is correlated with PIN, but uncorrelated with firm value shortfalls except through other independent variables. In this respect, I think of share turnover as a valid instrumental variable for PIN. Higher share turnover is associated with lower PIN, because stocks with larger trading volume tend to have more uninformed order flows (Ferreira, Ferreira and Raposo, 2011). I report the estimation results using instrumental variable method in last two columns of Table 1.4.

Column (5) presents the first stage regression that uses PIN as dependent variable. The estimated coefficient on Turnover is -0.0193 and significant at 1% level, consistent with the expectation that share turnover is negatively related to PIN. Column (6) shows the second stage results: the coefficient of PIN is still negative and significant at 1% level. Moreover, the results of Stock and Yogo (2005) weak instrument test reject the null hypothesis that the instrumental variable is weak.[15]

In sum, there is still evidence for a negative relationship between stock price informativeness and managerial inefficiency, after controlling for potential endogeneity issues. The evidence suggests a causal link from stock price informativeness to managerial inefficiency.

[15] The p-value for Stock and Yogo (2005) weak instrument test is less than 0.01.

1.4.4 Alternative Measures

In this subsection, I first examine whether my results are sensitive to using alternative measures of managerial inefficiency as the dependent variable. As discussed earlier, my managerial inefficiency proxy is influenced by the choice of benchmark firms within the industry. That is, the estimation of firm value shortfalls is influenced by the parameter α used in CLAD estimation. A high (low) α may underestimate (overestimate) the frontier value, as well as the firm value shortfalls. To check whether my results are sensitive to the choice of benchmark, I vary the parameter α in a wide range to calculate firm value shortfalls and estimate the baseline specification again.

Table 1.5 reports the results of the baseline regression with alternative choice for α. In the first two columns of Table 1.5, I vary α in a range between [0.10, 0.30]. In Column (1), the dependent variable Shortfall is calculated when α is set to 0.1. The estimated coefficient on PIN is negative and statistically significant, consistent with the results reported in Table 1.2. In Column (2), there is still evidence of a negative relationship between firm value shortfalls and PIN when I use $\alpha = 0.3$ to calculate firm value shortfalls.

Finally, I perform the same analysis for baseline specification but using $\alpha = 0.5$. That is, the median firm within the industry is chosen as the benchmark to calculate the measure of managerial inefficiency. The result is not qualitatively changed, as shown in Column (3) of Table 1.5. Since a high α tends to underestimate firm value shortfalls, I observe a decline in the estimated effect of stock price informativeness on managerial inefficiency, as α increases.

Table 1.5: Alternative Measures

This table presents coefficient estimates of stock price informativeness on managerial inefficiency, using alternative measures. First, I check whether my results are sensitive to the choice of benchmark firm. To do so, I vary the parameter α in a wide range to calculate the dependent variable, Shortfalls, and estimate the baseline specification again. In Column (1) and (2), I use α = 0.1 and α = 0.3 to estimate Shortfalls. In Column (3), I use the industry median firm, α = 0.5, to estimate Shortfalls. Second, I employ two alternative measures of stock price informativeness to corroborate my results. In Column (4), I use adjusted PIN measure (APIN) as main explanatory variable. In Column (5), I use price nonsynchronicity, Ψ, to proxy for stock price informativeness. All the variables are defined in the Appendix A.2. The sample period is from 1993 to 2010. The estimations correct the error term structure for heteroskedasticity and within-firm clustering. The t-statistics are in parentheses. ***, ** and * denote statistical significance at the 1%, 5% and 10% level, respectively.

	Alternative Benchmatrk						Alternative Informativeness Measure			
Variable	(1)		(2)		(3)		(4)		(5)	
PIN	-0.3279	***	-0.2980	***	-0.2905	***				
	(-4.42)		(-4.24)		(-4.22)					
APIN							-0.3609	**		
							(-2.40)			
Ψ									-0.0083	*
									(-1.77)	
Age	0.0021		0.0027		0.0017		-0.0035		0.0015	
	(0.32)		(0.49)		(0.34)		(-0.65)		(0.25)	
MktShr	-0.1266		-0.0120		-0.0105		0.0918		-0.0564	
	(-0.59)		(-0.05)		(-0.05)		(0.31)		(-0.26)	
HHISIC3	-0.0049		0.1036		0.1479		0.2567	*	0.0462	
	(-0.04)		(1.07)		(1.610		(1.77)		(0.45)	
Growth	-0.4444	***	-0.4422	***	-0.4568	***	-0.3200	***	-0.4379	***
	(-11.26)		(-11.89)		(-12.50)		(-4.40)		(-11.44)	
Segment	0.0113	*	0.0099	*	0.0098	*	0.0191	**	0.0110	*
	(1.76)		(1.65)		(1.69)		(2.24)		(1.77)	
Analyst	-0.0051	**	-0.0063	***	-0.0066	***	-0.0074	**	-0.0060	***
	(-2.24)		(-2.83)		(-2.96)		(-2.35)		(-2.65)	
Institution	-0.8243	***	-0.8357	***	-0.8609	***	-0.5007	***	-0.8395	***
	(-13.92)		(-14.86)		(-15.42)		(-5.50)		(-14.41)	
Spread	15.2948	***	15.9781	***	16.1346	***	7.5584	***	15.8365	***
	(15.24)		(17.22)		(17.59)		(3.36)		(16.26)	
CumRet	0.3484	***	0.3550	***	0.3586	***	0.2759	***	0.3514	***
	(37.42)		(39.58)		(40.25)		(19.38)		(38.41)	
Firm FE	Yes		Yes		Yes		Yes		Yes	
Year FE	Yes		Yes		Yes		Yes		Yes	
# of obs	41023		41023		41023		11974		40205	
Adj R2	0.233		0.237		0.243		0.182		0.238	

Second, I employ two alternative measures of stock price informativeness to corroborate my results. A concern of using PIN as price informativeness measure is that PIN may reflect other factors rather than private information in stock prices. Hence, I use the adjusted PIN (APIN) of Duarte and Young (2009) as an alternative measure of price informativeness. Duarte and Young (2009) argue that APIN is related to pure private information in stock prices.[16] The results are reported in Column (4) of Table 1.5. The coefficient estimated on APIN is negative and statistically significant, confirming that my previous findings are driven by private information flow into stock prices.

In addition, I use stock price non-synchronicity as another alternative measure of price informativeness in Column (5). I find that price non-synchronicity is also negatively and significantly related to firm value shortfalls. Thus, managerial inefficiency is lower in firms whose stock returns are less correlated with market and industry returns.

Overall, my findings are not sensitive to the choice of the benchmark used in calculating managerial inefficiency proxy or to the alternative measures of stock price informativeness. Empirical evidence reported since then provides support to my Hypothesis 1 that firms whose stock prices are more informative experience a lower level of managerial inefficiency in making corporate decisions.

1.4.5 Additional Robustness Tests

In this subsection, I further check whether my results are robust to different functional forms and to the inclusion of additional control variables. The results are summarized in Table 1.6.

In previous tests, I treat firm value shortfalls as a continuous variable. In Column (1) of Table 1.6, I instead define firm value shortfalls using a dummy variable. Specifically, I define a dummy

[16] The APIN data is obtained from Jefferson Duarte's personal website. I thank Jefferson Duarte for making APIN data available.

variable, Dummy_shortfall, equal to one for firm-year observations with Q lower than 80th percentile firm within the industry after controlling for fundamental variables (the X variables) and zero otherwise. Hence, Dummy_shortfall is an indicator whether a firm is inefficiently managed or not, compared to their industry peers. Then I use Dummy_shortfall as the dependent variable and estimate the baseline specification by a logit regression. Using dummy variables can overcome possible measurement errors in firm value shortfalls. The estimation results in Column (1) show that PIN coefficient is -0.6325 with t-statistics of -1.97, confirming my previous findings.[17]

Similarly, I also create a dummy variable: Dummy_PIN is equal to one for firm-years with PIN above the industry median at a given year and zero otherwise. Then I replace PIN by Dummy_PIN and re-estimate my baseline specification in Column (2). There is still evidence of a negative and significant relationship between firm value shortfalls and PIN.

Another concern of using PIN as price informativeness proxy is that PIN is related to extreme stock performance: stocks with more extreme abnormal returns tend to have higher PIN (Ferreira, Ferreira and Raposo, 2011). To mitigate this concern, I create two dummies: one indicating whether firm's past yearly abnormal returns is above the 80th percentile and another indicating whether firm's past yearly abnormal returns is below the 20th percentile. In Column (3) of Table 1.6, I include these two dummy variables into the baseline specification as additional control variables and find that my results do not change qualitatively.

Finally, I take into account the possible differences of stock liquidity and corporate governance requirements among stock exchanges. In Column (4) of Table 1.6, I include a dummy variable that equals to one if a firm is listed on the New York stock exchange and zero otherwise. The coefficient estimated on PIN is still negative and statistically significant.

[17] I report bootstrapped t-statistics in Column (1) of Table 1.6 where a logit regression with firm fixed effect is used.

Table 1.6: Additional Robustness Tests

This table presents coefficient estimates of stock price informativeness on managerial inefficiency, using different functional forms and additional control variables. In Column (1), I use Dummy_shortfalls as dependent variables. Dummy_shortfalls equals to one for firm-year observations with Q lower than 80th percentile firm within the industry after controlling for fundamental variables and zero otherwise. In Column (2), I use Dummy_PIN as main explanatory variable. Dummy_PIN is equal to one for firm-years with PIN above the industry median at a given year and zero otherwise. In Column (3), I control for extreme stock performance using two dummy variables, one indicating whether firm's past yearly abnormal returns is above 80th percentile and another indicating whether firm's past yearly abnormal returns is below 20th percentile. Finally, in Column (4), I include a dummy variable, Dummy_NYSE, which equals to one if a firm is listed in New York stock exchange and zero otherwise. All the variables are defined in the Appendix A.2. The sample period is from 1993 to 2010. The estimations correct the error term structure for heteroskedasticity and within-firm clustering. The t-statistics are in parentheses. ***, ** and * denote statistical significance at the 1%, 5% and 10% level, respectively.

	Dummy_shortfalls		Dummy_PIN		Extreme Performance		Dummy_NYSE	
Variable	(1)		(2)		(3)		(4)	
PIN	-0.6325	**			-0.2610	***	-0.3035	***
	(-1.97)				(-3.69)		(-4.23)	
Dummy_PIN			-0.0327	***				
			(-2.62)					
Dummy_AbRet (Top)					-0.1508	***		
					(-12.31)			
Dummy_AbRet (Bottom)					0.0820	***		
					(7.09)			
Dummy_NYSE							-0.0149	
							(-0.33)	
Age	-0.0031		0.0023		0.0021		0.0024	
	(-0.15)		(0.36)		(0.35)		(0.38)	
MktShr	0.0162		-0.0850		-0.0893		-0.0769	
	(0.03)		(-0.40)		(-0.42)		(-0.36)	
HHISIC3	0.0671		0.0570		0.0516		0.0565	
	(0.17)		(0.57)		(0.52)		(0.56)	
Growth	-0.9459	***	-0.4358	***	-0.4110	***	-0.4359	***
	(-8.88)		(-11.49)		(-10.99)		(-11.49)	
Segment	0.0316	*	0.0114	*	0.0106	*	0.0112	*
	(1.71)		(1.85)		(1.77)		(1.83)	
Analyst	-0.0305	***	-0.0058	***	-0.0071	***	-0.0061	***
	(-4.29)		(-2.59)		(-3.18)		(-2.70)	
Institution	-2.3742	***	-0.8328	***	-0.7961	***	-0.8344	***
	(-11.55)		(-14.63)		(-14.24)		(-14.64)	
Spread	43.3247	***	15.6772	***	13.9243	***	15.5408	***
	(9.21)		(16.30)		(14.62)		(16.16)	
CumRet	1.1667	***	0.3507	***	0.3454	***	0.3514	***
	(26.03)		(38.72)		(38.45)		(38.80)	
Firm FE	Yes		Yes		Yes		Yes	
Year FE	Yes		Yes		Yes		Yes	
# of obs	25198		41023		41023		41023	
Adj R2			0.237		0.245		0.237	

1.5 How Does Stock Price Informativeness Reduce Managerial Inefficiency?

Previously, I have shown a negative relationship between stock price informativeness and managerial inefficiency. Firms whose stock prices are more informative tend to have lower managerial inefficiency in making corporate decisions. This finding could be explained by the learning hypothesis (Hypothesis 2) and/or the contracting hypothesis (Hypothesis 3). In this section, I employ several tests to investigate the two explanations for how stock price informativeness affects managerial inefficiency.

1.5.1 Learning Hypothesis

Firms might be inefficiently managed if their managers lack necessary information to make corporate decisions. The learning hypothesis (Hypothesis 2) argues that managers can learn new information from stock prices and use it to guide their corporate decisions. Hence, higher stock price informativeness leads to lower managerial inefficiency.

To empirically test the learning hypothesis, I first examine whether the effect of stock price informativeness on managerial inefficiency is stronger for firms with a higher level of business risk or uncertainty. The intuition is that when firms are operated in an environment with greater uncertainty, the new information that managers can learn from stock prices is expected to play a more valuable role in guiding their corporate decisions.

I measure business risk by operating income volatility, IncVol, which is calculated as the standard deviation of quarterly operating income before depreciation divided by quarterly book value of total assets over a period of past 20 quarters. Then I interact PIN with IncVol in the baseline specification.

Table 1.7: Learning Hypothesis

This table presents coefficient estimates of stock price informativeness on managerial inefficiency, after extending the baseline specification to test learning hypothesis. The dependent variable is Shortfalls. In Column (1) and (2), I extend the baseline specification by including IncVol and an interaction term of IncVol with PIN as additional explanatory variables. In Column (3) and (4), I interact PIN with R&D in the baseline specification. All the variables are defined in the Appendix A.2. The sample period is from 1993 to 2010. The estimations correct the error term structure for heteroskedasticity and within-firm clustering. The t-statistics are in parentheses. ***, ** and * denote statistical significance at the 1%, 5% and 10% level, respectively.

Variable	(1)		(2)		(3)		(4)	
PIN	-0.0027		-0.1894		0.0417		-0.1287	*
	(-0.02)		(-1.59)		(0.54)		(-1.77)	
PIN*IncVol	-9.5926	*	-9.0128	*				
	(-1.88)		(-1.86)					
IncVol	-4.6252	***	-3.6771	***				
	(-3.79)		(-3.20)					
PIN*R&D					-0.3390	***	-0.3103	***
					(-4.09)		(-4.00)	
R&D					0.0958	***	0.0824	***
					(3.72)		(3.35)	
Age			0.0042				0.0021	
			(0.76)				(0.34)	
MktShr			-0.0724				-0.0623	
			(-0.32)				(-0.29)	
HHISIC3			0.0712				0.0582	
			(0.65)				(0.58)	
Growth			-0.4376	***			-0.4320	***
			(-10.01)				(-11.38)	
Segment			0.0131	**			0.0110	*
			(2.06)				(1.79)	
Analyst			-0.0067	***			-0.0066	***
			(-2.89)				(-2.92)	
Institution			-0.8558	***			-0.8395	***
			(-13.62)				(-14.75)	
Spread			15.1974	***			15.4393	***
			(13.54)				(16.05)	
CumRet			0.3555	***			0.3511	***
			(36.46)				(38.75)	
Firm FE	Yes		Yes		Yes		Yes	
Year FE	Yes		Yes		Yes		Yes	
# of obs	33348		33348		41023		41023	
Adj R2	0.113		0.251		0.109		0.239	

In both Column (1) and (2) of Table 1.7, I find that the estimated coefficients for interaction term of IncVol with PIN are negative and statistically significant. The interpretation is that the negative effect of stock price informativeness on managerial inefficiency is more prominent for firms whose operating income volatility is higher.

Moreover, Edmans, Jayaraman and Schneemeier (2016) argue that information from stock prices is particularly valuable to managers when firms' production function changes rapidly. They find that managers are more likely to learn from stock prices when their firms are more technologically complex. Hence, I expect that the effect of price informativeness on managerial inefficiency becomes stronger when firms are more technologically complex.

To test this prediction, I use R&D to measure firms' technological complexity and interact R&D with PIN in the baseline specification. The results in Column (3) and (4) show that the interaction variables are negative and significant, suggesting that the negative effect of PIN on firm value shortfalls is greater in R&D intensive firms.

Taken together, these empirical results show that the negative effect of stock price informativeness on managerial inefficiency is stronger when information from stock prices is more valuable and hence managers are more likely to learn from stock prices. My findings therefore provide support to the learning hypothesis that managers learn information from stock prices and use it to guide their corporate decisions.

1.5.2 Contracting Hypothesis

The contracting hypothesis (Hypothesis 3) argues that managerial inefficiency exists because managers are weakly incentivized. When managers' contracts are tied to stock prices, their incentives to make value-enhancing decisions depend on the extent to which their decisions are reflected in stock prices. Hence, more informative stock prices give managers more incentives to make value-enhancing decisions and hence lead to a lower degree of managerial inefficiency.

I investigate this hypothesis by examining whether the effect of stock price informativeness on managerial inefficiency becomes more prominent when managers' compensation is more sensitive to firm value. To do so, I follow the method used in Coles, Daniel and Naveen (2006) to compute a measure of pay-for-performance sensitivity, PPS, and interact it with PIN in the baseline model.

Column (1) and (2) of Table 1.8 present the regression results with the interaction term. The coefficients for PPS are negative and significant, consistent with the idea that pay-for-performance contracts provide incentives and therefore decrease managerial inefficiency. More importantly, I find that the interaction variable coefficients are negative and statistically significant, indicating that the negative effect of PPS on firm value shortfalls increases with PIN. These results suggest that when managers' compensation contracts are contingent on stock prices, higher stock price informativeness will enhance the incentive effect of managers' pay-for-performance contracts.

Furthermore, even if managers' compensation is not contingent on stock prices, managers can still be tied to stock prices due to corporate governance mechanisms. When stock prices are informative, poor decisions made by managers will translate into low stock prices. The low stock prices caused by mismanagement might trigger takeover attempts from corporate control market, because acquirers would gain from correcting managerial inefficiency in the future (Edmans, Goldstein and Jiang, 2012). Hence, informative stock prices impose discipline on managers and hence reduce managerial inefficiency. I thus expect that the effect of price informativeness on managerial inefficiency is stronger when firms adopt less takeover defenses and therefore managers are more likely to face takeover threats from corporate control market.

Table 1.8: Contracting Hypothesis

This table presents coefficient estimates of stock price informativeness on managerial inefficiency, after extending the baseline specification to test contract hypothesis. The dependent variable is Shortfalls. In Column (1) and (2), I extend the baseline specification by interacting PIN with PPS. In Column (3) and (4), I define a dummy variable, Dummy_GIM, which equals to one if a firm has a GIM index higher than the median in a given year and zero otherwise. Then I extend the baseline specification by including Dummy_GIM and an interaction term of Dummy_GIM with PIN as additional explanatory variables. All the variables are defined in the Appendix A.2. The sample period is from 1993 to 2010. The estimations correct the error term structure for heteroskedasticity and within-firm clustering. The t-statistics are in parentheses. ***, ** and * denote statistical significance at the 1%, 5% and 10% level, respectively.

Variable	(1)		(2)		(3)		(4)	
PIN	0.3676	**	0.1569		-0.9450	**	-1.0301	***
	(2.00)		(0.93)		(-2.37)		(-2.78)	
PIN*PPS	-1.4599	***	-1.1330	***				
	(-5.04)		(-4.39)					
PPS	-0.4611	***	-0.3805	***				
	(-11.09)		(-9.92)					
PIN*Dummy_GIM					1.0072	**	0.9832	**
					(2.08)		(2.14)	
Dummy_GIM					-0.2157**		-0.1473	
					(-1.96)		(-1.45)	
Age			-0.0041				-0.0029	
			(-0.91)				(-0.64)	
MktShr			0.1725				-0.0853	
			(0.74)				(-0.31)	
HHISIC3			0.1853				-0.0112	
			(1.12)				(-0.05)	
Growth			-0.5214	***			-0.4641	***
			(-7.22)				(-4.38)	
Segment			0.0120				0.0158	
			(1.55)				(1.54)	
Analyst			-0.0020				-0.0093	**
			(-0.77)				(-2.18)	
Institution			-0.9992	***			-0.6521	***
			(-9.27)				(-4.45)	
Spread			7.6576	***			-2.9291	
			(2.66)				(-0.56)	
CumRet			0.3387	***			0.3391	***
			(21.89)				(16.13)	
Firm FE	Yes		Yes		Yes		Yes	
Year FE	Yes		Yes		Yes		Yes	
# of obs	14933		14933		4648		4648	
Adj R2	0.264		0.365		0.129		0.264	

To investigate this prediction, I use the governance index constructed by Gompers, Ishii, and Metrick (2003) to measure firms' number of takeover defenses and create a dummy variable that equals to one if a firm has a GIM index higher than the median in a given year and zero otherwise.[18] Then I interact this dummy variable with PIN in the baseline specification. The results in Column (3) and (4) show that the coefficients for PIN are still negative and significant. Moreover, the interaction variable coefficients are positive and significant, indicating that the negative effect of PIN on firm value shortfalls is weaker when firms adopt more takeover defenses. The evidence is consistent with my expectation that the negative relationship between PIN and firm value shortfalls is stronger for firms with lower GIM index.

Overall, these results are consistent with the contracting hypothesis that when managers are tied to stock prices, informative stock prices can incentivize managers to make value-enhancing decisions and hence reduce managerial inefficiency.

1.6 Conclusion

This paper empirically investigates the relationship between stock price informativeness and managerial inefficiency. In particular, using established measures from prior literature, I find a negative relationship between PIN and firm value shortfalls. In addition, PIN is also negatively related to operating profitability shortfalls. These results are compatible with the hypothesis that stock price informativeness can reduce managerial inefficiency in making corporate decisions. Further analyses show that the negative relationship between PIN and firm value shortfalls is unchanged when I control for potential endogeneity issues and perform a variety of robustness tests. Overall, my results suggest that stock market (informational) efficiency enhances real economy efficiency at firm level.

[18] The GIM index data is obtained from Andrew Metrick's personal website. I thank Andrew Metrick for making GIM data available to us.

Furthermore, after establishing a relationship between stock price informativeness and managerial inefficiency, two possible explanations responsible for this finding are explored. On the one hand, in line with learning hypothesis, I show that the negative effect PIN on firm value shortfalls is greater when information from stock prices is more valuable and hence managers are more likely to learn from stock prices. On the other hand, I find that because managers are tied to stock prices, more informative stock prices give managers more incentives to make value-enchaning decisions and lead to a lower level of managerial inefficiency. This finding is consistent with contracting hypothesis. Therefore, I conclude that stock price informativeness can reduce managerial inefficiency through learning hypothesis and contacting hypothesis.

Appendix A

A.1 Construction of Firm Value Shortfalls

I use the following equation to estimate a firm's frontier value:

$$Q_{i,t} = \beta_0 + \beta_1 \ln\left(LogAsset_{i,t}\right) + \beta_2 \ln\left(LogAsset_{i,t}\right)^2 + \beta_3 R\&D_{i,t} + \beta_4 Adv_{i,t} + \beta_5 Capex_{i,t}$$
$$+ \beta_6 Tang_{i,t} + \beta_7 (Tang_{i,t})^2 + \beta_8 Leverage_{i,t} + \text{missing dummies}_{i,t} + \varepsilon_{i,t}$$

The definitions of fundamental variables (X variables) are shown in Appendix A.2. In addition, if data on any of variables R&D, Adv, or Capex, are missing, I set the missing values of that variable to zero and include a dummy that equals to one when data on that variable are missing and zero otherwise. This avoids significantly reducing my sample size by dropping firm-year observations whose data on any of variables R&D, Adv, or Capex, are missing.[19]

As I described previously, I use censored least absolute deviation (CLAD) method to estimate a firm's frontier value in this paper. In CLAD method, the choice of α determines the benchmark used to estimate frontier value. A firm whose value is at $(1 - \alpha)$th percentile or higher among its industry peers is perceived as efficiently managed, while a firm with value below $(1 - \alpha)$th percentile is inefficiently managed. Hence, when $\alpha = 0$, the firm with maximum value is used as benchmark; when $\alpha = 0.5$, the median firm is the benchmark.

In this paper, I do not choose $\alpha = 0$ to calculate a firm's frontier value. This is because a firm could have extremely high valuation due to pure luck or mispricing. In addition, a firm with highest valuation could have a core competency that is distinctive from its peers. Thus, using the firm with maximum value as benchmark incorrectly assumes that all firms could have the same

[19] For example, about 68% of firm-year observations in my sample have missing values of Adv.

core competency. Furthermore, this kind of competency might be unobservable and cannot be included in the estimation of frontier value. Therefore, using a positive α in CLAD to calculate a firm's frontier value can accommodate these features.

To estimate a firm's frontier value, I first classify a firm into an industry according to its three-digit SIC code. Then I estimate the coefficients for X variables using CLAD method for each industry. Hence, I compare a firm's value with its three-digit SIC industry peers. I require at least 100 firm-year observations for a given industry to estimate the coefficients.[20] After obtaining the coefficient, a firm's frontier value is calculated as the predicted value from the above equation. Finally, firm value shortfalls are computed as the estimated frontier value minus firms' actual value.

[20] This number is determined to have a sufficient amount of observations for accurate CLAD estimation.

A.2 Variable Definitions

Variable	Definition
Q	Ratio of market value of the firm divided by book value of the firm's total assets
LogAsset	Logarithm of total assets
R&D	Research and development expenditures divided by property, plant, and equipment (ppe)
Adv	Advertising expenditures divided by ppe
Capex	Capital expenditures divided by ppe
Tang	Tangible long-term assets divided by sales
Leverage	Net debt divided by total assets, where net debt is defined as total debt minus cash
Shortfalls	The estimated frontier value minus firm's actual value
PIN	Probability of informed trading, data from Stephen Brown
Age	Firm age, calculated as years from firm's first appearance in CRSP
MktShr	Sales divided by total sales of all firms in three-digit SIC industry
HHISIC3	Herfindahl index of sales by all firms in three-digit SIC industry from Compustat
Growth	Average sales growth of a firm during past (up to) 3 years
Segment	Number of a firm's segments reported in Compustat
Analyst	Number of analysts that issue one-year forward forecasts on earnings per share for the firm
Institution	Fraction of shares outstanding held by institutional shareholders
Spread	Bid-ask spread measure estimated from daily high and low prices (Corwin and Schultz, 2012)
CumRet	Cumulative market-adjusted excess returns over a time period of 36 months subsequent to the measurement of firm value shortfalls
ROA(ROE)	Percentage of operating income before depreciation, interest and taxes to the book value of total assets (total equity)
Turnover	Annual number of shares traded divided by number of shares outstanding
IncVol	Standard deviation of quarterly operating income before depreciation divided by quarterly book value of total assets over a period of past 20 quarters
PPS	Change in CEO's wealth (in million dollars) associated with one percent change in firm's stock price

Chapter 2

Do Managers Learn from Short Sellers?

2.1 Introduction

The informational role of stock prices in guiding real decisions has been recently addressed in finance research. The key idea is that managers can learn new information from stock prices and use this information in corporate decisions.[21] While a large number of studies provide evidence that managers learn useful information from stock prices, little attention has been paid to the source of this information: who has the information that is *ex ante* unknown to managers and trade on it? This paper tries to fill this gap by examining whether managers seek to learn short sellers' information from stock prices and use it in corporate decisions.

Short sellers are often believed to be sophisticated investors with private information in finance literature.[22] Recent studies argue that short sellers may have private information that is *ex ante* unknown to managers. Chu (2015) finds that short sellers have information about customers' preference that is new to managers. This information is transmitted to managers through short sellers' trading activities and further helps managers improve firms' product market performance. Massa et al. (2015) show that when the presence of short sellers improve stock price efficiency,

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[21] Several papers have documented empirical evidence that managers learn information from stock prices and use it to make investment decisions (Chen, Goldstein and Jiang, 2007, and Bakke and Whited, 2010), merger and acquisition decisions (Luo, 2005), and cash saving decisions (Fresard, 2012). For a detailed survey on this literature, see Bond, Edmans and Goldstein (2012).

[22] For example, see Boehmer, Jones and Zhang (2008).

managers become more likely to learn information from stock prices to guide long-term investment decisions.

These evidence suggest that when short sellers are active in the market, stock prices are likely to incorporate information from short sellers that is *ex ante* unknown to managers, thus managers may have incentives to learn short sellers' information from stock prices and use such information to make corporate decisions. If so, short selling activities can affect corporate decisions through an information channel.

However, to empirically identify whether managers learn short sellers' information from stock prices is challenging for two reasons. First, there is no natural empirical proxy for the information incorporated in stock prices from short sellers. Second, short selling activities can affect stock prices and managers' decisions simultaneously through channels other than the information channel. For instance, short selling activities can affect corporate decisions by influencing firms' financial constraints. Moreover, short sellers can affect managers' decisions by alleviating or aggravating agency problems. Therefore, even if information transmission from short sellers to managers via stock prices exists, it is difficult to identify the information channel empirically.

In this paper, I address these difficulties and study the information channel by exploring a special feature in Hong Kong stock market. In Hong Kong market, whether a stock is eligible for short sales is determined by regulators when a stock meets certain requirements, and only stocks on an official list are allowed for short sales.[23] Based on whether the stocks are eligible for short sales, there are two groups of firms in the market, shortable firms and non-shortable firms. Since only shortable firms' stocks are eligible for short sales, information from short sellers is reflected only in shortable firms' stock prices.

Using this institutional feature, I study whether managers learn from short sellers by examining whether non-shortable firms' investment is influenced by the stock prices of their shortable peer

[23] For more details on the regulation of short sales in Hong Kong stock market, see Appendix B.1.

firms in the same industry. On one hand, while managers, as insiders, have an informational advantage on firms' internal conditions, it is highly plausible that short sellers, as outsiders, have more information about firms' external conditions than managers.[24] Hence, managers may wish to learn from short sellers about additional information on external conditions. On the other hand, as a firm and its industry peers face a similar external environment, the information on external conditions reflected in its peers' stock prices is also relevant to the firm's managers.[25] Hence, when non-shortable firms' managers wish to learn short sellers' information on external conditions, they have incentives to pay attention to their shortable peers' stock prices, which may provide them with incremental information about the common demand and productivity from short sellers.

Under the information channel, non-shortable firms' managers can learn short sellers' information on external conditions from shortable peers' stock prices and use it in their corporate decisions. Therefore, I expect to see that non-shortable firms' investment decisions are sensitive to their shortable peers' stock prices. This is the main hypothesis tested in this paper.

Furthermore, as non-shortable firms' own stocks are not affected by short selling activities directly, short sellers are unlikely to affect non-shortable firms' investment by influencing these firms' financing constraints or by influencing their managers' incentives. Thus, the observed sensitivity of non-shortable firms' investment to shortable peers' stock prices is unlikely to be driven by channels other than the information channel, which suggests that non-shortable firms' managers use information from shortable peers' stock prices to guide investment decisions.

In this paper, I empirically test my hypothesis using a sample of firms listed in Hong Kong market from 2002 to 2013. Consistent with my hypothesis, I find that non-shortable firms' investment is positively and significantly related to the stock prices of their shortable peers in the

[24] Edmans, Jayaraman and Schneemeier (2016) argue that outside investors are better informed about industry prospects, and hence managers may wish to learn outsiders' information from observing stock prices.
[25] See, for example, Foucault and Fresard (2014), Ozoguz and Rebello (2015), and Huang and Zeng (2015).

same two-digit SIC industry. However, such a relationship is not found between non-shortable firms' investment and the stock prices of their peers that are also non-shortable. These findings suggest that non-shortable firms' managers pay attention to the stock prices of shortable peers that may aggregate information from short sellers. In terms of economic significance, a one standard deviation decrease in the average stock prices of shortable peers is related to a decrease in non-shortable firms' average investment level by around 10%. Further analyses confirm that my findings are not driven by shortable peers' firm characteristics other than short-sale eligibility. This relationship is also robust to alternative peer definitions and to a variety of additional tests.

Next, I support my hypothesis by looking at the cross-sectional variation of non-shortable firms' investment sensitivity to their shortable peers' stock prices in different situations. Specifically, I examine whether non-shortable firms' investment sensitivity to shortable peers' stock prices becomes stronger in situations where non-shortable firms' managers are more likely to learn short sellers' information from stock prices.

First, I predict that non-shortable firms' managers are less motivated to learn from shortable peers' stock prices when their own firms' stock prices incorporate a greater amount of negative information. This is due to two reasons. On one hand, managers can learn more negative information from their own firms' stock prices directly, when their own firms' stock prices contain a greater amount of negative information from investors. On the other hand, managers can incorporate their private information into stock prices through insider trading, hence more negative information in stock prices may suggest that managers already have more negative private information. Using two measures that capture the amount of negative information in stock prices, I find that non-shortable firms' investment is more sensitive to their shortable peers' stock prices when their own firms' stock prices incorporate less negative information.

Second, I expect that non-shortable firms' investment sensitivity to shortable peers' stock prices is weaker when the information environment of these firms is richer and thus their managers can obtain negative information from other sources. I operationalize this intuition by looking at financial analysts: when analysts' opinion is less optimistically biased, managers are more likely to obtain negative information from analysts and thus are less motivated to learn from shortable peers' stock prices. Consistent with this prediction, I find that non-shortable firms' investment sensitivity to shortable peers' stock prices becomes weaker when these firms are covered by more analysts or when the analysts following these firms do not issue upward biased earnings forecasts.

Third, managers are more likely to learn negative information from shortable peers' stock prices when negative information is more valuable for investment decisions. Negative information is more valuable to managers if their firms will suffer more from future negative productivity shocks. Cooper (2006) argues that when hit by adverse productivity shocks, firms with a higher proportion of tangible assets or a higher degree of investment irreversibility tend to experience a larger loss in productivity efficiency and firm value. In line with this argument, I show that non-shortable firms' investment becomes more sensitive to shortable peers' stock prices when they have more tangible assets in place or when they face a higher level of investment irreversibility. I also find that this sensitivity becomes stronger when non-shortable firms have a higher level of business risk or uncertainty. This is consistent with the intuition that when firms operate in an environment with greater uncertainty, managers are more likely to learn new information from other sources, such as short sellers.

Finally, I examine whether my findings are driven by a primary market channel. When shortable peers' stock prices are high, an arbitrageur who shorts these stocks may purchase non-shortable firms' stocks to hedge industry risk, resulting in an increase in non-shortable firms' stock prices. Hence, high shortable peers' stock prices are associated with a decline in cost of capital and therefore a loosening of financial constraints for non-shortable firms. If so, non-shortable firms' investment sensitivity to shortable peers' stock prices should be greater in financially constrained firms. However, my findings do not support the primary market channel.

Furthermore, if shortable peers' stock prices contain short sellers' information that is new to non-shortable firms' managers and hence help managers make better investment decisions, I expect that non-shortable firms' investment efficiency would be improved when their managers can learn more information from shortable peers' stock prices. Consistent with this prediction, I find that within an industry, when relatively more firms are shortable, the overall investment efficiency level of non-shortable firms becomes higher. Moreover, this improvement is more pronounced for non-shortable firms that might be overinvesting. These findings lend additional support to my hypothesis that non-shortable firms' managers learn information from shortable peers' stock prices and use it in corporate investment decisions.

In the final exploration, by employing a regulatory change (Regulation SHO) that relaxes short-sale constraints on a random sample of firms in U.S. stock market, I show that my previous findings in Hong Kong stock market also carry over to U.S. stock market.

This paper contributes to the literature in several ways. First, it contributes to a recent literature, which shows that managers learn information from stock prices when making corporate decisions. While a significant portion of this literature has shown evidence of managerial learning, this paper presents the first effort, to the best of my knowledge, to identify a specific source of information learned by managers from stock prices. My findings suggest that managers learn short sellers' information from stock prices and use it in corporate investment decisions. In this regard, this paper also contributes to the studies on the information advantage of short sellers. A large body of literature has shown that short sellers have access to private information that is known to managers. My paper suggests that short sellers possess information on external conditions that is *ex ante* unknown to managers.

Finally, this paper contributes to the literature that studies the real effects of short selling activities on corporate decisions. Prior studies typically focus on the effects of short selling activities on firms' financing constraints or managers' incentives. This paper differs by showing that short selling activities can affect corporate decisions through an information channel. That is, short selling enhances the informational role of stock prices by revealing information that is new to managers, and then managers learn this information from stock prices and use it in corporate decisions.

The remainder of this paper is organized as follows. Section 2.2 discusses related literature. Section 2.3 describes data and empirical testing issues. Section 2.4 and Section 2.5 present main empirical results and cross-sectional analyses. Section 2.6 presents further analyses. Section 2.7 concludes.

2.2 Related Literature

This paper is closely related to three strands of literature. First, it relates to the literature on the information feedback from stock prices to corporate decisions. The idea that managers can learn new information from stock prices to guide their corporate decisions has been studied theoretically by Dow and Gorton (1997) and Subrahmanyam and Titman (1999), among others. On the empirical side, a growing literature has shown evidence that managers learn from stock prices when making corporate decisions. Chen, Goldstein and Jiang (2007) find that corporate investment decisions are more sensitive to stock prices when stock prices contain more private information, suggesting that managers learn information from stock prices and use it to guide corporate investment. Fresard (2012) shows that cash saving decisions are also more sensitive to stock prices when stock prices are more informative. Luo (2005) finds that managers use the information from stock returns around acquisition announcements to determine whether to consummate the deals later. Moreover, recent studies, such as Foucault and Fresard (2014), Ozoguz and Rebello (2015), and Huang and Zeng (2015), show theoretically and empirically that besides from their own firms' stock prices, managers also seek to learn from peer firms' stock prices to obtain additional information about common shocks when making corporate investment decisions.

Second, this paper is related to studies on the information advantage of short sellers. While a significant portion of extant literature shows that short sellers have access to private information that is also known to managers, a few recent studies suggest that short sellers possess valuable information that is new to managers.[26] Chu (2015) finds that short sellers have information about customers' preference that is *ex ante* unknown to managers. This information is transmitted to managers through short sellers' trading activities and further helps managers improve product market performance. Massa et al. (2015) find when the presence of short sellers improves stock price efficiency, managers become more likely to learn from stock prices to guide long-term investment decisions. Their findings suggest that short sellers have information that managers wish to learn.

Last but not least, this paper is related to literature that studies how short selling activities affect managers' decisions. On one hand, prior studies suggest that short selling activities can affect corporate decisions by influencing firms' financial constraints. For example, Grullon, Michenaud and Weston (2015) find that upon the relaxation of short-sale constraints, increased short selling activities cause stock prices to fall, leading to a decrease in equity issuance and corporate investment for financially constrained firms. On the other hand, several papers show that short selling can affect managers' decisions by alleviating or aggravating agency problems. Massa, Zhang and Zhang (2015) and Chang, Lin and Ma (2014) find that short selling has a disciplining effect on managers' decisions by deterring earnings manipulation or empire building behavior. He and Tian (2014) find a positive relationship between short selling activities and innovation, suggesting that short selling induces managers to invest in long-term innovative projects. In contrast, Nezafat, Shen and Wang (2014) show that short selling activities cause overinvestment when managers have short-term incentives.

[26] See, for example, Christophe, Ferri and Angel (2004), and Massoud et al. (2011).

2.3 Data and Methodology

2.3.1 Sample Construction

In this paper, I empirically test my hypothesis by exploring the institutional feature in Hong Kong stock market that only stocks on an official list are allowed for short sales. I use a panel of firms listed in Hong Kong market for empirical analysis. The empirical goal is to examine whether non-shortable firms' investment is sensitive to their shortable peers' stock prices. First, I need to identify whether a firm's stock is allowed for short sales at any given time point.

The Hong Kong Stock Exchange (hereafter, HKSE) publishes the most recent official list of stocks eligible to short sales, as well as the announcement of each past revision to the list on its website.[27] To obtain the historical lists of shortable stocks, I collect data on each list revision announcement and then deduct the historical official lists for short sales from the most recent one.[28] Finally, I obtain the historical lists of stocks for short sales in each year from 2002 to 2013.

According to the historical lists of stocks for short sales, for each year, I classify firms into two groups. For each year, firms that appear in the official lists for short sales are classified as shortable firms, and the remaining firms are called non-shortable firms.[29] Then I match these firms with the Compustat Global database to obtain financial statement data and stock price data. I exclude firms in financial and banking industries (SIC code 6000-6999) and utility industries (SIC code 4900-4999). I also exclude firm-year observations with negative book value of total assets or equity, or with less than 30 days of trading activities in a year. After these adjustments, my final sample consists of 4,963 firm-year observations associated with 722 firms from 2002 to 2013.

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[27] See https://www.hkex.com.hk/eng/index.htm.

[28] My data cleaning process is similar to that used in Hwang, Liu and Xu (2015).

[29] In case that a firm is included into the official list in the middle of the year, this firm is defined as shortable if it is allowed for short sales for at least six months before its fiscal year end. This guarantees enough time for stock prices to incorporate information from short sellers. However, eliminating these observations does not qualitatively change my results.

Table 2.1: Number of Shortable and Non-shortable Firms

This table presents the yearly distribution of shortable and non-shortable firms for the sample from 2002 to 2013. I exclude firms in the financial and banking industries (SIC code 6000-6999) and utility industries (SIC code 4900-4999). I also exclude firm-year observations with negative book value of total assets or equity, or with less than 30 days of trading activities in a year.

Year	# of shortable firms	# of non-shortable firms	# of total firms	% of shortable firms
2002	25	131	156	16%
2003	31	257	288	11%
2004	29	264	293	10%
2005	46	363	409	11%
2006	67	380	447	15%
2007	49	367	416	12%
2008	100	405	505	20%
2009	72	375	447	16%
2010	49	374	423	12%
2011	117	412	529	22%
2012	117	415	532	22%
2013	95	423	518	18%

Table 2.1 summarizes the distribution of shortable firms and non-shortable firms across years in my sample. In the early years of my sample, around 10% of firms are shortable in Hong Kong stock market; however, this number almost doubles in the second half of my sample period.

Table 2.2 presents the summary statistics for my sample. Panel B and C show that shortable firms have higher Tobin's Q than non-shortable firms. The average values of Q are 1.679 and 1.488 for shortable firms and non-shortable firms, respectively. In addition, shortable firms also have a higher level of investment and cash flows than non-shortable firms. These differences are mainly due to the fact that shortable firms are on average larger than non-shortable firms. According to the information revealed by HKSE, firms are required to meet a minimum level of market capitalization and trading turnover to become eligible for short sales. Hence, shortable firms have substantially larger market capitalization and higher trading turnover than non-shortable firms in my sample. The median market capitalization and trading turnover for shortable firms are HK$ 5,346 million and 0.514. This compares to a median market capitalization of HK$ 412 million and a median trading turnover of 0.264 for non-shortable firms.

Table 2.2: Summary Statistics

This table presents the summary statistics for the sample. The sample consists of 4963 firm-year observations associated with 722 firms from 2002 to 2013. Detailed variable definitions are in Appendix B.2. All unbounded variables are winsorized at 1% and 99% levels for each panel year. Panel A presents the summary statistics for all firms, while Panel B (Panel C) presents the summary statistics for only shortable (non-shortable) firms. In this paper, I mainly use the sample of non-shortable firms (in Panel C) for empirical analysis.

Variables	# Obs	Mean	Std Dev	Q1	Median	Q3
			Panel A: All firms			
Inv	4963	0.0453	0.0665	0.0066	0.0225	0.0549
Q	4963	1.5190	1.7181	0.7545	1.0149	1.5649
CF	4963	0.0153	0.2326	-0.0270	0.0532	0.1165
ASSET (in HK$ millions)	4963	3767.61	12061.15	387.18	1017.60	2760.77
MV (in HK$ millions)	4963	2796.75	9738.50	215.06	549.90	1668.50
Turnover	4963	0.6978	1.4070	0.1115	0.3116	0.7621
			Panel B: Shortable firms			
Inv	797	0.0527	0.0584	0.0144	0.0370	0.0685
Q	797	1.6792	1.2173	0.9260	1.2995	1.9913
CF	797	0.0929	0.1184	0.0404	0.0916	0.1546
ASSET (in HK$ millions)	797	14774.94	26692.46	2935.00	6093.63	15037.48
MV (in HK$ millions)	797	12043.47	20619.79	2548.74	5346.24	12171.02
Turnover	797	0.7515	1.1571	0.2566	0.5135	0.8492
			Panel C: Non-shortable firms			
Inv	4166	0.0439	0.0679	0.0060	0.0203	0.0513
Q	4166	1.4883	1.7966	0.7351	0.9702	1.4801
CF	4166	0.0005	0.2458	-0.0459	0.0444	0.1067
ASSET (in HK$ millions)	4166	1661.78	3085.40	318.46	786.40	1785.04
MV (in HK$ millions)	4166	1027.75	3498.12	185.54	412.40	916.36
Turnover	4166	0.6875	1.4498	0.0964	0.2642	0.7256

2.3.2 Baseline Model

To test the hypothesis that non-shortable firms' investment is sensitive to the stock prices of their shortable peers, I use the following specification:

$$\mathrm{Inv}_{ijt} = \delta_j + \eta_t + \beta_1 Q_{ijt-1} + \beta_2 \mathrm{Control}_{ijt} + \beta_3 Q_{jt-1,-i}^{\mathrm{Shortable}} + \beta_4 \mathrm{Control}_{jt,-i}^{\mathrm{Shortable}} + \beta_5 Q_{jt-1,-i}^{\mathrm{Non-shortable}} + \beta_6 \mathrm{Control}_{jt,-i}^{\mathrm{Non-shortable}} + \varepsilon_{ijt}$$

where the dependent variable Inv_{ijt} represents the investment of a non-shortable firm i in industry j at year t, measured as capital expenditures scaled by book value of beginning-of-year total assets.[30] On the right-hand side of the model, following Chen, Goldstein and Jiang (2007) and Ozoguz and Rebello (2015), I first include firm i's own stock price measure Q_{ijt-1}, which is calculated as the market value of equity plus book value of assets minus book value of equity, scaled by book value of assets, all measured at the end of year t-1. I also include a set of control variables for firm i, including CF_{ijt} and $1/\mathrm{ASSET}_{ijt-1}$. CF_{ijt} is included to control for the well-known effect of cash flow on investment, while $1/\mathrm{ASSET}_{ijt-1}$ is included to isolate the spurious correlation between Inv_{ijt} and Q_{ijt-1} that are scaled by common variable.

The main explanatory variable is a measure for the stock prices of firm i's shortable peers, $Q_{jt-1,-i}^{\mathrm{Shortable}}$. In this paper, I mainly use two-digit SIC code to define industry peers. That is, I define shortable peers of firm i as all shortable firms that belong to the same two-digit SIC industry as firm i at a given year. This choice aims to achieve a trade-off between obtaining a reasonable number of shortable peers for each firm and minimizing the possibility that a firm and its peers are in unrelated businesses. $Q_{jt-1,-i}^{\mathrm{Shortable}}$ is calculated as the equally-weighted average value of Q across all shortable peers of firm i in industry j at year t-1.

[30] Since I only look at the investment decisions of non-shortable firms, the final sample used in my main analysis consists of 4166 firm-year observations associated with 679 non-shortable firms.

In addition, I include a set of peer-level control variables constructed from firm i's shortable peers, $\text{Control}_{jt,-i}^{\text{Shortable}}$, in my specification. Prior studies show that firms' corporate decisions are influenced by their peer's decisions.[31] Since peers' investment decisions are correlated with peers' stock prices, a correlation between firms' investment and their peers' stock prices may be simply caused by the fact that firms are mimicking their peers' investment decisions. To address this concern, I add to the baseline model $\text{Inv}_{jt,-i}^{\text{Shortable}}$, which is calculated as the equally-weighted average capital expenditures of all shortable peers of firm i in industry j at year t. In addition, I include $\text{CF}_{jt,-i}^{\text{Shortable}}$, as measured by the equally-weighted average cash flows of all shortable peers, to control for product market characteristics (Foucault and Fresard, 2014).

Furthermore, I include the same set of peer-level variables constructed from firm i's non-shortable peers ($Q_{jt-1,-i}^{\text{Non-shortable}}$ and $\text{Control}_{jt,-i}^{\text{Non-shortable}}$). Finally, I include δ_j and η_t to control for industry and year fixed effects. The definitions of all variables are presented in Appendix B.2.

2.4 Empirical Results

2.4.1 Baseline Model Tests

In this subsection, I test whether non-shortable firms' investment is sensitive to their shortable peers' stock prices. Before estimating the model, I normalize all stock price variables (Q_{ijt-1}, $Q_{jt-1,-i}^{\text{Shortable}}$ and $Q_{jt-1,-i}^{\text{Non-shortable}}$ in the model) to unit standard deviation. Hence, the estimated coefficient for each stock price variable represents the change in firm i's investment for a one standard deviation increase in the corresponding stock price variable.

[31] For example, Leary and Roberts (2014) show that firms mimic their peer firms' capital structures when making their own capital structure decisions.

Table 2.3 summarizes the estimation results for the baseline model. Column (1) presents the results from estimating baseline model including only shortable peers' variables. The estimated coefficient for Q_{ijt-1} is positive and statically significant, consistent with prior findings that managers use information reflected in their firms' own stock prices to make investment decisions (e.g., Chen, Goldstein, and Jiang, 2007).

More importantly, the coefficient for $Q_{jt-1,-i}^{Shortable}$ is 0.0030 and significant at 10% level, indicating that non-shortable firms' investment is also sensitive to their shortable peers' stock prices. This result is consistent with my hypothesis that non-shortable firms' managers learn information from shortable peers' stock prices; when shortable peers' stock prices decline, non-shortable firms' managers perceive it as a negative signal relevant to them, and hence decrease their investment.[32]

Column (2) of Table 2.3 estimates the baseline model including only non-shortable peers' variables. If non-shortable firms' managers seek to learn short sellers' information from peers' stock prices, it would be unlikely for these managers to pay attention to the stock prices of their peers that are also non-shortable. Hence, non-shortable firms' investment should not be sensitive to their non-shortable peers' stock prices. Consistent with this prediction, I find that the coefficient for $Q_{jt-1,-i}^{Non-shortable}$ is small and insignificant, indicating that non-shortable firms' managers do not alter their investment decisions in response to a change in their non-shortable peers' stock prices.

Finally, Column (3) includes both shortable peers' variables and non-shortable peers' variables in the baseline model. I obtain similar results: the coefficient for $Q_{jt-1,-i}^{Shortable}$ is 0.0041 and significant at 5% level. In terms of economic significance, this means that a one standard deviation decrease in shortable peers' stock prices is associated with a decrease in non-shortable

[32] For example, a decrease in peers' stock prices may reflect the declining product demand for the whole industry.

firms' investment by 0.0041. Given that the mean value of non-shortable firms' investment is 0.0439, this implies a decrease in non-shortable firms' investment by around 10%.

Table 2.3: Baseline Model Results

This table presents the coefficient estimates of baseline model. The dependent variable is the investment of non-shortable firms. In Column (1), I include only shortable peers' variables, while in Column (2) I include only non-shortable peers' variables. In Column (3), I include both shortable and non-shortable peers' variables. Detailed variable definitions are in Appendix B.2. The sample period is from 2002 to 2013. The estimations correct the error term structure for heteroskedasticity and within-firm clustering. The t-statistics are in parentheses. ***, ** and * denote statistical significance at the 1%, 5% and 10% level, respectively.

	Dependent variable = Inv_i					
	(1)		(2)		(3)	
Q_i	0.0103	***	0.0098	***	0.0099	***
	(4.45)		(4.28)		(4.32)	
CF_i	0.0389	***	0.0392	***	0.0392	***
	(4.76)		(4.83)		(4.84)	
1/ASSET	-0.0900		-0.0230		-0.0459	
	(-0.34)		(-0.09)		(-0.18)	
$Q_{-i}^{Shortable}$	0.0030	*			0.0041	**
	(1.95)				(2.58)	
$Inv_{-i}^{Shortable}$	-0.0238				-0.0267	
	(-0.73)				(-0.84)	
$CF_{-i}^{Shortable}$	0.0247	*			0.0394	***
	(1.74)				(2.74)	
$Q_{-i}^{Non-shortable}$			-0.0012		-0.0009	
			(-0.95)		(-0.79)	
$Inv_{-i}^{Non-shortable}$			-0.2237	***	-0.2469	***
			(-4.49)		(-4.80)	
$CF_{-i}^{Non-shortable}$			0.0097		0.0098	
			(0.93)		(0.94)	
Year FE	Yes		Yes		Yes	
Industry FE	Yes		Yes		Yes	
Adj-R2	0.092		0.100		0.102	
N	4166		4166		4166	

In addition, the coefficient for $Q_{jt-1,-i}^{Non-shortable}$ remains small and statistically insignificant in Column (3). The null hypothesis that the estimated coefficients are equal for $Q_{jt-1,-i}^{Shortable}$ and

$Q_{jt-1,-i}^{Non-shortable}$ is rejected at 5% level, suggesting that non-shortable firms' investment decisions respond differently to the stock prices of shortable peers and non-shortable peers.[33]

With respect to the control variables, consistent with findings in prior literature, Table 2.3 shows that firms' investment is positively and significantly related to their own stock prices as well as cash flows. In addition, the coefficients for $Inv_{jt,-i}^{Shortable}$ and $Inv_{jt,-i}^{Non-shortable}$ are negative, suggesting that firms lower their investment when their peers make more investment to expand production capacity. This finding is consistent with the intuition that managers take into account product market competition when they make investment decisions. Finally, the coefficients for $CF_{jt,-i}^{Shortable}$ and $CF_{jt,-i}^{Non-shortable}$ are positive, indicating that cash flows of both shortable and non-shortable peers are positively related to firms' investment. This result suggests that firms in more profitably industries tend to make more investment.

Overall, these findings are consistent with my hypothesis that non-shortable firms' managers seek to learn short sellers' information from shortable peers' stock prices and use it in their investment decisions.

2.4.2 Controlling for Firm Characteristics

In this subsection, I examine whether my findings are driven by firm characteristics rather than short selling activities. Leary and Roberts (2014) show that smaller firms tend to mimic the capital structure of their larger peers. In addition, Ozoguz and Rebello (2015) find that firms' investment is more sensitive to the prices of peers with more liquid stocks. Hence, if short sale eligibility of a firm's stock is influenced by certain firm characteristics (e.g. firm size), then it is possible that my findings are influenced by these firm characteristics.

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[33] Since the estimated coefficients for $Q_{jt-1,-i}^{Shortable}$ and $Q_{jt-1,-i}^{Non-shortable}$ have opposite signs, I also test whether the two coefficients are equal in absolute value. The null hypothesis $|Q_{jt-1,-i}^{Shortable}| = |Q_{jt-1,-i}^{Non-shortable}|$ is rejected at 10% level.

Indeed, whether a firm's stock is eligible for short sales is highly correlated with at least two firm characteristics. As shown in Appendix B.1, HKSE requires firms to meet a minimum level of market capitalization and trading turnover to become eligible for short sales.[34] Table 2.2 shows that shortable firms have larger market capitalization and higher trading turnover than non-shortable firms. Therefore, my findings are plagued by the possibility that firms' investment decisions are more sensitive to the stock prices of their peers with larger market capitalization or higher trading turnover.

First, I check whether my previous results are driven by firms' market capitalization. To do so, for each year in the sample, I match each shortable firm with a non-shortable firm closest in market capitalization and from the same two-digital SIC industry. The firm with closest market capitalization is chosen by the smallest ratio of market capitalization (MV), which is defined as $\max(\mathrm{MV}_{\mathrm{shortable}}, \mathrm{MV}_{\mathrm{non-shortable}})/\min(\mathrm{MV}_{\mathrm{shortable}}, \mathrm{MV}_{\mathrm{non-shortable}})$. I require that the ratio of market capitalization is less than two and perform one-to-one matching without replacement. I plot the distribution of logarithm of market capitalization for shortable and non-shortable firms at the top of Figure 2.1. The two distributions become nearly identical after matching.

Then, I re-calculate peer-level variables using firm i's shortable and non-shortable peers from this matched sample. Hence, $\mathrm{Q}_{\mathrm{jt-1,-i}}^{\mathrm{Shortable}}$ and $\mathrm{Q}_{\mathrm{jt-1,-i}}^{\mathrm{Non-shortable}}$ are constructed using firm i's shortable and non-shortable peers with close market capitalization, respectively. I re-estimate the baseline model and the results are reported in Column (1) of Table 2.4.

If my findings are driven by market capitalization rather than short selling activities, I should expect to see that non-shortable firms' investment is sensitive to the stock prices of both shortable and non-shortable (large) peers. However, this is not the case. Column (1) shows that the coefficient for $\mathrm{Q}_{\mathrm{jt-1,-i}}^{\mathrm{Shortable}}$ is positive and significant at 5% level, while the coefficient for

[34] Though the selection of shortable stocks is mainly driven by market capitalization and trading turnover, not all stocks that meet the criteria are include into the list immediately. The delay is mainly due to the regulatory capacity constraint (Gao et al., 2011).

$Q_{jt-1,-i}^{Non-shortable}$ remains small and insignificant. In addition, the null hypothesis that the coefficients are equal for $Q_{jt-1,-i}^{Shortable}$ and $Q_{jt-1,-i}^{Non-shortable}$ is rejected at 5% level.

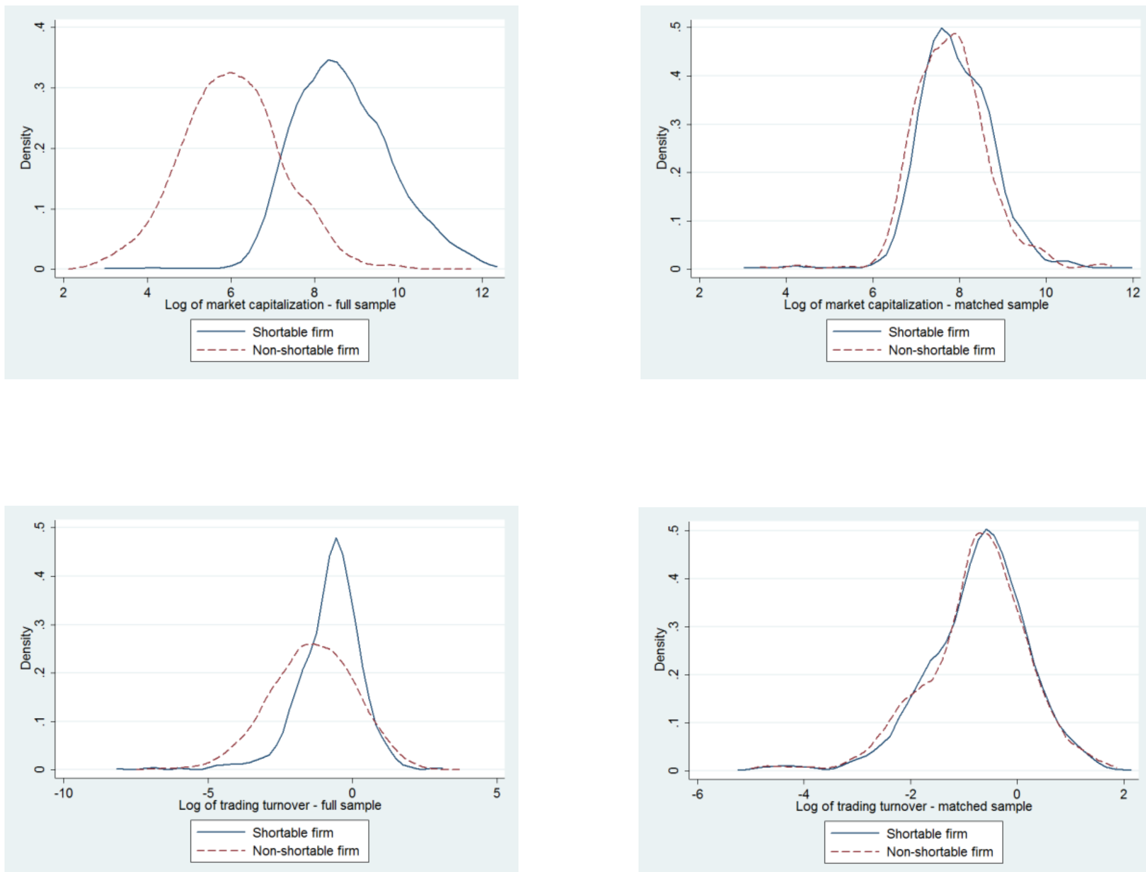

Figure 2.1: Market Capitalization and Trading Turnover Distribution of Shortable and Non-shortable Firms. The top graphs show the market capitalization of shortable and non-shortable firms in full sample and matched sample. The bottom graphs show the trading turnover of shortable and non-shortable firms in full sample and matched sample. I plot the Epanechnikov kernel densities of the natural logarithm of market capitalization and trading turnover.

Second, I repeat the same analysis but using a sample of shortable and non-shortable firms matched on trading turnover. The bottom graphs in Figure 2.1 show that matching produces almost perfectly overlapped trading turnover distributions. Column (2) of Table 2.4 shows that my results remain qualitatively unchanged: the estimated coefficient for $Q_{jt-1,-i}^{Shortable}$ is 0.0049 and significant at 5% level, while the coefficient for $Q_{jt-1,-i}^{Non-shortable}$ remains insignificant. Moreover, the null hypothesis that the coefficients are equal for $Q_{jt-1,-i}^{Shortable}$ and $Q_{jt-1,-i}^{Non-shortable}$ is rejected at 5% level. Therefore, these results indicate that my findings are unlikely to be driven by market capitalization or trading turnover.[35]

In addition, Ozoguz and Rebello (2015) find that when managers seek to learn from peers' stock prices, they pay more attention to peers whose stock prices contain a greater amount of information, such as peers with higher stock price non-synchronicity (1-R2) or with higher Amihud (2002) ratio. Hence, it is possible that my results are driven by the likelihood that shortable peers' stock prices are on average more informative than non-shortable peers' stock prices.

To address this concern, I repeat the previous analysis by using a sample of shortable and non-shortable firms matched on stock price non-synchronicity and Amihud ratio to construct peer-level variables in Column (3) and (4), respectively. In both columns, the estimated coefficient for $Q_{jt-1,-i}^{Shortable}$ is positive and statistically significant, while the coefficient for $Q_{jt-1,-i}^{Non-shortable}$ remains insignificant. These findings indicate that even when the stock prices of shortable and non-shortable peers contain a similar amount of information, non-shortable firms' managers still seek to learn from shortable peers' stock prices, which are more likely to incorporate information from short sellers.

[35] In unreported analysis, I employ another method to address this concern. Specifically, I interact firm i's market capitalization with $Q_{jt-1,-i}^{Shortable}$ in the baseline model. If relative market capitalization matters, I should observe that non-shortable firms' investment sensitivity to shortable peers' stock prices decreases with firms' market capitalization. However, the coefficient for the interaction term is insignificant. I also interact firm i's trading turnover with $Q_{jt-1,-i}^{Shortable}$ and find no significant results.

Table 2.4: Controlling for Firm Characteristics

This table presents the coefficient estimates of baseline model, using different groups of firms to calculate peer-level variables. The dependent variable is the investment of non-shortable firms. In Column (1), (2), (3) and (4), I calculate peer-level variables using a group of shortable and non-shortable firms matched on market capitalization, trading turnover, stock price non-synchronicity and Amihud ratio, respectively. In Column (5) and (6), I use a group of firms that experienced (at least one) change of short-sale eligibility during the sample period and calculate peer-level variables using these peers when they are shortable and non-shortable, respectively. Detailed variable definitions are in Appendix B.2. The sample period is from 2002 to 2013. The estimations correct the error term structure for heteroskedasticity and within-firm clustering. The t-statistics are in parentheses. ***, ** and * denote statistical significance at the 1%, 5% and 10% level, respectively.

	Dependent variable = Inv_i											
	(1)		(2)		(3)		(4)		(5)		(6)	
Q_i	0.0083	***	0.0101	***	0.0095	***	0.0089	***	0.0086	***	0.0084	***
	(3.11)		(4.19)		(4.27)		(3.48)		(3.57)		(3.54)	
CF_i	0.0351	***	0.0385	***	0.0386	***	0.0426	***	0.0358	***	0.0358	***
	(3.61)		(4.56)		(4.61)		(4.47)		(4.24)		(4.25)	
1/ASSET	0.1861		-0.0337		-0.0231		0.0800		0.1031		0.1315	
	(0.62)		(-0.12)		(-0.08)		(0.31)		(0.38)		(0.48)	
$Q_{-i}^{Shortable}$	0.0035	**	0.0049	**	0.0036	**	0.0021	*	0.0034	**		
	(2.09)		(2.30)		(2.22)		(1.70)		(2.05)			
$Inv_{-i}^{Shortable}$	-0.0051		-0.0225		-0.0166		0.0698		-0.0099			
	(-0.17)		(-0.67)		(-0.48)		(1.56)		(-0.28)			
$CF_{-i}^{Shortable}$	0.0086		0.0256		0.0275	*	0.0302	*	0.0242			
	(0.65)		(1.63)		(1.85)		(1.81)		(1.49)			
$Q_{-i}^{Non-shortable}$	-0.0015		-0.0011		-0.0008		0.0014				0.0005	
	(-1.54)		(-1.06)		(-1.18)		(0.90)				(0.38)	
$Inv_{-i}^{Non-shortable}$	-0.0563	***	-0.1000	***	-0.1023	***	-0.0220				-0.0745	**
	(-2.97)		(-3.30)		(-3.44)		(-1.52)				(-2.56)	
$CF_{-i}^{Non-shortable}$	-0.0011		-0.0017		0.0029		0.0137	**			-0.0025	
	(-0.51)		(-0.53)		(0.50)		(2.10)				(-0.45)	
Year FE	Yes		Yes		Yes		Yes		Yes		Yes	
Industry FE	Yes		Yes		Yes		Yes		Yes		Yes	
Adj-R2	0.070		0.095		0.092		0.080		0.078		0.078	
N	3335		4007		4050		2911		3709		3709	

Finally, I examine whether my findings are affected by peers' unobservable time-invariant firm characteristics. For example, when making investment decisions, a firm's manager may look at the stock prices of "bellwether" peers as a barometer for market or industry future performance, no matter these peers' stocks are shortable or not. To address this possibility, I exploit the dynamic change of stocks' eligibility for short sales and examine whether non-shortable firms' investment is sensitive to the stock prices of a certain group of peer firms when these peers are shortable or non-shortable at different time points. Specifically, I identify a sample of peer firms that experienced (at least one) change of short-sale eligibility during my sample period, and re-calculate peer-level variables using peers from this sample. Thus, $Q_{jt-1,-i}^{Shortable}$ and $Q_{jt-1,-i}^{Non-shortable}$ are calculated using the same group of peers when they are shortable and non-shortable, respectively.

The estimation results are reported in Column (5) and (6) of Table 2.4. Consistent with my previous findings, non-shortable firms' investment are sensitive to these peers' stock prices when these peers are shortable: in Column (5), the coefficient for $Q_{jt-1,-i}^{Shortable}$ is positive and significant at 5% level. However, when the same peers become non-shortable, non-shortable firms' investment is no longer sensitive to these peers' stock prices: in Column (6), the coefficient for $Q_{jt-1,-i}^{Non-shortable}$ is close to zero and statistically insignificant. These findings suggest that non-shortable firms' investment is sensitive to the stock prices of their peers, only when these peers' stocks are shortable.

Overall, these results provide additional support to my hypothesis that non-shortable firms' managers learn short sellers' information from their shortable peers' stock prices.

2.4.3 Alternative Peer Definitions

In this subsection, I test whether my findings are sensitive to the way peers are defined. In previous analysis, I define peers of firm i as all other firms that belong to the same two-digit SIC industry as firm i at a given year. Using a relatively coarse peer definition allows me to obtain a reasonable number of (shortable and non-shortable) peers for each firm, but bears the risk that firms and their peers might be in unrelated businesses.

To alleviate this concern, I re-estimate the baseline model using three-digit SIC code to define peers. Switching to a narrower industry classification lowers the possibility that firms and their peers are in unrelated businesses.[36]

The estimation results in Column (1) of Table 2.5 show that my findings are essentially unchanged when switching to this narrower classification of industry peers: the estimated coefficient for $Q_{jt-1,-i}^{Shortable}$ is 0.0037 and significant at 5% level. In addition, the coefficient for $Q_{jt-1,-i}^{Non-shortable}$ remains both statistically and economically insignificant.

Furthermore, I examine the robustness of my findings by using another scheme of industry classification, Global Industry Classifications Standard (hereafter, GICS), to define peers. Compared to SIC that uses production and technology based framework to organize industry groups, GICS categorizes firms on the basis of their primary business activity. Bhojraj, Lee and Oler (2003) find that GICS performs better than SIC in identifying and grouping firms based on future sales growth. If the future sales growth of firms and their peers are closely correlated, the information about future demand reflected in their peers' stock prices should be useful to the firms' managers in making investment decisions.[37]

[36] However, switching to three-digit SIC code reduces my sample size by around 40%. Since the results remain unaffected by switching to this narrower industry classification as shown in this subsection, I mainly use two-digit SIC code to define peers throughout this paper.
[37] This is consistent with the model setup used by Foucault and Fresard (2014).

Table 2.5: Alternative Peer Definitions

This table presents the coefficient estimates of baseline specification, using alternative peer definitions. The dependent variable is the investment of non-shortable firms. In Column (1), I define a firm's peers as all other firms that belong to the same three-digit SIC industry as the firm. In Column (2) I use four-digit GICS code to define peers. In Column (3), I use six-digit GICS code to define peers. Finally, in Column (4), I select a set of pseudo peers by drawing a random sample of firms from other industries. Detailed variable definitions are in Appendix B.2. The sample period is from 2002 to 2013. The estimations correct the error term structure for heteroskedasticity and within-firm clustering. The t-statistics are in parentheses. ***, ** and * denote statistical significance at the 1%, 5% and 10% level, respectively.

	Dependent variable = Inv_i							
	(1)		(2)		(3)		(4)	
Q_i	0.0072	**	0.0085	***	0.0115	***	0.0088	***
	(2.35)		(4.10)		(4.48)		(4.28)	
CF_i	0.0355	***	0.0371	***	0.0338	***	0.0276	***
	(2.81)		(4.81)		(4.43)		(3.43)	
1/ASSET	0.2527		0.1600		-0.0514		0.0532	
	(0.86)		(0.62)		(-0.17)		(0.25)	
$Q_{-i}^{Shortable}$	0.0037	**	0.0034	**	0.0042	**	-0.0005	
	(2.28)		(2.05)		(2.00)		(-0.51)	
$Inv_{-i}^{Shortable}$	-0.0619	*	0.1371	***	0.0620	**	0.0315	
	(-1.68)		(3.00)		(2.16)		(0.73)	
$CF_{-i}^{Shortable}$	0.0457	***	-0.0054		-0.0213		0.0000	
	(2.96)		(-0.29)		(-1.45)		(0.00)	
$Q_{-i}^{Non-shortable}$	-0.0007		0.0011		-0.0003		0.0003	
	(-0.39)		(1.13)		(-0.33)		(0.44)	
$Inv_{-i}^{Non-shortable}$	-0.2956	***	-0.1065	*	-0.1940	***	-0.0378	
	(-4.73)		(-1.76)		(-3.29)		(-1.31)	
$CF_{-i}^{Non-shortable}$	0.0023		0.0281	**	0.0159		-0.0012	
	(0.14)		(2.30)		(1.17)		(-0.42)	
Year FE	Yes		Yes		Yes		Yes	
Industry FE	Yes		Yes		Yes		Yes	
Adj-R2	0.105		0.078		0.084		0.077	
N	2563		4690		3767		3838	

Column (2) of Table 2.5 shows the estimation results of baseline model using four-digit GIC code to define industry peers. The main result remains virtually unchanged: the estimated coefficient for $Q_{jt-1,-i}^{Shortable}$ is positive and statistically significant, while the coefficient for $Q_{jt-1,-i}^{Non-shortable}$ remains small and insignificant. In addition, I obtain similar results when using six-digit GIC code to define peers in Column (3).[38] Therefore, I conclude that my findings are not affected by the choice of peer definitions.

In the last column of Table 2.5, I perform a falsification test. One premise for non-shortable firms' managers to learn from shortable peers' stock prices is that information incorporated in shortable peers' stock prices is relevant for non-shortable firms. I therefore check this premise by examining whether non-shortable firms' investment is sensitive to the stock prices of shortable firms that are unlikely to contain relevant information.

Specifically, at a given year, for each firm i in the sample, I select a set of pseudo peers by drawing a random sample of shortable and non-shortable firms from other industries, and then construct peer-level variables using these pseudo peers. Since these pseudo peers are not in the same industry as firm i, the information in pseudo shortable peers' stock prices is not relevant to firm i. Therefore, I expect that firm i's investment decisions should be not sensitive to these pseudo shortable peers' stock prices.

Column (4) shows that the estimated coefficient for $Q_{jt-1,-i}^{Shortable}$ is statistically insignificant. This evidence suggests that non-shortable firms' investment is not related to stock prices of shortable firms from different industries, that is, when these shortable firms' stock prices are unlikely to contain relevant information for non-shortable firms.

2.4.4 Additional Robustness Tests

This subsection discusses several additional robustness checks.

[38] According to Bhojraj, Lee and Oler (2003), four-digit (six-digit) GIC code is at the similar level to SIC two-digit (three-digit) code.

First of all, I re-estimate the baseline model by replacing industry fixed effects with firm fixed effects to control for unobserved time-invariant firm characteristics. Column (1) of Table 2.6 shows that the main result remains unchanged: the coefficient for $Q_{jt-1,-i}^{Shortable}$ is 0.0026 and significant at 10% level after the inclusion of firm fixed effects.

Second, I re-estimate the baseline specification using the Fama-MacBeth approach as an alternative way to tackle with potential cross-sectional error correlation. In Column (2), I also obtain a positive and significant coefficient for $Q_{jt-1,-i}^{Shortable}$.

Third, I check whether my findings are robust to the way investment is defined. In Column (3), I re-estimate the baseline model by defining investment as the sum of capital expenditures and research and development (R&D) expenses scaled by book value of beginning-of-year total assets. The result is essentially identical. This finding suggests that non-shortable firms' managers also use the incremental negative information from their shortable peers' stock prices in long-term investment decisions.

In addition, while the finding that the non-shortable firms' investment is sensitive to shortable peers' stock prices is consistent with my hypothesis, it could be also driven by the fact that the investment opportunities of firms and their peers are correlated. To address this concern, I re-estimate the baseline model by replacing stock price variables with non-price based measures of investment opportunities. If my finding is driven by correlated investment opportunities rather than managers learning information from peers' stock prices, I should observe similar results when using non-price based measures. Otherwise, I expect to see that non-shortable firms' investment is not related to shortable peers' non-price based measures of investment opportunities. In Column (4) of Table 2.6, I use one-year sales growth as the non-price based measures of investment opportunities. The results show a weak and insignificant relationship between non-shortable firms' investment and their shortable peers' average sales growth.

Table 2.6: Additional Robustness Tests

This table presents the coefficient estimates for several additional robustness tests. The dependent variable is the investment of non-shortable firms. In Column (1), I re-estimate the baseline model by replacing industry fixed effects with firm fixed effects. In Column (2), I use the Fama-MacBeth method to estimate the baseline model. In Column (3), I alter the dependent variable to the sum of capital expenditures and R&D expenses scaled by beginning-of-year total assets. In Column (4), I replace stock price variable with non-price based measure of investment opportunity, SGR, for firm i and its shortable and non-shortable peers. Finally, in Column (5) I include CumRet to control for stock mispricing. Detailed variable definitions are in Appendix B.2. The sample period is from 2002 to 2013. The estimations correct the error term structure for heteroskedasticity and within-firm clustering. The t-statistics are in parentheses. ***, ** and * denote statistical significance at the 1%, 5% and 10% level, respectively.

	Dependent variable = Inv_i									
	(1)		(2)		(3)		(4)		(5)	
Q_i	0.0099	***	0.0099	***	0.0103	***			0.0106	***
	(4.03)		(5.33)		(4.13)				(4.17)	
CF_i	0.0276	***	0.0569	***	0.0414	***	0.0365	***	0.0415	***
	(2.75)		(5.13)		(4.78)		(4.35)		(4.75)	
1/ASSET	-0.1992		0.1724		0.8137	**	0.5827	**	-0.0588	
	(-0.54)		(0.78)		(2.50)		(2.48)		(-0.21)	
$Q_{-i}^{Shortable}$	0.0026	*	0.0053	*	0.0038	**			0.0042	**
	(1.85)		(2.15)		(2.42)				(2.45)	
$Inv_{-i}^{Shortable}$	-0.0087		0.0714		0.0053		-0.0377		-0.0299	
	(-0.28)		(0.74)		(0.16)		(-1.13)		(-0.89)	
$CF_{-i}^{Shortable}$	0.0234	*	0.0482		0.0370	**	0.0340	**	0.0418	**
	(1.65)		(1.24)		(2.47)		(2.43)		(2.49)	
$Q_{-i}^{Non-shortable}$	0.0009		0.0005		-0.0014				-0.0005	
	(0.81)		(0.19)		(-1.17)				(-0.34)	
$Inv_{-i}^{Non-shortable}$	-0.1084	***	-0.4488	**	-0.2872	***	-0.2582	***	-0.2879	***
	(-3.29)		(-3.08)		(-5.43)		(-4.98)		(-5.50)	
$CF_{-i}^{Non-shortable}$	0.0066		0.0798	*	0.0106		0.0120		0.0104	
	(0.65)		(2.12)		(0.97)		(1.18)		(0.98)	
CumRet									0.0005	
									(0.44)	
SGR							0.0025	*		
							(1.84)			
$SGR_{-i}^{Shortable}$							-0.0000			
							(-0.02)			
$SGR_{-i}^{Non-shortable}$							-0.0002			
							(-0.48)			
Year FE	Yes		Yes		Yes		Yes		Yes	
Industry FE	No		Yes		Yes		Yes		Yes	
Firm FE	Yes		No		No		No		No	
Adj-R2	0.056		0.153		0.110		0.090		0.108	
N	4166		4166		4166		4040		3704	

Moreover, besides the information channel, another mechanism that links firms' investment to stock prices is market timing theory, which argues that firms invest more when their stock prices are overvalued (e.g. Baker, Wurgler and Stein, 2003). Thus, my findings might be driven by the correlation between firms' investment and a market-level or industry-level overvaluation component that is contained in peers' stock prices. To address this concern, I include firms' future returns ($\mathrm{CumRet}_{\mathrm{ij,t+3}}$) as an additional control for stock mispricing in my specification. Baker and Wurgler (2002) argue that because stock mispricing is a transient phenomenon, overvalued stocks will experience negative returns in the future when mispricing is corrected. Following their argument, my proxy for stock mispricing is calculated as cumulative market-adjusted returns over a time period of three years subsequent to the measurement of firms' investment. The estimation results in Column (5) show that my findings are not affected after controlling for mispricing.

From another perspective, my findings are also unlikely to be explained by market timing theory. Prior studies argue that stocks are likely to be overvalued in the presence of short-sale constraints. Using the same institutional feature in Hong Kong market, Chang, Cheng and Yu (2007) find that stocks experience negative cumulative returns after becoming eligible for short sales, suggesting that shortable firms' stocks are less likely to be overvalued than non-shortable firms' stocks. Therefore, if market timing theory matters, I should observe that firms' investment is related to non-shortable peers' stock prices rather than to shortable peers' stock prices. However, this is opposite to my findings.

Finally, I discuss the possibility of reverse causality that firms' investment may directly affect their peers' stock prices. This might happen in two ways. On one hand, when firms' investment is high, it might be perceived as a signal of good growth opportunities for the industry and lead to an increase in peers' stock prices. However, in this scenario, I should find that that firms' investment is related to the stock prices of both shortable and non-shortable peers. On the other hand, if firms and their peers are competing in product market, an expansion of firms' productive ability by increasing investment may cause a loss of market share for their peers and result in a decrease in peers' stock prices. If so, I should observe a negative relationship between non-shortable firms' investment and their shortable peers' stock prices. Therefore, I conclude that my findings are unlikely to be driven by reverse causality.

2.5 Cross-sectional Analyses

In this section, I take a closer look at the cross-sectional variation on the sensitivity of non-shortable firms' investment to their shortable peers' stock prices. I expect that this sensitivity should become stronger in situations where non-shortable firms' managers are more likely to learn negative information from short sellers.

I first examine how this sensitivity varies with the amount of negative information incorporated in non-shortable firms' own stock prices. When there is a greater amount of negative information in non-shortable firms' stock prices, their managers are less likely to learn from shortable peers' stock prices for two reasons.

On one hand, managers can learn more negative information from their own firms' stock prices directly, when their own firms' stock prices contain a greater amount of negative information from investors. On the other hand, managers can incorporate their private information into stock prices through insider trading, hence more negative information in stock prices may suggest that managers already have more negative private information. In both cases, managers are less likely to learn from shortable peers' stock prices. In both cases, managers are less motivated to learn from shortable peers' stock prices.

Therefore, I expect that when non-shortable firms' own stock prices reflect less negative information, their investment becomes more sensitive to shortable peers' stock prices.

To test this prediction, I employ two measures to capture the amount of negative information in stock prices. The first measure is downside-minus-upside R2 from Bris, Goetzmann and Zhu

(2007). This measures is derived from Roll (1988)'s idea that more firm-specific information incorporated into stock prices results in lower R2 (stock price synchronicity). Bris, Goetzmann and Zhu (2007) further decompose R2 into downside R2 and upside R2, and argue that the difference between downside and upside R2 measures the asymmetry of stock prices in incorporating positive and negative information. Hence, downside-minus-upside R2 measures the extent to which negative information is incorporated into stock prices; the higher downside-minus-upside R2, the less negative information in stock prices.

I follow Bris, Goetzmann and Zhu (2007) to calculate downside-minus-upside R2 and then define a dummy variable, $\text{High\_R2Diff}_{\text{ijt}-1}$, that equals to one if firm i's downside-minus-upside R2 is higher than the industry median at year t-1, and zero otherwise. I extend the baseline model by including $\text{High\_R2Diff}_{\text{ijt}-1}$ and an interaction term of $\text{High\_R2Diff}_{\text{ijt}-1}$ with $\text{Q}_{\text{jt}-1,-\text{i}}^{\text{Shortable}}$ as additional independent variables.

The estimation results are reported in Column (1) of Table 2.7, Panel A. The coefficient for the interaction term, $\text{High\_R2Diff}_{\text{ijt}-1} * \text{Q}_{\text{jt}-1,-\text{i}}^{\text{Shortable}}$, is 0.0052 and significant at 10% level, indicating that non-shortable firms' investment becomes more sensitive to their shortable peers' stock prices, when their own stock prices reflect less negative information.

The second measure is equity market-to-book ratio. Figlewski (1981) argues that short-sale constraints prevent negative information from being incorporated into stock prices and lead to overvaluation. Therefore, the stock prices of non-shortable firms with a higher equity market-to-book ratio are more likely to be overvalued, and hence reflect less negative information. I create a dummy variable, $\text{High\_M/B}_{\text{ijt}-1}$, that equals to one if firm i's equity market-to-book is higher than the industry median at year t-1, and zero otherwise, and then interact the dummy variable, $\text{High\_M/B}_{\text{ijt}-1}$, with $\text{Q}_{\text{jt}-1,-\text{i}}^{\text{Shortable}}$.

Table 2.7: Cross-sectional Analyses - Panel A

This table presents the results of the cross-sectional variation in non-shortable firms' investment sensitivity to shortable peers' stock prices. In Column (1), I interact $Q_{-i}^{Shortable}$ with $High\_R2Diff_{ijt-1}$, which equals to one if firm i's downside-minus-upside R2 is higher than the industry median at year t-1, and zero otherwise. In Column (2), I interact $Q_{-i}^{Shortable}$ with $High\_M/B_{ijt-1}$, which equals to one if firm i's equity market-to-book is higher than the industry median at year t-1, and zero otherwise. Detailed variable definitions are in Appendix B.2. The sample period is from 2002 to 2013. The estimations correct the error term structure for heteroskedasticity and within-firm clustering. The t-statistics are in parentheses. ***, ** and * denote statistical significance at the 1%, 5% and 10% level, respectively.

	Dependent variable = Inv_i			
	(1)		(2)	
Q_i	0.0103	***	0.0069	***
	(4.22)		(3.04)	
CF_i	0.0400	***	0.0382	***
	(4.74)		(4.76)	
1/ASSET	-0.0537		-0.1312	
	(-0.19)		(-0.50)	
$Q_{-i}^{Shortable}$	0.0014		0.0015	
	(1.13)		(1.28)	
$Q_{-i}^{Shortable}$ * High_R2Diff	0.0052	*		
	(1.95)			
High_R2Diff	0.0004			
	(1.13)			
$Q_{-i}^{Shortable}$ * High_M/B			0.0049	*
			(1.89)	
High_M/B			0.0150	***
			(5.89)	
$Inv_{-i}^{Shortable}$	-0.0398		-0.0296	
	(-1.17)		(-0.96)	
$CF_{-i}^{Shortable}$	0.0449	***	0.0426	***
	(2.86)		(2.94)	
$Q_{-i}^{Non-shortable}$	-0.0007		0.0000	
	(-0.46)		(0.02)	
$Inv_{-i}^{Non-shortable}$	-0.2569	***	-0.2445	***
	(-4.93)		(-4.76)	
$CF_{-i}^{Non-shortable}$	0.0104		0.0106	
	(0.90)		(1.01)	
Year FE	Yes		Yes	
Industry FE	Yes		Yes	
Adj-R2	0.103		0.113	
N	3850		4166	

In Column (2) of Table 2.7, Panel A, the coefficient for the interaction term is positive and statistically significant, suggesting that non-shortable firms' investment responds more strongly to shortable peers' stock prices when their own stocks are more likely to be overvalued.

In addition, I expect that non-shortable firms' investment sensitivity to shortable peers' stock prices is weaker when the information environment of these firms is richer and thus managers are more likely to obtain negative information from other sources. Financial analysts, as an important source of information in financial industry, are assumed to produce information about firms' future prospects. However, prior studies point out that analysts' opinion might be optimistically biased.[39] If analysts' opinion is optimistically biased, non-shortable firms' managers are unlikely to obtain negative information from analysts but may have to learn from shortable peers' stock prices.

I test this prediction in two ways. First, I look at analyst coverage. Hong and Kacperczyk (2010) find that higher analyst coverage leads to less optimistically biased opinion from analysts. Hence, I expect that when firms are covered by more analysts, negative information is more likely to be revealed to managers, resulting in a weaker relationship between non-shortable firms' investment and shortable peers' stock prices.

To test this prediction, I define a dummy variable, $\text{High\_Coverage}_{ijt-1}$, equal to one if the number of analysts following firm i is above the industry median at year t-1, and zero otherwise, and interact it with $Q_{jt-1,-i}^{Shortable}$ in the baseline model. Consistent with my prediction, Column (1) of Table 2.7, Panel B shows that the estimated coefficient for the interaction term, $\text{High\_Coverage}_{ijt-1} * Q_{jt-1,-i}^{Shortable}$, is negative and significant at 10% level.

[39] For example, Hong and Kacperczyk (2010) argue that analysts' earnings forecasts can be excessively optimistic due to interest conflicts between firms and analysts.

Table 2.7: Cross-sectional Analyses - Panel B

This table presents the results of the cross-sectional variation in non-shortable firms' investment sensitivity to shortable peers' stock prices. In Column (1), I interact $Q_{-i}^{Shortable}$ with $High\_Coverage_{ijt-1}$, which equals to one if the number of analysts following firm i is above the industry median at year t-1, and zero otherwise. In Column (2), I interact $Q_{-i}^{Shortable}$ with $High\_Bias_{ijt-1}$, which equals to one if firm i's mean forecasted earnings is higher than the actual earnings and zero otherwise. Detailed variable definitions are in Appendix B.2. The sample period is from 2002 to 2013. The estimations correct the error term structure for heteroskedasticity and within-firm clustering. The t-statistics are in parentheses. ***, ** and * denote statistical significance at the 1%, 5% and 10% level, respectively.

	Dependent variable = Inv_i			
	(1)		(2)	
Q_i	0.0105	***	0.0094	***
	(3.92)		(3.19)	
CF_i	0.0587	***	0.0666	***
	(4.11)		(4.72)	
1/ASSET	-2.1669	**	-1.4959	
	(-2.39)		(-1.56)	
$Q_{-i}^{Shortable}$	0.0372	*	-0.0010	
	(1.93)		(-0.33)	
$Q_{-i}^{Shortable}$ * High_Coverage	-0.0362	*		
	(-1.96)			
High_Coverage	-0.0009			
	(-0.15)			
$Q_{-i}^{Shortable}$ * High_Bias			0.0053	
			(1.36)	
High_Bias			-0.0059	
			(-1.39)	
$Inv_{-i}^{Shortable}$	0.1043		0.0453	
	(1.08)		(0.53)	
$CF_{-i}^{Shortable}$	0.0072		0.0269	
	(0.29)		(0.87)	
$Q_{-i}^{Non-shortable}$	-0.0007		-0.0011	
	(-0.45)		(-0.48)	
$Inv_{-i}^{Non-shortable}$	-0.2729	***	-0.2944	***
	(-2.92)		(-3.29)	
$CF_{-i}^{Non-shortable}$	-0.0145		-0.0119	
	(-0.82)		(-0.59)	
Year FE	Yes		Yes	
Industry FE	Yes		Yes	
Adj-R2	0.227		0.225	
N	973		940	

Second, I look at the upward bias in analyst forecasts. I predict that non-shortable firms' investment sensitivity to their shortable peers' stock prices becomes stronger when the analysts following them issue upward biased earnings forecasts. To test this prediction, I create a dummy variable, High_Bias_{ijt-1}, that equals to one if firm i's mean forecasted earnings is higher than the actual earnings and zero otherwise. I include the interaction term between High_Bias_{ijt-1} and $Q_{jt-1,-i}^{Shortable}$ in the baseline model to test my prediction.

Column (2) of Table 2.7, Panel B shows that non-shortable firms' managers rely more on their shortable peers' stock prices when analysts' earnings forecasts are upward biased: the coefficient for the interaction term of High_Bias_{ijt-1} with $Q_{jt-1,-i}^{Shortable}$ is 0.0053 but only significant at 20% level.[40]

Furthermore, I examine whether non-shortable firms' managers become more likely to learn from shortable peers' stock prices when negative information is more valuable for investment decisions, that is, when their firms will suffer more from future negative productivity shocks. Cooper (2006) argues that when hit by adverse productivity shocks, firms with a higher proportion of tangible assets in place will have more redundant productive ability and hence suffer a larger loss in productivity efficiency and firm value. Moreover, this dampening effect becomes pronounced when firms' investment in these assets is largely irreversible. Therefore, I expect that non-shortable firms' investment becomes more sensitive to shortable peers' stock prices when they have more tangible assets in place or when they face a higher level of investment irreversibility.

I define asset tangibility as the ratio of property, plants and equipment to total assets, and then create a dummy variable, $\text{High\_Tangibility}_{ijt-1}$, that takes value of one if firm i's asset tangibility is higher than the industry median at year t-1, and zero otherwise. In Column (1) of Table 2.7, Panel C, the coefficient for the interaction term of $\text{High\_Tangibility}_{ijt-1}$ with $Q_{jt-1,-i}^{Shortable}$ is positive and significant at 10% level.

[40] The p-value for the interaction term of High_Bias_{ijt-1} with $Q_{jt-1,-i}^{Shortable}$ in Column (2) of Table 7, Panel B is 0.176. One explanation for this weak result is the reduced sample size due to missing analyst data on I/B/E/S.

Chirinko and Schaller (2009) argue that when selling excess assets is costly, firms can only reduce their assets through depreciation. Hence, firms in the industries with higher depreciation rates face a lower level of investment irreversibility. Therefore, non-shortable firms' investment sensitivity to shortable peers' stock prices should be weaker when they are in the industries with higher depreciation rates.

I measure the depreciation rate as the ratio of depreciation of tangible capital assets to property, plants and equipment and compute the average at two-digit SIC industry level. Then, I define a dummy variable, $\text{High\_Depreciation}_{\text{ijt}-1}$, equal to one if the average depreciation rate of industry j that firm i belongs to is above the median depreciation rate of all industries in the sample, and zero otherwise. Consistent with my prediction, the coefficient for the interaction term of $\text{High\_Depreciation}_{\text{ijt}-1}$ with $Q^{\text{Shortable}}_{\text{jt}-1,-\text{i}}$ is -0.0091 and statistically significant in Column (2) of Table 2.7, Panel C.

In the last column of Panel C, I examine whether non-shortable firms' investment sensitivity to shortable peers' stock prices becomes greater when these firms have a higher level of business risk or uncertainty. The intuition is that when firms operate in an environment with greater uncertainty, managers are more likely to learn information from other sources, such as short sellers, to guide their corporate decisions.

I measure business risk by operating income volatility, which is calculated as the standard deviation of quarterly operating income before depreciation divided by quarterly book value of total assets over a period of past eight quarters. Then I define a dummy variable, $\text{High\_IncVol}_{\text{ijt}-1}$, equal to one if firm i's income volatility is higher than the sample median at year t-1, and zero otherwise, and interact it with $Q^{\text{Shortable}}_{\text{jt}-1,-\text{i}}$ in the baseline model. Consistent with my prediction, Column (3) of Table 2.7, Panel C shows that the coefficient for the interaction term, $\text{High\_IncVol}_{\text{ijt}-1} * Q^{\text{Shortable}}_{\text{jt}-1,-\text{i}}$, is positive and significant at 10% level.

Table 2.7: Cross-sectional Analyses - Panel C

This table presents the results of the cross-sectional variation in non-shortable firms' investment sensitivity to shortable peers' stock prices. In Column (1), I interact $Q_{-i}^{Shortable}$ with $High\_Tangibility_{ijt-1}$, which equals to one if firm i's asset tangibility is higher than the industry median at year t-1, and zero otherwise. In Column (2), I interact $Q_{-i}^{Shortable}$ with $High\_Depreciation_{ijt-1}$, which equals to one if the average depreciation rate of industry j that firm i belongs to is above the median depreciation rate of all industries in the sample, and zero otherwise. In Column (3), I interact $Q_{-i}^{Shortable}$ with $High\_IncVol_{ijt-1}$, which equals to one if firm i's income volatility is higher than the sample median at year t-1, and zero otherwise. Detailed variable definitions are in Appendix B.2. The sample period is from 2002 to 2013. The estimations correct the error term structure for heteroskedasticity and within-firm clustering. The t-statistics are in parentheses. ***, ** and * denote statistical significance at the 1%, 5% and 10% level, respectively.

	Dependent variable = Inv_i					
	(1)		(2)		(3)	
Q_i	0.0103	***	0.0099	***	0.0087	***
	(4.55)		(4.32)		(3.21)	
CF_i	0.0366	***	0.0392	***	0.0368	***
	(4.56)		(4.84)		(4.04)	
1/ASSET	0.0798		-0.0372		0.1306	
	(0.33)		(-0.14)		(0.38)	
$Q_{-i}^{Shortable}$	0.0018		0.0126	**	0.0005	
	(1.26)		(2.49)		(0.40)	
$Q_{-i}^{Shortable}$ * High_Tangibility	0.0046	*				
	(1.74)					
High_Tangibility	0.0227	***				
	(8.94)					
$Q_{-i}^{Shortable}$ * High_Depreciation			-0.0091	*		
			(-1.77)			
High_Depreciation			0.0068			
			(0.37)			
$Q_{-i}^{Shortable}$ * High_IncVol					0.0034	*
					(1.72)	
High_IncVol					0.0045	
					(1.59)	
$Inv_{-i}^{Shortable}$	-0.0295		-0.0351		-0.0973	***
	(-0.95)		(-1.11)		(-3.00)	
$CF_{-i}^{Shortable}$	0.0405	***	0.0387	**	0.0366	**
	(2.79)		(2.57)		(2.22)	
$Q_{-i}^{Non-shortable}$	-0.0006		-0.0004		-0.0012	
	(-0.45)		(-0.26)		(-0.75)	
$Inv_{-i}^{Non-shortable}$	-0.2414	***	-0.2577	***	-0.2400	***
	(-4.76)		(-4.94)		(-3.77)	
$CF_{-i}^{Non-shortable}$	0.0094		0.0107		0.0094	
	(0.90)		(1.01)		(0.71)	
Year FE	Yes		Yes		Yes	
Industry FE	Yes		Yes		Yes	
Adj-R2	0.131		0.103		0.103	
N	4166		4166		2917	

Finally, I investigate how non-shortable firms' investment sensitivity to shortable peers' stock prices varies with financing constraints. According to my hypothesis, shortable peers' stock prices affect non-shortable firms' investment through a secondary market channel: the shortable peers' stock prices contain short sellers' information that is new to non-shortable firms' managers.

An alternative explanation is through a primary market channel: high shortable peers' stock prices are associated with a loosening of financial constraints for non-shortable firms due to industry hedging. Specifically, when shortable peers' stock prices are high, an arbitrageur who shorts these stocks may purchase non-shortable firms' stocks to hedge industry risk, which leads to an increase in non-shortable firms' stock prices. As a result, non-shortable firms' investments might increase due to a decline in cost of capital and a relaxation of financial constraints. Therefore, if my findings are due to the primary market channel, the non-shortable firms' investment sensitivity to shortable peers' stock prices should be stronger in firms that are more financially constrained.

I use two measures of financial constraints to test this prediction.[41] The first is firm size as measured by the logarithm of total assets. Bakke and Whited (2010) argue that larger firms tend to be less financially constrained. I define a dummy variable, $\text{High\_Size}_{\text{ijt}-1}$, equal to one if firm i's size is larger than the industry median at year t-1, and zero otherwise, and further interact it with $Q_{\text{jt}-1,-\text{i}}^{\text{Shortable}}$ in the baseline model. Column (1) of Table 2.7, Panel D shows that the estimated coefficient for the interaction term is close to zero and statistically insignificant, inconsistent with the primary market channel.

[41] I use the same measures of financial constraints as used by Edmans, Jayaraman and Schneemeier (2016).

Table 2.7: Cross-sectional Analyses - Panel D

This table presents the results of the cross-sectional variation in non-shortable firms' investment sensitivity to shortable peers' stock prices. In Column (1), I interact $Q_{-i}^{Shortable}$ with $High\_Size_{ijt-1}$, which equals to one if firm i's size is larger than the industry median at year t-1, and zero otherwise. In Column (2), I interact $Q_{-i}^{Shortable}$ with $High\_EF_{ijt-1}$, which equals to one if the external financing of industry j that firm i belongs to is above the median external financing of all industries in the sample, and zero otherwise. Detailed variable definitions are in Appendix B.2. The sample period is from 2002 to 2013. The estimations correct the error term structure for heteroskedasticity and within-firm clustering. The t-statistics are in parentheses. ***, ** and * denote statistical significance at the 1%, 5% and 10% level, respectively.

	Dependent variable = Inv_i			
	(1)		(2)	
Q_i	0.0100	***	0.0097	***
	(4.35)		(4.24)	
CF_i	0.0389	***	0.0390	***
	(4.78)		(4.84)	
1/ASSET	0.0024		-0.0487	
	(0.01)		(-0.19)	
$Q_{-i}^{Shortable}$	0.0041	**	0.0037	**
	(1.98)		(2.28)	
$Q_{-i}^{Shortable}$ * High_Size	0.0000			
	(0.02)			
High_Size	0.0019			
	(0.46)			
$Q_{-i}^{Shortable}$ * High_EF			0.0165	**
			(2.59)	
High_EF			-0.0098	
			(-0.54)	
$Inv_{-i}^{Shortable}$	-0.0298		-0.0233	
	(-0.93)		(-0.73)	
$CF_{-i}^{Shortable}$	0.0423	***	0.0345	**
	(2.87)		(2.26)	
$Q_{-i}^{Non-shortable}$	-0.0005		-0.0012	
	(-0.33)		(-0.88)	
$Inv_{-i}^{Non-shortable}$	-0.2556	***	-0.2699	***
	(-4.98)		(-5.08)	
$CF_{-i}^{Non-shortable}$	0.0105		0.0079	
	(0.98)		(0.74)	
YearFE	Yes		Yes	
IndustryFE	Yes		Yes	
Adj-R2	0.102		0.104	
N	4166		4166	

The second measure is external financing used by Rajan and Zingales (1998). External financing is calculated at the industry-level as the difference between capital expenditures and cash flows scaled by capital expenditures. A higher value indicates greater external financing and thus lower financing constraints. Then I define a dummy variable, High_EF_{ijt-1}, equal to one if the external financing of industry j that firm i belongs to is above the median external financing of all industries, and zero otherwise. In Column (2) of Table 2.7, Panel D, the coefficient for the interaction term of High_EF_{ijt-1} with $Q^{\text{Shortable}}_{jt-1,-i}$ is positive and statistically significant, indicating that non-shortable firms' investment is more sensitive to shortable peers' stock prices when they are less financially constrained. This finding is opposite to the prediction of the primary market channel.

In summary, the overall evidence is consistent with my hypothesis that non-shortable firms' managers learn short sellers' information from shortable peers' stock prices and use it in investment decisions.

2.6 Further Analyses

2.6.1 Learning from Shortable Peers' Stock Prices and Corporate Investment Efficiency

In this paper, I argue that non-shortable firms' managers seek to learn information from shortable peers' stock prices, because shortable peers' stock prices incorporate information from short sellers that is *ex ante* unknown to managers. If so, I expect that non-shortable firms' investment should become more efficient, when their managers can learn a greater amount of information from shortable peers' stock prices to guide their investment decisions. In this subsection, I test this prediction in an industry-year panel.

Following Durnev, Morck and Yeung (2004), I measure the investment efficiency at industry level by the deviation of marginal q (hereafter, $\dot{q}$) from one; the smaller the deviation, the higher the investment efficiency level for the industry. For each two-digit SIC industry j at year t, I estimate $\dot{q}_{jt}$ by running the following regression using a subsample of all non-shortable firms in industry j:

$$\Delta EV_{it} = \lambda_0 + \dot{q}\Delta NFA_{it} + \lambda_1 D_{it} + \lambda_2 EV_{i,t-1} + u_{it}$$

where ΔEV_{it} is the change in market value of firm i, ΔNFA_{it} is the change in fixed assets, D_{it} is the cash flow distributed to investors and u_{it} is an error term.[42] Therefore, the estimated $\dot{q}_{jt}$ measures the overall investment efficiency level of all non-shortable firms in industry j at year t.

Since there is no natural empirical proxy for the amount of information that managers can learn from shortable peers' stock prices, I look at the relative number of shortable firms within an industry. Under the two-factor framework in Huang and Zeng (2015), each firm's stock price is a noisy but informative signal for common shocks. Thus, I expect that the joint observation of more shortable peers' stock prices within the industry provides a greater amount of information on industry-level shocks from short sellers.[43]

I form an industry-year panel and estimate the following regression to test my prediction:

$$|\dot{q} - 1|_{jt} = \delta_j + \eta_t + \alpha_1 \text{Shortable ratio}_{j,t-1} + \alpha_2 \overline{\text{Leverage}}_{j,t-1} + \alpha_3 \overline{Q}_{j,t-1} + \alpha_4 \overline{\text{Market Cap}}_{j,t-1} + \alpha_5 \text{Total number of firms}_{j,t-1} + \varepsilon_{jt}$$

[42] I follow the method used by Ferreira and Laux (2007) to estimate $\dot{q}$. Ferreira and Laux (2007) modify Durnev, Morck and Yeung (2004)'s method to allow for estimating $\dot{q}$ for each industry-year. Moreover, I drop firms whose absolute change in firm value is more than 300% and require at least 10 non-shortable firms in each industry-year to estimate $\dot{q}$. Finally, I drop industry-years with estimated $\dot{q}$ of more than five in absolute value.

[43] Another interpretation is that the joint observation of more peers' stock prices provides more precise information on industry-level shocks. This is compatible with my prediction in this subsection; managers make better decisions when they can obtain more precise information from peers' stock prices.

where $\text{Shortable ratio}_{j,t-1}$ is the percentage of shortable firms in industry j at year t-1. I control for the industry average of all non-shortable firms' leverage, Q and market capitalization, as well as the total number of firms in industry j. I also include industry and year fixed effects in my specification.

The estimation results are presented in Column (1) of Table 2.8. The coefficient for $\text{Shortable ratio}_{j,t-1}$ is negative and significant at 10% level, indicating that that the overall investment efficiency level of non-shortable firms becomes higher, when their managers can obtain a greater amount of information from shortable peers' stock prices.

Furthermore, I split the sample into two subsamples based on whether the estimated $\dot{q}$ is above or below one. Durnev, Morck and Yeung (2004) state that $\dot{q} > 1$ implies underinvestment and $\dot{q} < 1$ implies overinvestment. Miller (1977) points out that, in the presence of short-sale constraints, once managers make investment decisions based on their own firms' stock prices, an overinvestment problem may occur. Thus, if non-shortable firms' investment efficiency improves because their managers learn additional information from shortable peers' stock prices and use it in their investment decisions, I expect that this improvement is more pronounced for the subsample where $\dot{q} < 1$, that is, firms that might be overinvesting.

Column (2) and (3) of Table 2.8 report the estimation results using the subsample where $\dot{q} > 1$ and where $\dot{q} < 1$, respectively. Though the coefficient for $\text{Shortable ratio}_{j,t-1}$ is negative in both columns, this coefficient is larger in magnitude and more statistically significant in Column (3). These findings suggest that the information from shortable peers' stock prices helps non-shortable firms' managers mitigate overinvestment and thus improve investment efficiency.

Table 2.8: Learning from Shortable Peers' Stock Prices and Corporate Investment Efficiency

This table presents the results for the relationship, at two-digit SIC industry level, between non-shortable firms' overall investment efficiency level and the relative number of shortable firms in an industry. The dependent variable is $|\dot{q} - 1|$, for which $\dot{q}$ is estimated using a subsample of all non-shortable firms in the industry at a given year. The independent variable of interest is the percentage of shortable firms in the industry. In Column (1), I use the full sample. In Column (2), I use a subsample where $\dot{q} > 1$. Finally, in Column (3), I use a subsample where $\dot{q} < 1$. The sample period is from 2002 to 2013. The estimations correct the error term structure for heteroskedasticity and within-industry clustering. The t-statistics are in parentheses. ***, ** and * denote statistical significance at the 1%, 5% and 10% level, respectively.

	Dependent variable = $|\dot{q} - 1|$					
	(1)		(2)		(3)	
Shortable ratio	-1.7655	*	-0.5100		-2.8426	**
	(-1.71)		(-0.23)		(-1.99)	
$\overline{\text{Leverage}}$	3.2384		3.0467		0.4621	
	(0.92)		(0.44)		(0.10)	
$\overline{Q}$	-0.0345		0.3733	**	-0.0631	
	(-0.47)		(2.16)		(-0.63)	
$\overline{\text{Market Cap}}$	0.0312		0.3771		0.1201	
	(0.10)		(0.66)		(0.28)	
Total number of firms	-0.0304		-0.0196		-0.0283	
	(-1.24)		(-0.38)		(-0.96)	
Year FE	Yes		Yes		Yes	
Industry FE	Yes		Yes		Yes	
Adj-R2	0.086		0.212		0.154	
N	194		64		130	

2.6.2 U.S. Evidence

In previous parts, I find evidence from Hong Kong market that non-shortable firms' managers seek to learn information from shortable peers' stock prices. In this subsection, I examine whether this finding also applies to U.S. stock market. However, in U.S. market, there is no such institutional feature as in Hong Kong market that I can employ to conduct previous analysis.

Thus, I rely on a regulatory change that relaxes short-sale constraints on a random sample of firms to perform my analysis.

On July 28, 2004, SEC announced a pilot program of Regulation SHO. Under this pilot program, a random sample of firms selected from Russell 3000 index (hereafter, pilot firms) were suspended from the uptick rule from 2005, while the remaining firms in Russell 3000 index (hereafter, control firms) were still subject to the uptick rule for short sales.[44] Upon the relaxation of short-sale constraints on pilot firms, Reg SHO leads to increased short selling activities in pilot firms, compared to control firms (Grullon, Michenaud, and Weston, 2015).

In this context, I expect that when firms' managers seek to learn information from short sellers, they pay attention to the stock prices of pilot peers that are subject to a relatively higher level of short selling activities.

To test this prediction, I look at the investment decisions of U.S. firms that are not included in Russell 3000 index (hereafter, non-Russell firms) from 2004 to 2007 and employ a specification similar to the baseline model used in previous analysis:[45]

$$\mathrm{Inv}_{ijt} = \delta_j + \eta_t + \beta_1 Q_{ijt-1} + \beta_2 \mathrm{Control}_{ijt} + \beta_3 Q^{Pilot}_{jt-1,-i} + \beta_4 \mathrm{Control}^{Pilot}_{jt,-i} + \beta_5 Q^{Control}_{jt-1,-i} + \beta_6 \mathrm{Control}^{Control}_{jt,-i} + \varepsilon_{ijt}$$

where Inv_{ijt} is the investment of a non-Russell firm i in industry j at year t. On the right-hand side of the model, I calculate peers-level variables using firm i's peers that are pilot and control firms in Russell 3000 index, respectively.

Column (1) of Table 2.9 estimates the model including only pilot peers' variables. The coefficient for $Q^{Pilot}_{jt-1,-i}$ is positive and significant at 5% level. This finding is consistent with my

[44] See Grullon, Michenaud, and Weston (2015) for more details on Regulation SHO and the uptick rule.
[45] The sample ends at 2007, because SEC repealed the uptick rule to all firms on August 2007.

expectation that non-Russell firms' managers learn information from pilot peers' stock prices and use it in investment decisions.

Table 2.9: U.S. Evidence

This table presents the coefficient estimates of baseline model using a sample firms in U.S. stock market from 2004 to 2007. I rely on a regulatory change (Reg SHO) that relaxes short-sale constraints on a random sample of firms in Russell 3000 index to perform my analysis. The dependent variable is the investment of a non-Russell firm i. The independent variables, $Q^{Pilot}_{jt-1,-i}$ and $Q^{Control}_{jt-1,-i}$, are calculated using firm i's peers that are pilot and control firms in Russell 3000 index, respectively. In Column (1), I include only pilot peers' variables, while in Column (2) I include only control peers' variables. In Column (3), I include both pilot and control peers' variables. Finally, in Column (4), I repeat the same analysis as in Column (3) but using a sample of firms in the period before Reg SHO (from 2001 to 2003). The estimations correct the error term structure for heteroskedasticity and within-firm clustering. The t-statistics are in parentheses. ***, ** and * denote statistical significance at the 1%, 5% and 10% level, respectively.

	Dependent variable = Inv_i							
	(1)		(2)		(3)		(4)	
Q_i	0.0127	***	0.0126	***	0.0126	***	0.0116	***
	(6.61)		(6.59)		(6.59)		(5.73)	
CF_i	0.0313	***	0.0313	***	0.0312	***	0.0309	***
	(3.95)		(3.95)		(3.94)		(4.36)	
1/ASSET	-0.1145	*	-0.1141	*	-0.1157	*	0.0306	
	(-1.84)		(-1.82)		(-1.85)		(0.91)	
Q^{Pilot}_{-i}	0.0056	**			0.0054	*	0.0014	
	(2.10)				(1.93)		(0.70)	
Inv^{Pilot}_{-i}	0.1764				0.1832		-0.1350	
	(0.66)				(0.66)		(-1.52)	
CF^{Pilot}_{-i}	-0.0255				-0.0208		0.0153	
	(-0.47)				(-0.38)		(0.54)	
$Q^{Control}_{-i}$			-0.0004		-0.0034		-0.0020	
			(-0.07)		(-0.57)		(-0.96)	
$Inv^{Control}_{-i}$			0.2448		0.2290		0.1355	
			(1.37)		(1.28)		(1.48)	
$CF^{Control}_{-i}$			-0.0156		-0.0247		0.0192	
			(-0.34)		(-0.52)		(0.41)	
Year FE	Yes		Yes		Yes		Yes	
Industry FE	Yes		Yes		Yes		Yes	
Adj-R2	0.367		0.367		0.367		0.277	
N	3489		3489		3489		3782	

In Column (2) where only control peers' variables are included, the coefficient for $Q^{Control}_{jt-1,-i}$ is small and insignificant, indicating that non-Russell firms' investment is not sensitive to the prices of control peers' stocks that are subject to the same degree of short-sale constraints as their own firms' stocks. Since $Q^{Pilot}_{jt-1,-i}$ and $Q^{Control}_{jt-1,-i}$ are constructed using two groups of peers that are both included in Russell 3000 index and have similar firm characteristics, this finding alleviates the concern that the result in Column (1) is driven by Russell 3000 index inclusion or other firm characteristics.[46]

Finally, Column (3) of Table 2.9 presents the estimation results from the model including both pilot and control peers' variables. The coefficient for $Q^{Pilot}_{jt-1,-i}$ remains positive and statistically significant, while the coefficient for $Q^{Control}_{jt-1,-i}$ is still insignificant.

Furthermore, to confirm that the above results are driven by the increased short selling activities in pilot peers, I check whether similar results can be obtained in the period before Reg SHO. Specifically, I use a sample from 2001 to 2003 and re-estimate the model to see whether non-Russell firms' investment is sensitive to pilot peers' stock prices even during the pre-Reg SHO period.

Column (4) of Table 2.9 shows that the coefficients for $Q^{Pilot}_{jt-1,-i}$ is smaller and statistically insignificant in the pre-Reg SHO period. This finding suggests that non-Russell firms' investment only responds to the stock prices of pilot peers when these pilot peers' short-sale constraints are relaxed.

[46] Grullon, Michenaud, and Weston (2015) find no significant differences in firm characteristics between pilot and control firms, such as market capitalization or stock trading volume.

2.7 Conclusion

This paper investigates whether short selling activities affect corporate decisions through an information channel. It is challenging to empirically identify this channel for two reasons. First, there is no natural empirical proxy for the information incorporated in stock prices from short sellers. Second, short selling activities can affect stock prices and managers' decisions simultaneously through channels other than the information channel. To overcome these empirical difficulties, I exploit a special institutional feature of the Hong Kong stock market that only stocks included in an official list are allowed for short sales.

I find robust empirical evidence that non-shortable firms' investment is positively and significantly related to their shortable peers' stock prices. However, such a relationship is not found between non-shortable firms' investment and the stock prices of their peers that are also non-shortable. These findings suggest that non-shortable firms' managers pay attention to the stock prices of shortable peers that may aggregate information from short sellers. Further analyses confirm that my findings are not driven by shortable peers' other firm characteristics and are robust to alternative peer definitions and to a variety of additional tests. In addition, the cross-sectional analyses show that non-shortable firms' investment becomes more sensitive to shortable peers' stock prices when (1) their own firms' stock prices reflect less negative information; (2) their managers are less likely to obtain negative information from financial analysts; and (3) negative information is more valuable for their corporate investment decisions. Taken together, these results are consistent with my hypothesis that non-shortable firms' managers seek to learn short sellers' information on external conditions from shortable peers' stock prices and use this information in their corporate investment decisions.

Appendix B

B.1: Short-sale Constraints in Hong Kong Stock Market

Short sales are not permitted in Hong Kong stock market until 1994. In January 1994, Hong Kong Stock Exchange (HKSE) introduced a pilot scheme for regulated short sales to keep in line with the reform of securities borrowing and lending in Hong Kong stock market. Under this pilot scheme, 17 securities that are included in an official list are allowed for short sales. Further, in March 1996, this pilot scheme was revised to include more securities into the official list. Nowadays, the official list for short sales is revised in a quarterly basis by HKSE.[47]

According to the information revealed by HKSE on its website in December 2014, securities that are selected in the official list for short sales need to satisfy at least one of the following criteria:[48]

1. All constituent stocks of indices which are the underlying indices of equity index products traded on the Exchange;

2. All constituent stocks of indices which are the underlying indices of equity index products traded on Hong Kong Futures Exchange (hereafter, HKFE);

3. All underlying stocks of stock options traded on the Exchange;

4. All underlying stocks of Stock Futures Contracts (as defined in the rules, regulations and procedures of HKFE) traded on HKFE;

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[47] Before 2001, the official list for short sales was not revised in a quarterly basis. Considering the changing market conditions, HKSE, at its discretion, revises the list in a yearly or semi-yearly basis. In addition, during my sample period, occasional revisions also exist between quarterly revisions.
[48] See "Regulated Short Selling" on the website of Hong Kong Exchanges and Clearing Limited (https://www.hkex.com.hk/eng/market/sec_tradinfo/regshortsell.htm).

5. Stocks eligible for structured product issuance pursuant to Rule 15A.35 of the Main Board Listing Rules or underlying stocks of Structured Product traded on the Exchange;
6. Stocks with market capitalization of not less than HK$3 billion and an aggregate turnover during the preceding 12 months to market capitalization ratio of not less than 50%;[49]
7. Exchange Traded Funds approved by the Board in consultation with the Commission;
8. All securities traded under the Pilot Program;
9. Stocks that have been listed on the Exchange for not more than 60 trading days, with a public float capitalization of not less than HK$10 billion for a period of 20 consecutive trading days commencing from the date of their listing on the Exchange and an aggregate turnover of not less than HK$200 million during such period;
10. All underlying stocks of Structured Product which is based on one single class of shares traded on the Exchange; and
11. Applicable Market Making Securities approved by the Board in consultation with the Commission.

At the end of 2014, a total number of 797 securities are included in the official list and eligible for short sales. According to the statistics reports published by HKSE, in 2014, short sale activities are estimated to make up around 10% of the trading volume in Hong Kong stock market.[50]

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[49] The criterion related to market capitalization and aggregate turnover is not constant but subject to changes. For example, in May 2012, HKSE tightened this criterion by increasing market capitalization requirement from $1 billion to $3 billion and turnover requirement from 40 percent to 50 percent. See http://www.hkex.com.hk/eng/newsconsul/hkexnews/2012/120510news.htm.

[50] This is calculated based on the statistics from HKEx Fact Book 2014. See http://www.hkex.com.hk/eng/stat/statrpt/factbook/factbook2014/fb2014.htm.

B.2: Variable Definitions

Variable	Definition
Inv	Capital expenditures scaled by book value of beginning-of-year total assets
Q	Market value of equity plus book value of assets minus book value of equity, scaled by book value of total assets
CF	Sum of net income before extraordinary depreciation and amortization expenses, scaled by beginning-of-year total assets
1/ASSET	The inverse of total assets
$Q_{-i}^{Shortable}$ ($Q_{-i}^{Non-shortable}$)	The equally-weighted average value of Q across all shortable (non-shortable) peers of firm i in same industry at a given year, excluding firm i itself
$Inv_{-i}^{Shortable}$ ($Inv_{-i}^{Non-shortable}$)	The equally-weighted average value of Inv across all shortable (non-shortable) peers of firm i in same industry at a given year, excluding firm i itself
$CF_{-i}^{Shortable}$ ($CF_{-i}^{Non-shortable}$)	The equally-weighted average value of CF across all shortable (non-shortable) peers of firm i in same industry at a given year, excluding firm i itself
MV	Stock price times the number of total shares outstanding (in HK$ millions)
Turnover	The ratio of yearly aggregate trading volume (in HK$) to market capitalization
1-R2	One minus R2 from regressing weekly returns on market and industry returns over year t
Amihud	Average daily ratio of a stock absolute return by dollar trading volume
SGR	Sales growth, defined as one-year growth in total revenues
$SGR_{-i}^{Shortable}$ ($SGR_{-i}^{Non-shortable}$)	The equally-weighted average value of SGR across all shortable (non-shortable) peers of firm i in same industry at a given year, excluding firm i itself
CumRet	Cumulative market-adjusted returns over a time period of three years subsequent to the measurement of firms' investment
R2Diff	Downside R2 minus upside R2. Downside R2 (upside R2) is the R2 computed from a market model regression using only negative (positive) market returns
M/B	The ratio of market value of equity to book value of equity
Coverage	The number of analysts that issue one-year forward forecasts on earnings per share for the firm
Tangibility	The ratio of property, plants and equipment to total assets
Depreciation	The ratio of depreciation of tangible capital assets to property, plants and equipment and compute the average at two-digit SIC industry level across years
IncVol	Standard deviation of quarterly operating income before depreciation divided by quarterly book value of total assets over a period of past eight quarters
Size	The logarithm of total assets
EF	The difference between capital expenditures and cash flows scaled by capital expenditures, calculated at two-digit SIC industry level

Chapter 3

The Real Effects of Long-Term Option Trading

3.1 Introdution

A long standing view in finance research is that stock prices provide accurate signals for resource allocation, leading to efficient production and investment decisions (Fama and Miller, 1972). Recent studies have shown that managers can learn information from stock prices to guide their corporate decisions.[51] This happens because stock prices aggregate many pieces of information from investors and hence are informative about firms' fundamentals. Therefore, the allocational role of stock prices depends on the information acquired by investors.

Prior studies point out that investors are more likely to collect short-term information than long-term information, because it is more costly to trade on long-term information. Dow and Gordon (1994) show that when arbitrage is accomplished through a chain of traders, traders with limited horizons find it costly to trade on long-term private information, because they are not sure that another informed trader will arrive in the future when they have to liquidate their portfolio. Shleifer and Vishny (1990) also show that arbitrage in long-term is more costly than in short-term. In addition, Holden and Subrahmanyam (1996) show that due to risk aversion, investors prefer to collect short-term information and trade on it. In both cases, stock prices will incorporate more short-term information and less long-term information, leading to reduced

[51] For example, see Dow and Gorton (1997), Subrahmanyam and Titman (1999), Chen, Goldstein and Jiang (2007), and Bai, Philippon and Savov (2014). In addition, Bond, Edmans and Goldstein (2012) provide a survey paper on this topic.

stock price informativeness about firms' long-run fundamentals. Therefore, when managers are making long-term corporate decisions, the allocational role played by stock prices might be limited.

This paper investigates whether introducing long-term options can resolve this problem. More specifically, I study whether long-term option trading stimulates the production of long-term private information and thus leads to an increase in stock price informativeness about firms' long-term fundamentals. Therefore, managers can learn more information from stock prices to guide their long-term investment decisions.

To do so, I look at the Long-term Equity AnticiPation Securities (LEAPS), which were introduced by Chicago Board Options Exchange (CBOE) in 1990. Similar to regular options, LEAPS are standardized American-style options listed in CBOE. However, different from regular options that usually expire in less than one year, LEAPS are long-dated options and have a time to maturity that is up to three years.[52]

Prior studies have shown that introducing derivatives, such as options, alters investors' incentives to acquire private information and hence affects the informational efficiency of underlying stock prices.[53] Moreover, because the leverage afforded by options lowers the transaction cost for informed investors, option trading can increase the informational efficiency of stock prices by stimulating informed trading. Therefore, I hypothesize that LEAPS trading stimulates the production of long-term information, which managers can use to guide their long-term investment decisions.

To test this hypothesis, I use R&D investment as a proxy for long-term investment and examine whether firms' R&D investment is more sensitive to stock prices in the presence of active

[52] Regular options usually expire in 3, 6, or 9 months. In contrast, Equity LEAPS have more than 9 months until expiration and always expire in January. Suppose today were July 2004, investors could buy firm X's call/put options that would expire in January 2005, Juanuary 2006, or Jannuray 2007. Only the latter two options are considered as LEAPS.

[53] For example, see Cao (1999), Massa (2002), and Huang (2014).

LEAPS trading in the market. Using a large sample of U.S. firms over the period from 1999 to 2009, I show that the sensitivity of R&D investment to stock prices is higher for firms with active LEAPS trading. In terms of economic significance, the R&D investment to stock price sensitivity will increase by around 80%, if a firm has active LEAPS trading in the market. This result is robust to various subsamples, including the subsample of firms matched on size and the subsample of firms with non-zero R&D expenditure.

Since LEAPS are introduced by CBOE on certain firms, a potential concern regarding my previous findings is the selection bias in decisions to introduce LEAPS on firms. To address this concern, I employ the treatment effect model approach and show that my results are unchanged after controlling for the potential selection bias. Moreover, I show that my results are robust to controlling for other competing information sources, such as public information and managerial information. This finding suggests that LEAPS trading stimulates the production of information that is new to managers.

I conduct several additional tests to further support my hypothesis. First, using capital investment as a proxy for fixed investment, I show that LEAPS trading activities do not change capital investment sensitivity to stock prices. This finding suggests that LEAPS trading does not contribute to the production of information that managers can use in making fixed investment decisions. Second, because the existence of LEAPS could benefit investors with improved ability to hedge long-term risks, LEAPS trading may enable firms to respond more easily to the investment opportunities by enhancing firms' external financing. Inconsistent with this possibility, I demonstrate that the presence of LEAPS trading does not increase the sensitivity of R&D investment to non-price based measures of investment opportunities. Finally, I show that the effect of LEAPS trading on firms' R&D investment sensitivity to stock prices becomes stronger in situations in which LEAPS trading is more likely to increase investors' incentives to acquire long-term private information.

Therefore, the overall evidence is consistent with my hypothesis that LEAPS trading stimulates the production of long-term information, which managers can use in making long-term investment decisions.

Further analyses show that active LEAPS trading helps managers make more efficient R&D investment by overcoming the problem of under-investment. I also find that the R&D investment induced by LEAPS trading has a positive effect on firms' future operating performance and growth. These findings confirm the beneficial effects of LEAPS trading activities on firms' R&D investment decisions and their effects on firms' future performance.

This paper contributes to the literature by empirically investigating the real effects of long-term option trading. First, I show that the R&D investment sensitivity to stock price is significantly higher for firms with active LEAPS trading than firms without LEAPS trading. Second, I show that this effect exists because LEAPS trading stimulates the production of long-term information that is new to managers and hence helps manager in making R&D investment decisions. Taken together, these findings suggest that long-term option trading activities can have real effects by enhancing the allocational role of stock prices.

This paper is closely related two papers in the literature. In a recent paper, Roll, Schwartz and Subrahmanyam (2009) find a positive relationship between option trading volume and investment to stock price sensitivity. They argue that option trading activities enhance the informational efficiency of underlying stock prices and thus affect managers' investment decisions. However, Roll, Schwartz and Subrahmanyam (2009) look at regular option trading and total investment decisions (sum of capital investment and R&D investment), while this paper focuses on long-term option trading, which has a specific effect on R&D investment decisions.

Another related paper is Holden and Lundstrum (2009), which study the effect of LEAPS introduction on firms' R&D investment. Bond, Edmans and Goldstein (2012) argue that the trading activities occur in secondary financial markets can affect real activities via two channels: contracting channel and learning channel. Holden and Lundstrum (2009) posit that because

LEAPS lower the trading cost of long-term information, stock prices incorporate more information about managers' effort on long-term projects, increasing managers' incentives to invest in long-term projects. Hence, the finding of Holden and Lundstrum (2009) is consistent with the contracting channel in Bond, Edmans and Goldstein (2012).

However, this paper investigates the possibility that LEAPS trading stimulates the production of long-term information that is new to managers and hence helps manager make long-term investment decisions. Thus, in contrast to Holden and Lundstrum (2009) that study the first-order effect of LEAPS trading on firms' R&D investment, I focus on the effect of LEAPS trading on firms' the R&D investment sensitivity to stock prices. Therefore, this paper supports the idea of learning channel in Bond, Edmans and Goldstein (2012).

The remainder of the paper is organized as follows. Section 3.2 discusses related literature. Section 3.3 describes data and sample construction. Section 3.4 presents main empirical results. Section 3.5 presents further analyses. Section 3.6 concludes.

3.2 Related Literature

This paper is related to a recent literature on the idea that managers can learn new information from stock prices and use this information to guide corporate decisions. In theory, Dow and Gorton (1997) argue that investors are willing to produce important information about future probability of investment opportunities that managers do not have, and to trade profitably on it. Ultimately, this information is incorporated in stock prices and transmitted to managers via stock prices. In a different way, Subrahmanyam and Titman (1999) argue that through day-to-day activities, investors may obtain serendipitous information that is valuable to managers.

On the empirical side, Chen, Goldstein and Jiang (2007) find that corporate investments are more sensitive to stock prices when stock prices contain more private information from investors.

Their findings suggest that managers learn information from stock prices and use it to guide corporate investments. Fresard (2012) shows that cash saving decisions are also more sensitive to stock prices when stock prices are more informative. Moreover, Luo (2005) finds that abnormal returns around merger and acquisition announcements predict whether firms consummate the deals later. He interprets this finding as evidence that managers learn information from stock market for merger and acquisition decisions. These studies show that stock prices are an important source for managers to gain information when they are making corporate decisions.

This paper is also related to literature that studies how option trading affects the informational efficiency of underlying stock prices. First, in theory, some prior studies suggest that introducing options alters investors' incentives to acquire private information and hence affects the informational efficiency of underlying stock prices.

Cao (1999) argues that the introduction of derivative assets improves the trading opportunities of investors and hence increases investors' incentives to acquire private information about underlying assets. Consequently, the introduction of derivative assets increases the amount of information collected and leads to more informative prices of the underlying assets. Therefore, Cao (1999) suggests that option introduction causes investors to acquire more private information and makes the prices of optioned stocks more informative. Moreover, Massa (2002) finds that introducing a derivative, such as an option, increases investors' incentives to acquire private information when investors intend to acquire information to gain an informational advantage. In his model, the derivative price conveys additional information, which leads to an increase in the underlying asset's price informativeness. In a recent paper, Huang (2014) finds that when information acquisition cost is high, option introduction increases investors' incentives to acquire private information and hence increases the population of informed investors in the market. As a result, option introduction increases the price informativeness for underlying asset.

In addition, because the leverage afforded by options lowers the transaction cost for informed investors, option trading can increase the informational efficiency of stock prices by stimulating informed trading.

Using order flow data of stocks and options, Hu (2014) finds that option order flow contains important stock price information that is not in stock market. The information from option trading will flow into stock market via option market makers' hedging activities. Furthermore, Chakravarty, Gulen, and Mayhew (2004) find that option prices reflect some new information earlier than stock prices. Their findings suggest that option trading activities contribute to the price discovery of underlying stocks. Easley, O'Hara, and Srinivas (1998) and Pan and Poteshman (2006) find that option trading contains private information about future stock prices. Their results indicate an important informational role for option trading.

Furthermore, Jennings and Starks (1986) compare the stock price adjustment processes after earnings announcements for stocks with and without listed options. They find that option trading helps underlying stock prices adjust faster after earnings announcements.[54] Skinner (1990) finds that the reaction of stock prices to firms' earnings announcements becomes lower after option listing, suggesting that more private information is produced and incorporated into underlying stock prices after option introduction. These studies indicate that option trading increases the amount of private information incorporated in stock prices.

Finally, this paper is related to the studies on LEAPS. Though LEAPS have attracted more attention from investors in recent years, there are few studies on issues related to LEAPS. Lundstrum and Walker (2006) empirically investigate how LEAPS introduction affects the prices of underlying stocks. They find that introducing LEPAS is associated with negative cumulative returns for the underlying stocks. In addition, using intraday data, Bakshi, Cao and Chen (2000) show that S&P 500 regular options and LEAPS convey distinct information. Their results indicate that LEAPS contain different information than short-term options.

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[54] See also Mendenhall and Fehrs (1999).

3.3 Data and Sample Construction

To construct my sample, I collect data from several sources. I obtain financial statement data from Compustat, stock return data from the Center for Research in Security Prices (CRSP), institutional ownership data and insider trading data from ThomsonReuters, analyst coverage data from Institutional Brokers Estimates System (I/B/E/S), and short-term option trading data from OptionMetrics.

I start with all Compustat firms to form the main sample. Roll, Schwartz and Subrahmanyam (2009) argue that the enhancement of informational efficiency induced by options is more likely from active option trading activities. Thus, I first need to identify firms with active LEAPS trading activities in the market. To do so, I collect LEAPS trading data from the website of Chicago Board Options Exchange (CBOE). In its annual market statistics from 1999 to 2009, CBOE provides details on equity LEAPS contract volume, including name of underlying stock and traded contract volume. Then I create a dummy variable, LEAPS, that equals to one if a firm-year observation has positive LEAPS trading volume and zero otherwise.

Then, I exclude firms in the financial and banking industries (SIC code 6000-6999) and utility industries (SIC code 4900-4999). I also exclude firm-year observations with less than $10 million book value of equity or with less than 30 trading days in a year. In addition, because CBOE only introduces LEAPS to firms that already have listed short–term options, I require firm-year observations to have listed short-term options to mitigate the potential effect of short-term option listing on firms' investment decisions.

Finally, my sample consists of an unbalanced panel of 11571 firm-year observations associated with 2262 unique firms over a period from 1999 to 2009, including 3685 LEAPS observations and 7886 non-LEAPS observations.

Table 3.1: Summary Statistics

This table presents the summary statistics for the sample. The sample consists of 11571 firm-year observations associated with 2262 unique firms during a period from 1999 to 2009, including 3685 LEAPS observations and 7886 non-LEAPS observations. Detailed variable definitions are in Appendix C.1. All unbounded variables are winsorized at 1% and 99% levels for each year. Panel A presents the summary statistics for all firms, while Panel B (Panel C) presents the summary statistics for LEAPS (non-LEAPS) firms.

Panel A: All firms						
Variable	# of obs	Mean	Std Dev	25%	50%	75%
R&D	11571	0.0532	0.0851	0.0000	0.0119	0.0794
Capex	11571	0.0560	0.0639	0.0183	0.0350	0.0674
Q	11571	2.1658	1.3375	1.2840	1.7359	2.5873
CF	11571	0.1079	0.1337	0.0646	0.1152	0.1720
LogAsset	11571	6.9983	1.6018	5.8093	6.8766	8.0162
CumRet	11571	0.1306	0.6825	-0.3150	0.0089	0.3962
ROA	11571	0.1087	0.1405	0.0685	0.1258	0.1834
LogAge	11571	2.5900	0.8864	1.9459	2.5649	3.2581
Leverage	11571	0.1795	0.1709	0.0057	0.1543	0.2981
Cash	11571	0.2175	0.2232	0.0379	0.1346	0.3370
SGR	11571	0.1752	0.4017	0.0111	0.1074	0.2426
Institution	11571	0.7160	0.2230	0.5849	0.7450	0.8687
RetStd	11571	0.0328	0.0163	0.0209	0.0286	0.0409

Panel B: LEAPS firms						
Variable	# of obs	Mean	Std Dev	25%	50%	75%
R&D	3685	0.0530	0.0805	0.0000	0.0168	0.0818
Capex	3685	0.0561	0.0612	0.0194	0.0363	0.0686
Q	3685	2.2347	1.3561	1.3134	1.8025	2.6972
CF	3685	0.1192	0.1335	0.0708	0.1233	0.1855
LogAsset	3685	8.2132	1.5700	7.1838	8.2618	9.3700
CumRet	3685	0.1208	0.6464	-0.2917	0.0018	0.3567
ROA	3685	0.1237	0.1313	0.0811	0.1340	0.1919
LogAge	3685	2.9117	0.8677	2.3026	2.8332	3.5835
Leverage	3685	0.2104	0.1708	0.0512	0.1960	0.3209
Cash	3685	0.2076	0.2083	0.0447	0.1353	0.3044
SGR	3685	0.1574	0.3625	0.0116	0.1015	0.2260
Institution	3685	0.7644	0.1950	0.6477	0.7778	0.8883
RetStd	3685	0.0289	0.0150	0.0180	0.0250	0.0358

Table 3.1: Summary Statistics (Cont.)

Panel C: Non-LEAPS firms						
Variable	# of obs	Mean	Std Dev	25%	50%	75%
R&D	7886	0.0534	0.0871	0.0000	0.0097	0.0781
Capex	7886	0.0560	0.0651	0.0178	0.0343	0.0666
Q	7886	2.1336	1.3276	1.2702	1.7067	2.5128
CF	7886	0.1026	0.1334	0.0616	0.1110	0.1665
LogAsset	7886	6.4307	1.2654	5.5048	6.3844	7.3425
CumRet	7886	0.1351	0.6987	-0.3313	0.0111	0.4163
ROA	7886	0.1017	0.1441	0.0601	0.1226	0.1793
LogAge	7886	2.4397	0.8546	1.7918	2.3979	3.0445
Leverage	7886	0.1651	0.1690	0.0017	0.1242	0.2845
Cash	7886	0.2222	0.2297	0.0351	0.1343	0.3527
SGR	7886	0.1836	0.4185	0.0110	0.1100	0.2525
Institution	7886	0.6934	0.2315	0.5518	0.7280	0.8580
RetStd	7886	0.0346	0.0166	0.0225	0.0305	0.0427

Table 3.1 shows the summary statistics for my sample. Panel A reports the summary statistics for full sample, while Panel B and C present the summary statistics for subsamples of LEAPS and non-LEAPS firm-year observations, respectively.

In line with prior studies, I measure firms' long-term investment by R&D expenses and measure firms' stock prices by Tobin's Q. Panel B and C show that though the mean values of R&D are close for LEAPS and non-LEAPS firms, the median value of R&D is higher for LEAPS firms than non-LEAPS firms. In addition, LEAPS firms have a higher level of Q than non-LEAPS firms.

Regarding other firm characteristics, LEAPS firms are significantly larger than non-LEAPS firms in terms of total assets. Moreover, compared to non-LEAPS firms, LEAPS firms have a higher level of cash flows, return on assets, age, leverage and institutional holdings, but a lower level of cash holdings, sales growth and stock return volatility. A detailed definition of all variables is presented in Appendix C.1.

3.4 Empirical Results

3.4.1 Baseline Specification Tests

I first test my hypothesis by examining whether the sensitivity of R&D investment to stock prices is higher for LEAPS firms. Chen, Goldstein and Jiang (2007) argue that when stock prices provide more private information that is new to managers, managerial learning from the stock prices will result in a higher sensitivity of investment to stock prices. Therefore, if LEAPS trading activities increase the amount of long-term private information being incorporated in stock prices, and thus managers can learn more information from stock prices when making long-term investment decisions, I should expect to see that firms' R&D investment sensitivity to stock prices is higher for LEAPS firms.

To test this prediction, my baseline specification is as follows:

$$\mathrm{R\&D}_{i,t} = \delta_i + \eta_t + \beta_1 \cdot \mathrm{LEAPS}_{i,t-1} + \beta_2 \cdot \mathrm{Q}_{i,t-1} + \beta_3 \cdot \mathrm{LEAPS}_{i,t-1} \cdot \mathrm{Q}_{i,t-1} + \gamma \cdot \mathrm{Control} + \varepsilon_{i,t}$$

where $\mathrm{R\&D}_{i,t}$ is the proxy for long-term investment and is measured as firm i's R&D expenditure at year t, scaled by beginning-of-year book assets. $\mathrm{LEAPS}_{i,t-1}$ is a dummy variable that equals to one if firm i has active LEAPS trading activities at year t-1 and zero otherwise. $\mathrm{Q}_{i,t-1}$ is the proxy for firm i's stock prices and is calculated as the market value of equity plus book value of assets minus book value of equity, scaled by book value of assets, all measured at the end of year t-1.

In terms of control variables, I include $1/\mathrm{Asset}_{i,t-1}$ to isolate the spurious correlation between $\mathrm{R\&D}_{i,t}$ and $\mathrm{Q}_{i,t-1}$ that are scaled by common variable (Chen, Goldstein and Jiang, 2007). In addition, Baker, Wurgler and Stein (2003) find that firms invest more when their stock prices are overvalued. Hence, I include future returns ($\mathrm{CumRet}_{i,t+3}$) to control for stock mispricing, because overvalued stocks will experience negative returns in the future when mispricing is corrected (Baker and Wurgler, 2002). I also include $\mathrm{CF}_{i,t-1}$ and its interaction term with

$LEAPS_{i,t-1}$ to control for the well-known effect of cash flows on investment. Furthermore, following prior literature, I include a set of additional firm characteristics as control variables. Finally, I include both firm- and year-fixed effects in the baseline specification.

Table 3.2 summarizes the regression results for my baseline specification. Column (1) presents the results from estimating the baseline model including only 1/Asset and CumRet as control variables. The coefficient for Q is 0.0036 and significant at 1% level. This result indicates that firms' R&D investment is positively correlated with their stock prices.

I mainly focus on the coefficient for $LEAPS \cdot Q$. As shown in Column (1), this coefficient is estimated at 0.0030 with t-statistic of 2.24. This shows that the sensitivity of R&D investment to stock price is higher for firms with active LEAPS trading. Given the coefficient estimated on Q is 0.0036, this indicates that the R&D investment to stock price sensitivity will increase by about 80%, if a firm has active LEAPS trading activities in the market.

In Column (2), I further include CF and its interaction term with LEAPS into the baseline specification. The coefficient for $LEAPS \cdot Q$ is still positive and significant at 5% level. In addition, the coefficient for CF is 0.0112 and significant at 10% level, indicating that R&D investment positively depends on cash flows. I also find that the coefficient for $LEAPS \cdot CF$ is negative and significant at 5% level. This implies that LEAPS trading leads to more long-term information being incorporated into stock prices and hence enables manager to rely less on cash flows as a source of information on long-term investment profitability.

In Column (3), the main result remains qualitatively unchanged after controlling for additional firm characteristics: the estimated coefficient for $LEAPS \cdot Q$ is 0.0034 and significant at 5% level.[55]

[55] The results are qualitatively unchanged when I use log(R&D+1) instead of R&D as dependent variables in the baseline model.

Table 3.2: Baseline Specification Tests

This table presents the coefficient estimates of baseline model. The dependent variable is R&D. In Column (1) – (3), I estimate the baseline model with different set of control variables using the full sample. In Column (4), I use the matched sample to estimate baseline model. In Column (5), I estimate the baseline specification using a subsample of firms with non-zero R&D expenditure. Finally, in Column (6), I re-estimate the baseline specification using the Fama-MacBeth approach. Detailed variable definitions are in Appendix C.1. The sample period is from 1999 to 2009. The estimations correct the error term structure for heteroskedasticity and within-firm clustering. The t-statistics are in parentheses. ***, ** and * denote statistical significance at the 1%, 5% and 10% level, respectively.

	Dependent variable: R&D(t)											
	(1)		(2)		(3)		(4)		(5)		(6)	
LEAPS(t-1)	-0.0082	***	-0.0071	***	-0.0064	**	-0.0002		-0.0066		-0.0013	
	(-2.95)		(-2.63)		(-2.45)		(-0.04)		(-1.61)		(-0.76)	
Q(t-1)	0.0036	***	0.0033	***	0.0043	***	-0.0008		0.0056	***	0.0107	***
	(4.52)		(3.90)		(5.01)		(-0.43)		(5.22)		(5.64)	
LEAPS(t-1)*Q(t-1)	**0.0030**	**	**0.0036**	**	**0.0034**	**	**0.0065**	***	**0.0038**	**	**0.0043**	***
	(2.24)		**(2.52)**		**(2.52)**		**(3.15)**		**(2.18)**		**(6.95)**	
CF(t-1)			0.0112	*	0.0396	***	0.0874	***	0.0461	***	0.4459	***
			(1.72)		(4.49)		(3.42)		(4.06)		(6.56)	
LEAPS(t-1)*CF(t-1)			-0.0219	**	-0.0266	**	-0.0906	***	-0.0363	***	-0.0332	
			(-2.01)		(-2.37)		(3.63)		(-2.64)		(-1.60)	
1/Asset(t-1)	8.2362	***	8.3169	***	7.5733	***	11.7627	***	8.4495	***	1.3900	**
	(10.90)		(10.84)		(10.19)		(5.57)		(9.83)		(3.12)	
CumRet(t+3)	-0.0004		-0.0005		-0.0008		0.0007		-0.0016		0.0000	
	(-0.56)		(-0.59)		(-1.09)		(0.62)		(-1.24)		(0.02)	
ROA(t-1)					-0.0753	***	-0.0576	***	-0.0912	***	-0.4946	***
					(-5.26)		(-2.94)		(-4.91)		(-11.04)	
LogAge(t-1)					0.0099	***	0.0103		0.0156	***	0.0010	
					(3.29)		(1.54)		(2.84)		(1.16)	
Leverage(t-1)					-0.0106		-0.0275	**	-0.0238	**	0.0235	***
					(-1.41)		(-2.23)		(-2.08)		(3.97)	
Cash(t-1)					0.0139	*	0.0251	*	0.0216	**	0.0636	***
					(1.81)		(1.87)		(2.24)		(5.83)	
SGR(t-1)					-0.0011		0.0008		-0.0012		0.0005	
					(-0.65)		(0.29)		(-0.54)		(0.20)	
Institution(t-1)					-0.0023		0.0027		-0.0062		0.0037	**
					(-0.54)		(0.45)		(-0.81)		(2.68)	
RetStd(t-1)					-0.1417	**	-0.0264		-0.1996	**	0.2688	
					(-2.52)		(-0.26)		(-2.27)		(1.66)	
Firm FE	Yes		Yes		Yes		Yes		Yes		No	
Year FE	Yes		Yes		Yes		Yes		Yes		No	
# of obs	11571		11571		11571		4214		6638		11571	
Adj R2	0.148		0.149		0.171		0.124		0.203		0.691	

Acharya and Xu (2016) point out that firms' R&D expenses change substantially across industries and by firm size. In my sample, LEAPS firms are much larger than non-LEAPS firms in terms of total assets. Thus, it is possible that my results are driven by firm size. For example, larger firms are less likely to be affected by financial constraints and therefore can respond more easily to the long-term investment opportunities that are reflected in stock prices.

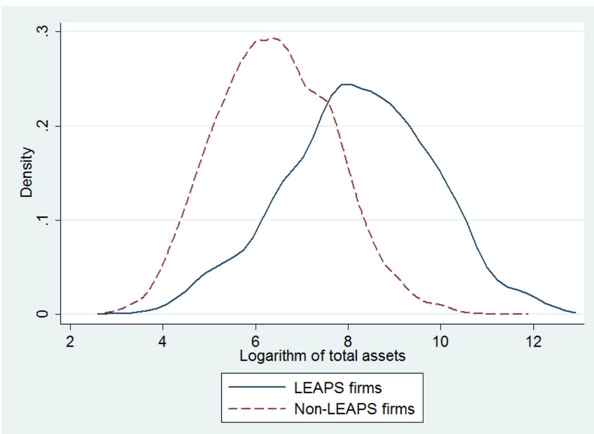

Figure 3.1.1

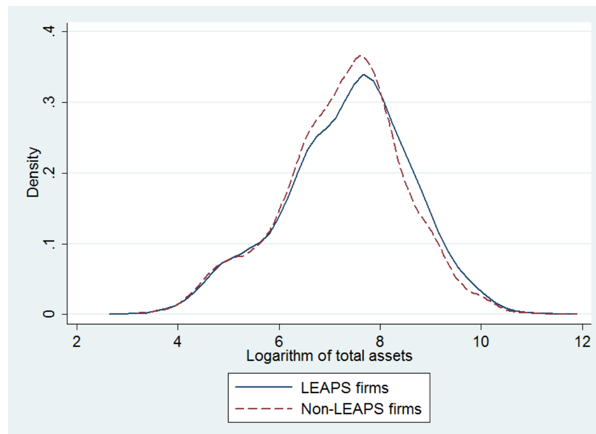

Figure 3.1.2

Figure 3.1: Size Distribution Before and After Matching. Figure 3.1.1 shows the total assets of LEAPS and non-LEAPS firms in full sample. Figure 3.1.2 shows the total assets of LEAPS and non-LEAPS firms in matched sample. I plot the Epanechnikov kernel densities of the natural logarithm of total assets.

To address this possibility, I follow the prior studies and use a matching procedure. Specifically, for each year in the sample, I match a LEAPS firm with a non-LEAPS firm that is closest in total assets and in the same two-digit SIC industry. The firm with closest firm size is chosen by the smallest ratio of total assets, which is defined as $\max(\mathrm{Asset}_{\mathrm{LEAPS}}, \mathrm{Asset}_{\mathrm{Non-LEAPS}})/\min(\mathrm{Asset}_{\mathrm{LEAPS}}, \mathrm{Asset}_{\mathrm{Non-LEAPS}})$. I require that the ratio of total assets is less than two and perform one-to-one matching without replacement.

After the matching procedure, there are finally 2107 matched pairs of firm-year observations with and without LEAPS trading activities. I plot the distribution of the logarithm of total assets for firm-year observations with and without LEAPS trading. Figure 3.1.1 shows that before matching LEAPS firms are on average larger in total assets than non-LEAPS firms. Figure 3.1.2 shows that the two distributions become nearly identical after matching.

The results in Column (4), in which I use the matched sample to estimate baseline model, show that the effect of LEAPS trading on firms' R&D investment sensitivity to stock prices is even stronger: the coefficient for $\mathrm{LEAPS} \cdot \mathrm{Q}$ is 0.0065 and significant at 1% level. This demonstrates that my previous results are not driven by firm size.

Another issue in my sample is that many firms have zero R&D expenditure, which may create a bias in an OLS framework. To alleviate this potential bias, I estimate the baseline specification using a sub-sample of firms with non-zero R&D expenditure in Column (5). The coefficient estimation for $\mathrm{LEAPS} \cdot \mathrm{Q}$ is 0.0038 and significant at 5% level.

Finally, I re-estimate the baseline specification using the Fama-MacBeth approach as an alternative way to deal with potential cross-sectional error correlation. In Column (6) of Table 3.2, I still obtain a positive and significant coefficient estimation for $\mathrm{LEAPS} \cdot \mathrm{Q}$.

As to the control variables, the estimated coefficients for LogAge and Cash are positive, indicating more matured firms and firms with more cash holdings invest more in long-term projects. I also find that the coefficient for RetStd is negative, suggesting that firms invest less in long-term projects when their stock returns are more volatile.

Overall, I find that the R&D investment sensitivity to stock prices is higher for firms with active LEAPS trading activities. This finding is consistent with my hypothesis that LEAPS trading contributes to long-term information production and hence increases the amount of long-term private information being incorporated in stock prices. This enables LEAPS firms' managers to learn more useful long-term information from stock prices when they are making long-term investment decisions.

3.4.2 Controlling for Selection Bias

Since LEAPS are introduced by CBOE on certain firms, a potential concern regarding my previous findings is the selection bias in decisions to introduce LEAPS on firms. In this subsection, I employ the treatment effect model to address this potential selection bias. The treatment effect model includes two equations. The first equation is the selection equation in which I model the decisions to list LEAPS on firms as follows:

$$\mathrm{LEAPS}_i^* = z_i \cdot \theta + \mu_i$$

$$\mathrm{LEAPS}_i = 1 \text{ if } \mathrm{LEAPS}_i^* > 0$$

$$\mathrm{LEAPS}_i = 0 \text{ if } \mathrm{LEAPS}_i^* < 0$$

where LEAPS_i^* is a latent variable and z_i is a set of observable variables affecting the listing decisions for LEAPS. In the second equation (regression equation), I use the baseline model but replace firm-fixed effect by industry-fixed effect.[56]

To estimate the selection equation, I need to identify the factors that may influence the listing decisions for LEAPS. Following Lundstrum and Walker (2006), I first use three firm characteristics that are found to affect the listing decisions of short-term options on firms by Mayhew and Mihov (2004), including lagged stock return volatility, lagged stock trading volume, and lagged market capitalization. Moreover, since CBOE only introduces LEAPS on firms that already have listed short–term options, the introduction decisions of LEAPS might be affected by the trading volume of short-term options. Hence, I also include lagged short-term option trading volume in the selection equation.

[56] Firm-fixed effect is not allowed in treatment effect model. Hence, I replace firm-fixed effect by industry-fixed effect. I use two-digit SIC code to define industry in this subsection.

Table 3.3: Controlling for Selection Bias

This table presents the coefficient estimates of baseline model after controlling for potential selection bias. More specifically, I use the treatment effect model that includes two equations. In the first equation (selection equation), Column (1) and (3), I regress LEAPS dummy on a set of factors that may influence the listing decisions for LEAPS. In the second equation (regression equation), Column (2) and (4), I use the baseline model but replace firm-fixed effect by two-digit SIC industry-fixed effect. Detailed variable definitions are in Appendix C.1. The sample period is from 1999 to 2009. The t-statistics are presented in parentheses below the coefficients, which are obtained through cluster-controlled bootstrap to adjust for firm-level clustering. ***, ** and * denote statistical significance at the 1%, 5% and 10% level, respectively.

Dependent Variable:	LEAPS(t-1)		R&D(t)		LEAPS(t-1)		R&D(t)	
	(1)		(2)		(3)		(4)	
LEAPS(t-1)			0.0190	***			0.0135	***
			(4.22)				(2.69)	
Q(t-1)			0.0076	***			0.0092	***
			(6.29)				(7.89)	
LEAPS(t-1)*Q(t-1)			**0.0038**	**			**0.0034**	**
			(2.09)				**(2.12)**	
CF(t-1)			0.0519	***			0.2467	***
			(4.32)				(13.15)	
LEAPS(t-1)*CF(t-1)			-0.0362	*			-0.0372	
			(-1.85)				(-1.47)	
1/Asset(t-1)			9.1266	***			2.5663	***
			(11.17)				(5.02)	
CumRet(t+3)			-0.0007				0.0010	
			(-0.47)				(0.87)	
ROA(t-1)							-0.3324	***
							(-24.33)	
LogAge(t-1)							-0.0023	**
							(-2.06)	
Leverage(t-1)							0.0081	
							(1.59)	
Cash(t-1)							0.0705	***
							(10.81)	
SGR(t-1)							-0.0030	
							(-1.15)	
Institution(t-1)							0.0099	**
							(2.19)	
RetStd(t-1)							0.3975	***
							(5.76)	
LogOpVol(t-2)	0.4668	***			0.4668	***		
	(11.59)				(11.59)			
RetStd(t-2)	-24.2782	***			-24.2782	***		
	(-12.92)				(-12.92)			
LogVol(t-2)	0.3852	***			0.3852	***		
	(5.97)				(5.97)			
LogMV(t-2)	0.0215				0.0215			
	(0.98)				(0.98)			
Industry FE			Yes				Yes	
Year FE			Yes				Yes	
# of obs			10620				10620	

In Column (1) and (2) of Table 3.3, I report the results without controlling for additional firm characteristics. The t-statistics are presented in parentheses below the coefficients, which are obtained through cluster-controlled bootstrap to adjust for firm-level clustering.[57]

Column (1) reports the estimation results for the selection equation. I find that LEAPS are more likely to be listed on firms with higher equity and short-term option trading volume. In addition, a high level of stock return volatility tends to decrease the probability of LEAPS listing.

I focus on the results of regression equation. The regression equation results in Column (2) show that the coefficient for $LEAPS \cdot Q$ is 0.0038 and significant at 5% level after controlling for the selection bias in the listing decisions for LEAPS. The results in Column (4) confirm that my findings are qualitatively unchanged after controlling for additional firm characteristics.

3.4.3 Controlling for Public and Managerial Information

So far, my results are consistent with the idea that LEAPS trading stimulates the production of long-term information that is new to managers and hence helps manager in making long-term investment decisions. However, the observed positive relationship between LEAPS trading activities and firms' R&D investment sensitivity to stock prices does not sufficiently imply that stock prices of LEAPS firms reveal more useful information to managers to guide their long-term investment decisions. This relationship would exist only because of the reflective role of stock prices; they reflect managerial or public information, which is already known to managers and is used in their decisions.

To address this possibility, I examine whether my previous findings are robust to controlling for other competing information sources. Specifically, I follow the method used in Chen, Goldstein and Jiang (2007) to construct my measures for public information and managerial information,

[57] I calculate the standard errors using a cluster-controlled bootstrap with 50 replications.

and then include these measures and their interaction terms with Q into the baseline model. The estimation results are shown in Table 3.4.

To measure the amount of public information, I rely on the number of analysts covering a firm. Column (1) and (2) of Table 3.4 show the estimation results after controlling for public information. In both columns, the estimated coefficients for $\text{Analyst} \cdot \text{Q}$ are positive but statistically insignificant.

More importantly, the inclusion of $\text{Analyst} \cdot \text{Q}$ has no bearing on the estimated coefficient for $\text{LEAPS} \cdot \text{Q}$: the coefficients for $\text{LEAPS} \cdot \text{Q}$ remain significantly positive in the presence of $\text{Analyst} \cdot \text{Q}$ in both Column (1) and (2). This finding indicates that LEAPS trading activities stimulate the information production that is not available from public information sources, such as financial analysts.

Then, I verify whether my previous findings are robust to controlling for managerial information. Following Chen, Goldstein and Jiang (2007), I rely on the insider trading activities to capture the amount of information held by managers. Insider trading is measured as the total number of shares bought and sold by insiders, scaled by the stock's total shares outstanding.

Column (3) and (4) of Table 3.4 present the estimation results after the inclusion of measures for managerial information. I find that the estimated coefficients for $\text{LEAPS} \cdot \text{Q}$ remain positive and highly significant in both columns. This suggests that LEAPS trading contributes to the production of information that is not known to managers. In addition, the coefficients for $\text{Insider} \cdot \text{Q}$ are positive but not statistically significant at conventional levels.

Taken together, the results in Table 3.4 provide additional support to my hypothesis. Indeed, my previous results are not altered after controlling for other information channels. Hence, the results in Table 3.4 confirm that LEAPS trading stimulates the production of some long-term private information that is new to managers.

Table 3.4: Controlling for Public and Managerial Information

This table presents the coefficient estimates of baseline model after controlling for public and managerial information. In Column (1) and (2), I include a proxy for public information, Analyst, and its interaction terms with Q into the baseline model. In Column (3) and (4), I include a proxy for managerial information, Insider, and its interaction terms with Q into the baseline model. Detailed variable definitions are in Appendix C.1. The sample period is from 1999 to 2009. The estimations correct the error term structure for heteroskedasticity and within-firm clustering. The t-statistics are in parentheses. ***, ** and * denote statistical significance at the 1%, 5% and 10% level, respectively.

	Dependent variable: R&D(t)							
	(1)		(2)		(3)		(4)	
LEAPS(t-1)	-0.0069	**	-0.0062	**	-0.0071	***	-0.0064	**
	(-2.55)		(-2.38)		(-2.63)		(-2.46)	
Q(t-1)	0.0028	***	0.0039	***	0.0033	***	0.0043	***
	(2.83)		(3.92)		(3.89)		(4.95)	
LEAPS(t-1)*Q(t-1)	**0.0033**	**	**0.0032**	**	**0.0036**	**	**0.0034**	**
	(2.34)		**(2.36)**		**(2.51)**		**(2.52)**	
Analyst(t-1)	0.0008		0.0007					
	(1.42)		(1.35)					
Analyst(t-1)*Q(t-1)	0.0002		0.0002					
	(1.06)		(0.84)					
Insider(t-1)					-0.0537		-0.0279	
					(-0.92)		(-0.50)	
Insider(t-1)*Q(t-1)					0.0029		0.0049	
					(0.15)		(0.26)	
CF(t-1)	0.0109	*	0.0390	***	0.0113	*	0.0397	***
	(1.67)		(4.43)		(1.73)		(4.49)	
LEAPS(t-1)*CF(t-1)	-0.0205	*	-0.0254	**	-0.0219	**	-0.0266	**
	(-1.90)		(-2.28)		(-2.02)		(-2.38)	
1/Asset(t-1)	8.5321	***	7.7591	***	8.3161	***	7.5734	***
	(10.94)		(10.26)		(10.83)		(10.19)	
CumRet(t+3)	-0.0005		-0.0009		-0.0005		-0.0008	
	(-0.62)		(-1.11)		(-0.61)		(-1.10)	
ROA(t-1)			-0.0744	***			-0.0753	***
			(-5.21)				(-5.26)	
LogAge(t-1)			0.0097	***			0.0098	***
			(3.26)				(3.29)	
Leverage(t-1)			-0.0106				-0.0106	
			(-1.41)				(-1.41)	
Cash(t-1)			0.0139	*			0.0139	*
			(1.82)				(1.81)	
SGR(t-1)			-0.0010				-0.0011	
			(-0.60)				(-0.64)	
Institution(t-1)			-0.0028				-0.0022	
			(-0.67)				(-0.53)	
RetStd(t-1)			-0.1404	**			-0.1405	**
			(-2.50)				(-2.49)	
Firm FE	Yes		Yes		Yes		Yes	
Year FE	Yes		Yes		Yes		Yes	
# of obs	11571		11571		11571		11571	
Adj R2	0.151		0.172		0.149		0.170	

3.4.4 Additional Robustness Tests

In this subsection, I perform several additional robustness tests.

First of all, I check whether LEAPS trading affects other types of investment in a similar way. It is possible that LEAPS trading stimulates information production for not only long-term information but also other types of information (e.g., short-term information). If so, I might find that LEAPS trading also affects other types of investment. Otherwise, if LEAPS trading activities only increase the amount of long-term private information in stock prices and thus affect managers' long-term investment decisions, I should expect to see that LEAPS trading has no effect on other types of investment.

To test this prediction, I examine whether firms' fixed investment is also more sensitive to stock prices for LEAPS firms. To do so, I replace the dependent variable $\mathrm{R\&D}_{i,t}$ in the baseline model with a proxy for fixed investment, $\mathrm{Capex}_{i,t}$, which is calculated as firm i's capital expenditure at year t, scaled by beginning-of-year book assets. The estimation results are reported in Table 3.5.

In Column (1), the coefficient for LEAPS is 0.0011 and statistically insignificant, suggesting that LEAPS trading has no first-order effect on firms' capital expenditure. The Q coefficient is 0.0085 with t-statistic of 11.58. This is consistent with a positive correlation between firms' capital investment and their stock prices found in the literature.

Most importantly, the estimated coefficient for $\mathrm{LEAPS} \cdot \mathrm{Q}$ is close to zero and statistically insignificant, indicating that LEAPS trading activities do not change capital investment sensitivity to stock prices. This finding suggests that LEAPS trading does not contribute to the production of information that managers can use to make fixed investment decisions.

Table 3.5: Additional Robustness Tests: Firms' Fixed Investment

In this table, I estimate the baseline model but replacing the dependent variable R&D by Capex. Detailed variable definitions are in Appendix C.1. The sample period is from 1999 to 2009. The estimations correct the error term structure for heteroskedasticity and within-firm clustering. The t-statistics are in parentheses. ***, ** and * denote statistical significance at the 1%, 5% and 10% level, respectively.

	Dependent variable: Capex(t)			
	(1)		(2)	
LEAPS(t-1)	0.0011		0.0015	
	(0.41)		(0.59)	
Q(t-1)	0.0085	***	0.0072	***
	(11.58)		(9.61)	
LEAPS(t-1)*Q(t-1)	**-0.0004**		**-0.0005**	
	(-0.43)		**(-0.48)**	
CF(t-1)	0.0274	***	-0.0107	**
	(6.12)		(-2.44)	
LEAPS(t-1)*CF(t-1)	0.0031		0.0041	
	(0.40)		(0.58)	
1/Asset(t-1)	1.7091	***	2.1891	***
	(5.14)		(5.82)	
CumRet(t+3)	-0.0040	***	-0.0032	***
	(-5.28)		(-4.33)	
ROA(t-1)			0.0659	***
			(8.17)	
LogAge(t-1)			-0.0061	*
			(-1.84)	
Leverage(t-1)			-0.0499	***
			(-7.43)	
Cash(t-1)			0.0071	
			(1.63)	
SGR(t-1)			-0.0005	
			(-0.47)	
Institution(t-1)			0.0137	***
			(3.09)	
RetStd(t-1)			-0.2515	***
			(-4.45)	
Firm FE	Yes		Yes	
Year FE	Yes		Yes	
# of obs	11571		11571	
Adj R2	0.141		0.171	

In Column (2) of Table 3.5, the results are qualitatively unchanged after controlling for additional firm characteristics: the estimated coefficient for $\mathrm{LEAPS} \cdot \mathrm{Q}$ remains small and statistically insignificant.

The results in Table 3.2 and Table 3.5 together suggest that LEAPS trading has different impact on investment projects with different types of uncertainty. LEAPS trading activities only affect R&D investment sensitivity to stock prices, supporting the notion that LEAPS trading stimulates the production of long-term information that is new to managers and hence affects managers' decisions in long-term investment projects.

Second, because the existence of LEAPS could benefit investors with improved ability to hedge long-term risks, LEAPS trading might be correlated with an enhancement of firms' external financing that facilitates the financing of long-term investment projects. Therefore, my previous findings might be driven by the possibility that LEAPS trading enables firms to respond more easily to the investment opportunities reflected in stock prices.

To address this concern, I re-estimate the baseline model by replacing stock price variable ($\mathrm{Q}_{\mathrm{i,t-1}}$) with non-price based measures of investment opportunities. Hence, if my finding is driven by the improvement of external financing rather than managers learning long-term information from stock prices, I should observe similar results when using non-price based measures. Otherwise, I wish to see that firms' R&D investment does not become more sensitive to non-price based measures of investment opportunities for LEAPS firms.

Following Edmans, Jayaraman and Schneemeier (2016), I employ three non-price based measures of investment opportunities, including cash flows ($\mathrm{CF}_{\mathrm{i,t-1}}$), firm age ($\mathrm{LogAge}_{\mathrm{i,t-1}}$) and sales growth ($\mathrm{SGR}_{\mathrm{i,t-1}}$). Table 3.2 has already shown that the estimated coefficient for $\mathrm{LEAPS} \cdot \mathrm{CF}$ is negative. So Table 3.6 only reports the estimation results using the other two measures.

Table 3.6: Additional Robustness Tests: Non-price Based Measures of Investment Opportunities

In this table, I include three non-price based measures of investment opportunities (CF, LogAge and SGR) and their interaction terms with LEAPS into the baseline model. Detailed variable definitions are in Appendix C.1. The sample period is from 1999 to 2009. The estimations correct the error term structure for heteroskedasticity and within-firm clustering. The t-statistics are in parentheses. ***, ** and * denote statistical significance at the 1%, 5% and 10% level, respectively.

	Dependent variable: R&D(t)							
	(1)		(2)		(3)		(4)	
LEAPS(t-1)	-0.0020		-0.0080	***	-0.0012		-0.0027	
	(-0.32)		(-2.90)		(-0.20)		(-0.46)	
Q(t-1)	0.0039	***	0.0037	***	0.0038	***	0.0044	***
	(4.67)		(4.39)		(4.36)		(5.03)	
LEAPS(t-1)*Q(t-1)	**0.0025**	*	**0.0031**	**	**0.0032**	**	**0.0034**	**
	(1.81)		**(2.23)**		**(2.15)**		**(2.43)**	
CF(t-1)	0.0027		0.0050		0.0110	*	0.0394	***
	(0.47)		(0.86)		(1.71)		(4.47)	
LEAPS(t-1)*CF(t-1)					**-0.0205**	*	**-0.0258**	**
					(-1.87)		**(-2.31)**	
LEAPS(t-1)*LogAge(t-1)	**-0.0019**				**-0.0019**		**-0.0013**	
	(-1.13)				**(-1.11)**		**(-0.78)**	
LEAPS(t-1)*SGR(t-1)			**-0.0016**		**-0.0019**		**-0.0010**	
			(-0.48)		(-0.57)		(-0.32)	
1/Asset(t-1)	8.3447	***	8.1567	***	8.3132	***	7.5857	***
	(10.90)		(10.67)		(10.77)		(10.17)	
CumRet(t+3)	-0.0004		-0.0005		-0.0005		-0.0008	
	(-0.47)		(-0.57)		(-0.59)		(-1.10)	
ROA(t-1)							-0.0751	***
							(-5.24)	
LogAge(t-1)	0.0102	***			0.0091	***	0.0095	***
	(3.31)				(2.91)		(3.13)	
Leverage(t-1)							-0.0106	
							(-1.41)	
Cash(t-1)							0.0138	*
							(1.80)	
SGR(t-1)			-0.0028		-0.0019		-0.0009	
			(-1.39)		(-0.92)		(-0.42)	
Institution(t-1)							-0.0023	
							(-0.55)	
RetStd(t-1)							-0.1427	**
							(-2.53)	
Firm FE	Yes		Yes		Yes		Yes	
Year FE	Yes		Yes		Yes		Yes	
# of obs	11571		11571		11571		11571	
Adj R2	0.151		0.149		0.152		0.171	

In Column (1) of Table 3.6, the estimate coefficient for $\text{LEAPS} \cdot \text{LogAge}$ is negative and statistically insignificant, while in Column (2) the coefficient for $\text{LEAPS} \cdot \text{SGR}$ is also negative and insignificant. In addition, when I include the interaction terms of all three non-price based measures with LEAPS in Column (3) of Table 3.6, the estimated coefficients for the three interaction terms remain qualitatively unchanged. In Column (4), I obtain similar results after controlling for additional firm characteristics. However, all columns in Table 3.6 show that the estimated coefficients for $\text{LEAPS} \cdot \text{Q}$ are positive and significant at conventional levels.

Therefore, these results demonstrate that LEAPS trading only increases the sensitivity of R&D investment to stock prices, supporting my hypothesis that managers learn information from stock prices when they are making long-term investment decisions.

Finally, I examine two other factors that may be related to LEAPS trading activities and may affect firms' R&D investment sensitivity to stock prices: short-term option trading volume and institutional ownership.

Roll, Schwartz and Subrahmanyam (2009) find that firms' (total) investment becomes more sensitive to stock prices when short-term option trading volume is higher.[58] Because LEAPS is introduced to firms that already have listed short–term options, LEAPS trading activities may be correlated with short-term option trading activities. Indeed, the results in Table 3.3 have shown that the listing decisions for LEAPS are positively correlated with short-term option trading volume. Hence, I first check whether my previous finding is affected after controlling for short-term option trading activities. To do so, I use the logarithm of annual option trading volume ($\text{LogOpVol}_{i,t-1}$) as a proxy for short-term option trading activities and interact it with $\text{Q}_{i,t-1}$ in the baseline model. The estimation results are reported in Column (1) and (2) of Table 3.7.

[58] Roll, Schwartz and Subrahmanyam (2009) measure investment as the sum of capital expenditure and R&D expenditure, scaled by beginning-of-year book assets.

Table 3.7: Additional Robustness Tests: Controlling for Other Factors

In this table, I include two other factors (LogOpVol and Institution) and their interaction terms with Q into the baseline model. Detailed variable definitions are in Appendix C.1. The sample period is from 1999 to 2009. The estimations correct the error term structure for heteroskedasticity and within-firm clustering. The t-statistics are in parentheses. ***, ** and * denote statistical significance at the 1%, 5% and 10% level, respectively.

	Dependent variable: R&D(t)							
	(1)		(2)		(3)		(4)	
LEAPS(t-1)	-0.0086	***	-0.0090	***	-0.0068	**	-0.0060	**
	(-3.03)		(-3.25)		(-2.54)		(-2.32)	
Q(t-1)	0.0076	**	0.0100	***	0.0020		0.0030	*
	(2.44)		(3.16)		(1.11)		(1.69)	
LEAPS(t-1)*Q(t-1)	**0.0045**	***	**0.0047**	***	**0.0035**	**	**0.0033**	**
	(3.05)		**(3.28)**		**(2.44)**		**(2.42)**	
LogOpVol(t-1)	0.0001		0.0007					
	(0.16)		(1.22)					
LogOpVol(t-1)*Q(t-1)	-0.0004		-0.0005	*				
	(-1.42)		(-1.89)					
Institution(t-1)			-0.0023		-0.0017		-0.0066	
			(-0.56)		(-0.31)		(-1.19)	
Institution(t-1)*Q(t-1)					0.0020		0.0021	
					(0.84)		(0.90)	
CF(t-1)	0.0108		0.0391	***	0.0109	*	0.0397	***
	(1.64)		(4.45)		(1.66)		(4.50)	
LEAPS(t-1)*CF(t-1)	-0.0223	**	-0.0266	**	-0.0217	**	-0.0265	**
	(-2.06)		(-2.38)		(-2.00)		(-2.36)	
1/Asset(t-1)	8.0815	***	7.3794	***	8.4080	***	7.6213	***
	(10.38)		(9.79)		(10.78)		(10.24)	
CumRet(t+3)	-0.0005		-0.0008		-0.0004		-0.0008	
	(-0.64)		(-1.03)		(-0.53)		(-1.03)	
ROA(t-1)			-0.0756	***			-0.0756	***
			(-5.27)				(-5.28)	
LogAge(t-1)			0.0103	***			0.0099	***
			(3.42)				(3.29)	
Leverage(t-1)			-0.0106				-0.0105	
			(-1.42)				(-1.40)	
Cash(t-1)			0.0141	*			0.0137	*
			(1.84)				(1.79)	
SGR(t-1)			-0.0011				-0.0011	
			(-0.64)				(-0.64)	
RetStd(t-1)			-0.1308	**			-0.1395	**
			(-2.18)				(-2.48)	
Firm FE	Yes		Yes		Yes		Yes	
Year FE	Yes		Yes		Yes		Yes	
# of obs	11571		11571		11571		11571	
Adj R2	0.150		0.171		0.149		0.171	

I focus on the effect of including $\mathrm{LogOpVol} \cdot \mathrm{Q}$ on the estimated coefficient for $\mathrm{LEAPS} \cdot \mathrm{Q}$. Both Column (1) and (2) of Table 3.7 show that the coefficients for $\mathrm{LEAPS} \cdot \mathrm{Q}$ remain positive and highly significant after the inclusion of $\mathrm{LogOpVol} \cdot \mathrm{Q}$. In addition, the estimated coefficients for $\mathrm{LogOpVol} \cdot \mathrm{Q}$ are negative in both columns, indicating that short-term option trading activities do not contribute to the information production that helps managers in making R&D investment decisions. This is reasonable, given the maturity for short-term options is usually less than one year, short-term option trading is more likely to produce short-term information rather than long-term information.

Then, I turn to investigate whether my previous results are robust to controlling for institutional ownership. My measure for institutional ownership ($\mathrm{Institution}_{i,t-1}$) is calculated as the percentage of shares outstanding held by institutional shareholders. Column (3) and (4) of Table 3.7 present the estimation results after controlling for institutional ownership. The estimated coefficients for $\mathrm{LEAPS} \cdot \mathrm{Q}$ remain significantly positive in the presence of $\mathrm{Instituion} \cdot \mathrm{Q}$. Moreover, the estimated coefficients for $\mathrm{Instituion} \cdot \mathrm{Q}$ are statistically insignificant in both Column (3) and (4).

3.4.5 When Does LEAPS Trading Matter?

I have shown robust evidence that LEAPS trading has a positive effect on firms' R&D investment sensitivity to stock prices. This is consistent with my hypothesis that LEAPS trading stimulates the production of long-term information that is new to managers and hence helps manager in making long-term investment decisions. My hypothesis also suggests that this effect should become stronger in situations where the existence of active LEAPS trading is more likely to stimulate the production of private information. In this subsection, I test this aspect of my hypothesis by investigating the cross-sectional variation on the effect of LEAPS trading activities on firms' R&D investment sensitivity to stock prices.

Massa (2002) points out that introducing derivatives will increase investors' incentives to acquire private information when there is less information in the market. Following this argument, I therefore hypothesize that the effect of LEAPS trading on the sensitivity of R&D investment to stock prices should be stronger for firms with a smaller amount of information available in the market.

I first operationalize this hypothesis by looking at analyst coverage. I predict that the effect of LEAPS trading on the sensitivity of R&D investment to stock prices is stronger when firms have a lower level of analyst coverage.

To test this prediction, I split my sample into high and low analyst coverage subsamples based on whether the number of financial analysts following a firm is above the industry median at a given year and further estimate the baseline model individually for each subsample.

Column (1) and (2) of Table 3.8 report the estimation results for each subsample using the full baseline specification with additional firm characteristics. Consistent with my prediction, I find that the effect of LEAPS trading on the sensitivity of R&D investment to stock prices is indeed greater for firms with a lower level of analyst coverage. The coefficient for $\mathrm{LEAPS} \cdot \mathrm{Q}$ is 0.0045 and significant at 1% level for firms with lower analyst coverage in Column (1), and is 0.0029 and statistically insignificant for firms with higher analyst coverage in Column (2).

In addition, Collins, Kothari and Rayburn (1987) argue that firm size is a proxy for the amount of information about a firm: the information set is broader and richer for larger firms. Hence, I expect that the effect of LEAPS trading on the sensitivity of R&D investment to stock prices should be greater for smaller firms. I measure firm size with the logarithm of total assets and split full sample into large and small subsamples based on the industry-year median firm size.

Table 3.8: When Does LEAPS Trading Matter?

This table presents the coefficient estimates of baseline model using subsamples. In Column (1) and (2), I use subsamples of firms with low and high analyst coverage, respectively. In Column (3) and (4), I use subsamples of firms with small and large size, respectively. Low and High (small and large) subsamples are formed based on the industry-year median level. Detailed variable definitions are in Appendix C.1. The sample period is from 1999 to 2009. The estimations correct the error term structure for heteroskedasticity and within-firm clustering. The t-statistics are in parentheses. ***, ** and * denote statistical significance at the 1%, 5% and 10% level, respectively.

	Dependent variable: R&D(t)							
	Low coverage		High coverage		Small size		Large size	
	(1)		(2)		(3)		(4)	
LEAPS(t-1)	-0.0067	**	-0.0085	**	-0.0102	**	-0.0034	
	(-2.17)		(-2.12)		(-2.41)		(-1.05)	
Q(t-1)	0.0047	***	0.0036	***	0.0049	***	0.0011	
	(3.68)		(2.91)		(4.57)		(0.77)	
LEAPS(t-1)*Q(t-1)	**0.0045**	***	**0.0029**		**0.0061**	***	**0.0025**	
	(2.71)		**(1.44)**		**(3.20)**		**(1.37)**	
CF(t-1)	0.0468	***	0.0212	*	0.0463	***	0.0185	
	(3.68)		(1.84)		(4.30)		(1.50)	
LEAPS(t-1)*CF(t-1)	-0.0341	*	-0.0121		-0.0354		-0.0177	
	(-1.96)		(-0.79)		(-1.62)		(-1.36)	
1/Asset(t-1)	7.5875	***	10.6551	***	7.3609	***	23.6837	***
	(8.43)		(5.14)		(9.45)		(6.32)	
CumRet(t+3)	-0.0015		0.0003		-0.0025	**	0.0002	
	(-1.48)		(0.21)		(-2.27)		(0.20)	
ROA(t-1)	-0.0743	***	-0.0457	*	-0.1029	***	0.0136	
	(-3.70)		(-1.91)		(-5.78)		(0.78)	
LogAge(t-1)	0.0107	***	0.0116	***	0.0120	**	0.0074	***
	(2.92)		(2.70)		(2.18)		(2.59)	
Leverage(t-1)	0.0008		-0.0197		-0.0012		-0.0067	
	(0.09)		(-1.53)		(-0.12)		(-0.77)	
Cash(t-1)	0.0069		0.0236	*	0.0103		0.0284	**
	(0.71)		(1.85)		(1.09)		(2.12)	
SGR(t-1)	0.0003		-0.0034		0.0026		-0.0023	
	(0.10)		(-1.55)		(0.99)		(-1.22)	
Institution(t-1)	-0.0033		-0.0027		-0.0002		0.0023	
	(-0.67)		(-0.35)		(-0.04)		(0.47)	
RetStd(t-1)	-0.1647	**	-0.0367		-0.1804	**	-0.0291	
	(-2.38)		(-0.38)		(-2.22)		(-0.47)	
Firm FE	Yes		Yes		Yes		Yes	
Year FE	Yes		Yes		Yes		Yes	
# of obs	6167		5271		5908		5663	
Adj R2	0.220		0.125		0.240		0.057	

Column (3) and (4) of Table 3.8 show that effect of LEAPS trading on the sensitivity of R&D investment to stock prices is stronger for smaller firms. The estimated coefficient for $\text{LEAPS} \cdot \text{Q}$ is positive and significant at 1% level for small firms in Column (1), but insignificant for large firms in Column (2). In term of magnitude, the coefficient for small firms is over double that for large firms (0.0061 versus 0.0025).

3.5 Further Analyses

3.5.1 LEAPS Trading and Over- or Under-Investment

In this paper, I argue that LEAPS trading stimulates the production of long-term information that is new to managers and thus helps managers make better long-term investment decisions. If so, I expect that the long-term investment of LEAPS firms should be more efficient than that of non-LEAPS firms. In this subsection, I test this prediction by investigating whether LEAPS trading helps a firm to achieve an optimal R&D investment level. More specifically, I examine whether LEAPS trading helps firms overcome the problem of over- or under-investment in long-term projects.

I follow the method used in Massa et al. (2015) to define an over-investment dummy, Prob(over-investment), and an under-investment dummy, Prob(under-investment). To estimate the degree of over- or under-investment, for each two-digit SIC industry, I estimate the following equation:

$$\begin{aligned} \text{R\&D}_{i,t} = {} & \delta_i + \eta_t + \beta_1 \cdot \text{LogAsset}_{i,t-1} + \beta_2 \cdot \text{LogAge}_{i,t-1} + \beta_3 \cdot \text{SGR}_{i,t-1} + \beta_4 \cdot \text{Leverage}_{i,t-1} \\ & + \beta_5 \cdot \text{Q}_{i,t-1} + \beta_6 \cdot \text{Cash}_{i,t-1} + \varepsilon_{i,t} \end{aligned}$$

So $\varepsilon_{i,t}$ measures the relative degree of over- or under-investment for a firm compared to its industry peers.[59]

Then, for each industry, I sort firm-year observations based on $\varepsilon_{i,t}$. The firm-year observations in top 20th are classified into the over-investment group, while the firm-year observations in bottom 20th are classified into the under-investment group. Finally, I test my prediction by estimating a logistic regression as follows:

$$\begin{aligned}\text{Prob}\big(\text{Over} - \text{investment}_{i,t} \text{ or } \text{Under} - \text{investment}_{i,t}\big) \\ = \delta_i + \eta_t + \beta_1 \cdot \text{LEAPS}_{i,t-1} + \beta_2 \cdot \text{ROA}_{i,t-1} + \beta_3 \cdot \text{Institution}_{i,t-1} + \beta_4 \\ \cdot \text{RetStd}_{i,t-1} + \theta_{i,t}\end{aligned}$$

The estimation results are presented in Table 3.9. The t-statistics presented in parentheses below the coefficients are calculated using cluster-controlled bootstrap to adjust for firm-level clustering.

In Column (1) where the dependent variable is Prob(over-investment), the estimated coefficient for LEAPS is negative but statistically insignificant. In Column (2) where the dependent variable is Prob(under-investment), the coefficient for LEAPS is negative and significant at 1% level. These results indicate that firms with active LEAPS trading activities are less likely to experience the problem of under-investment in long-term projects. This finding is reasonable. Since LEAPS trading contributes to the production of long-term information that is new to managers, it helps reduce the uncertainty related to long-term projects and hence increases firms' long-term investment level.

[59] I require at least 30 firm-year observations in each two-digit SIC industry to estimate $\varepsilon_{i,t}$.

Table 3.9: LEAPS Trading and Over- or Under-Investment

In this table, I examine whether LEAPS trading helps firms to overcome the problem of over- or under-investment. In Column (1), the dependent variable is an over-investment dummy, Prob(over-investment), while in Column (2), the dependent variable is an under-investment dummy, Prob(under-investment). Detailed variable definitions are in Appendix C.1. The sample period is from 1999 to 2009. The t-statistics are presented in parentheses below the coefficients, which are obtained through cluster-controlled bootstrap to adjust for firm-level clustering. ***, ** and * denote statistical significance at the 1%, 5% and 10% level, respectively.

Dependent variable:	Prob (over-investment)	Prob (under-investment)	
	(1)	(2)	
LEAPS(t-1)	**-0.0025**	**-0.4096**	***
	(-0.02)	**(-2.93)**	
ROA(t-1)	-0.6884	-0.6725	
	(-1.49)	(-1.34)	
Institution(t-1)	2.4863	5.8493	
	(0.54)	(1.15)	
RetStd(t-1)	-0.6341	1.0314	*
	(-1.34)	(1.80)	
Firm FE	Yes	Yes	
Year FE	Yes	Yes	
# of obs	4848	4172	

3.5.2 LEAPS Trading and Firms' Future Performance

In this subsection, I examine whether LEAPS trading affects firms' future performance by optimizing firms' R&D investment decisions. If LEAPS trading stimulates the production of long-term information that helps managers make better investment decisions, I should expect that LEAPS trading enhances firms' future performance by improving long-term investment decisions.

Table 3.10: LEAPS Trading and Firms' Future Performance

In this table, I examine whether LEAPS trading affects firms' future performance by optimizing firms' R&D investment decisions. More specifically, I regress measures of firms' future performance (ROA and VAG) on one year lagged LEAPS trading activities dummy and its interaction with R&D investment measure. Column (1) and (2) show the results for ROA over next one- and three-years, respectively, while Column (3) and (4) show the results for VAG. Detailed variable definitions are in Appendix C.1. The sample period is from 1999 to 2009. The estimations correct the error term structure for heteroskedasticity and within-firm clustering. The t-statistics are in parentheses. ***, ** and * denote statistical significance at the 1%, 5% and 10% level, respectively.

Dependent variable:	ROA(t+1)		ROA(t+1, t+3)		VAG(t+1)		VAG(t+1, t+3)	
	(1)		(2)		(3)		(4)	
LEAPS(t-1)	-0.0067	*	-0.0067	*	-0.0240		-0.0088	
	(-1.76)		(1.77)		(-1.10)		(-0.77)	
R&D(t)	-0.1867	***	-0.0399		-0.2368		-0.0689	
	(-4.01)		(-1.06)		(-0.68)		(-0.56)	
LEAPS(t-1)*R&D(t)	**0.1208**	*	**0.1304**	**	**0.9645**	**	**0.5614**	***
	(1.89)		**(2.43)**		**(2.42)**		**(3.24)**	
Q(t)	0.0205	***	0.0099	***	0.1501	***	0.0301	***
	(8.91)		(6.15)		(12.32)		(5.56)	
LogAsset(t)	-0.0150	***	-0.0349	***	-0.3255	***	-0.2831	***
	(-3.34)		(-7.17)		(-11.55)		(-16.11)	
ROA(t)					-5.0914	***	-2.9249	***
					(-22.64)		(-28.76)	
LogAge(t)	0.0099		0.0127		0.0202		0.0669	*
	(1.16)		(1.56)		(0.38)		(1.86)	
Leverage(t)	0.0266	*	0.0505	***	-0.0949		-0.0541	
	(1.95)		(4.06)		(-1.15)		(-1.26)	
Cash(t)	-0.0279		-0.0118		-0.2240	**	-0.0149	
	(-1.54)		(-0.86)		(-2.36)		(-0.27)	
SGR(t)	0.0401	***	0.0184	***	0.0915	**	0.0227	
	(7.27)		(5.79)		(2.44)		(1.39)	
Institution(t)	-0.0351	***	-0.0269	**	-0.1787	**	-0.0022	
	(-2.86)		(-2.44)		(-2.38)		(-0.06)	
RetStd(t)	-0.8996	***	-0.1529		-2.0685	**	0.7922	
	(-6.35)		(-1.23)		(-1.96)		(1.60)	
Firm FE	Yes		Yes		Yes		Yes	
Year FE	Yes		Yes		Yes		Yes	
# of obs	9814		6230		8295		5067	
Adj R2	0.109		0.108		0.229		0.468	

I construct two measures of firms' future performance. The first measure is return on asset (ROA). The second measure is value added growth (VAG) calculated as log change in the sum of operating income and labor expense. Then I regress the average future performance measures over the next one- or three-years on one-year lagged LEAPS trading activities dummy and its interaction term with R&D investment, and firm-level control variables as well as firm- and year-fixed effects.

$$\begin{aligned} ROA_{i,t+1}(ROA_{i,t+1,t+3}, VAG_{i,t+1}, VAG_{i,t+1,t+3}) \\ = \delta_i + \eta_t + \beta_1 \cdot LEAPS_{i,t-1} + \beta_2 \cdot R\&D_{i,t} + \beta_3 \cdot LEAPS_{i,t-1} \cdot R\&D_{i,t} + \beta_4 \\ \cdot Control_{i,t} + \theta_{i,t+1} \end{aligned}$$

I report the estimation results in Table 3.10. Column (1) and (2) show the results for ROA over next one- and three-years, respectively, while Column (3) and (4) show the results for VAG. In all columns, the estimated coefficients for LEAPS · R&D are positive and statistically significant. These results suggest that LEAPS trading has real effects on R&D investment efficiency: the R&D investment induced by LEAPS trading has a positive effect on firms' future operating performance and growth.

Overall, my results confirm the beneficial effects of LEAPS trading activities on firms' R&D investment decisions and their effects on firms' future performance.

3.6 Conclusion

This paper tests the hypothesis that LEAPS trading stimulates the production of long-term information, which managers can use to guide their long-term investment decisions.

Consistent with this hypothesis, I show that the sensitivity of R&D investment to stock prices is higher for firms with active LEAPS trading. This result holds after controlling for the potential selection bias and controlling for other competing information sources. In addition, I show that the effect of LEAPS trading on firms' R&D investment sensitivity to stock prices becomes stronger in situations in which LEAPS trading is more likely to increase investors' incentives to acquire long-term private information.

Further analyses show that active LEAPS trading helps managers make more efficient R&D investment by mitigating the problem of under-investment. Moreover, the R&D investment induced by LEAPS trading has a positive effect on firms' future operating performance and growth.

Taken together, these findings suggest that long-term option trading activities can have real effects by enhancing the allocational role of stock prices.

Appendix C

C.1: Variable Definitions

Variable	Definition
R&D	Research and development expenditures scaled by beginning-of-year total assets
Capex	Capital expenditures scaled by beginning-of-year total assets
Q	Market value of equity plus book value of assets minus book value of equity, scaled by book value of assets
CF	The sum of net income before extraordinary item, depreciation and amortization expenses, and R&D expenses, scaled by book value of assets
LogAsset	Logarithm of total assets
CumRet	Cumulative market-adjusted excess returns over a time period of 36 months subsequent to the measurement of investment
ROA	Percentage of operating income before depreciation, interest and taxes to the book value of total assets
LogAge	Logarithm of firm age, which is calculated as years from firm's first appearance in CRSP
Leverage	Net debt divided by total assets, where net debt is defined as total debt minus cash
Cash	Cash and cash equivalents scaled by total assets
SGR	Sales growth, defined as one-year growth in total revenues
Institution	Fraction of shares outstanding held by institutional shareholders
RetStd	Annualized standard deviation of monthly stock returns
LogOpVol	Logarithm of annual option trading volume (in number of contracts)
LogVol	Logarithm of annual stock trading volume (in shares)
LogMV	Logarithm of market capitalization
Analyst	Number of analysts that issue one-year forward forecasts on earnings per share for the firm
Insider	Total number of shares bought and sold by insiders, scaled by the stock's total shares outstanding
VAG	Log change in the sum of operating income and labor expense

Conclusion

In summary, my doctoral thesis show that stock prices play an important role in guiding corporate decisions due to the information feedback channel. Chapter one shows that when stock prices reflect a greater amount of information that managers care about, corporate decisions made by managers become more efficient. Chapter two shows that managers seek to learn short sellers' information from stock prices and use it in corporate decisions. Chapter three shows that long-term option trading stimulates the production of long-term information, which managers can use to guide their long-term investment decisions.

Overall, my doctoral thesis sheds light on the allocational role of stock prices by analyzing the way in which stock prices reveal information to guide managers' corporate decisions. Looking ahead to future research, there are at least two issues that could be addressed.

First, the information feedback channel assumes that stock prices efficiently reflect information from market participants and hence stock price changes reveal information on fundamental shocks. However, sometimes stock price changes might be caused by non-fundamental shocks, such as price pressure driven by mutual fund flows or market sentiment index. Therefore, stock prices could be contaminated by noise. If so, it is important to understand whether the noise in stock prices affects the information feedback from stock prices to corporate decisions. In recent studies, Yan (2016) and Dessaint et al. (2016) show that managers can not filter out the noise contained in stock prices when they rely on stock prices as a source of information. In this case, the informational role of stock prices in guiding corporate decisions might be contaminated by the noise. Therefore, it is important to understand how to help managers identify "true" information from stock prices. For example, does the presence of advisory directors on the board work in this way?

Second, it is possible that corporate decisions could affect investors' incentives to acquire private information and further stock price informativeness. Hence, the informational role of stock prices might be affected (or determined) by corporate decisions, especially the decisions made by managers in response to the new information in stock prices. In this sense, if managers are unwilling to change corporate decisions in response to the information reflected in stock prices, outsider investors are unlikely to acquire private information that is useful to managers, resulting in a limited allocational role of stock prices. Therefore, it is interesting to see how stock price informativeness varies with managers' willingness to learn from stock prices. To empirically study this question, it is necessary to construct a measure for managers' willingness to learn from stock prices. I plan to investigate these questions in future research.

Bibliography

Acharya, Viral and Zhaoxia Xu, 2016, Financial dependence and innovation: The case of public versus private firms. Journal of Financial Economics, forthcoming.

Aktas, Nihat, Eric de Bodt, Fany Declerck, and Herve Van Oppens, 2007, The PIN anomaly around M&A announcements. Journal of Financial Markets 10, 169-191.

Amihud, Yakov, 2002, Illiquidity and stock returns: Cross-section and time series effects. Journal of Financial Markets 5, 31-56.

Arellano, Manuel, and Stephen Bond, 1991, Some tests of specification for panel data: Monte Carlo evidence and an application to employment equations. Review of Financial Studies 58, 277-297.

Bai, Jennie, Thomas Philippon, and Alexi Savov, 2014, Have financial markets become more informative? Working paper.

Baker, Malcolm, Jeremy C. Stein, and Jeffrey Wurgler, 2003, When does the market matter? Stock prices and the investment of equity-dependent firms. Quarterly Journal of Economics 118, 969-1006.

Baker, Malcolm, and Jeffrey Wurgler, 2002, Market timing and capital structure. Journal of Finance 57, 1-32.

Bakke, Tor-Erik and Toni M. Whited, 2010, Which firms follow the market? An analysis of corporate investment decisions. Review of Financial Studies 23, 1941–1980.

Bakshi, Gurdip, Charles Cao, and Zhiwu Chen, 2000, Pricing and hedging long-term options. Journal of Econometrics 94, 277-318.

Bhojraj, Sanjeev, Charles Lee, and Derek Oler, 2003, What's my life? A comparison of industry classification schemes for capital market research. Journal of Accounting Research 41, 745-774.

Boehmer, Ekkehart, Charles M. Jones, and Xiaoyan Zhang, 2008, Which shorts are informed? Journal of Finance 63, 491-527.

Bond, Philip, Alex Edmans, and Itay Goldstein, 2012, The real effects of financial markets. Annual Review of Financial Economics 4, 339-360.

Bris, Arturo, William N. Goetzmann and Ning Zhu, 2007, Efficiency and the bear: Short sales and markets around the world. Journal of Finance 62, 1029-1079.

Brown, Stephen, Stephen A. Hillegeist, and Kin Lo, 2004, Conference calls and information asymmetry. Journal of Accounting and Economics 37, 343-366.

Cao, Henry H., 1999, The effect of derivative assets on information acquisition and price behavior in a rational expectation equilibrium. Review of Financial Studies 12, 131-163.

Chakravarty, Sugato, Huseyin Gulen, and Stewart Mayhew, 2004, Informed trading in stock and option markets. Journal of Finance 59, 1235-1257.

Chang, Eric C., Joseph W. Cheng, and Yinghui Yu, 2007, Short-sales constraints and price discovery: Evidence from the Hong Kong market. Journal of Finance 62, 2097-2121.

Chang, Eric C., Tse-Chun Lin, and Xiaorong Ma, 2014, Does short selling discipline overinvestment? Working paper.

Chen, Qi, Itay Goldstein, and Wei Jiang, 2007, Price informativeness and investment sensitivity to stock price. Review of Financial Studies 20, 619-650.

Chirinko, Robert S., and Huntley Schaller, 2009, The irreversibility premium. Journal of Monetary Economics 56, 390-408.

Christophe, Stephen E., Michael G. Ferri, and James J. Angel, 2004, Short-selling prior to earnings announcements. Journal of Finance 59, 1845-1875.

Chu, Yongqiang, 2015, Short selling and the product market: Evidence from SHO. Working paper.

Coles, Jeffrey L., Naveen D. Daniel, and Lalitha Naveen, 2006, Managerial incentives and risk-taking. Journal of Financial Economics 79, 431-468.

Collins, Daniel W., S. P. Kothari, and Judy D. Rayburn, 1987, Firm size and the information content of prices with respect to earnings. Journal of Accounting and Economics 9, 111-138.

Cooper, Ilan, 2006, Asset pricing implications of nonconvex adjustment costs and irreversibility of investment. Journal of Finance 61, 139-170.

Corwin, Shane A., and Paul Schultz, 2012, A simple way to estimate bid-ask spreads from daily high and low prices. Journal of Finance 67, 719-759.

David, Joel M., Hugo A. Hopenhayn, and Venky Venkateswaran, 2014, Information, misallocation and aggregate productivity. Working paper.

Dessaint, Olivier, Thierry Foucault, Laurent Frésard, and Adrien Matray, 2016, Ripple effects of noise on corporate investment. Working paper.

Dow, James, and Gary Gordon, 1994, Arbitrage chains. Journal of Finance 49, 819-849.

Dow, James, and Gary Gordon, 1997, Stock market efficiency and economic efficiency: Is there a connection? Journal of Finance 52, 1087-1129.

Duarte, Jefferson, and Lance Young, 2009, Why is PIN priced? Journal of Financial Economics 91, 119-138.

Durnev, Art, Randall Morck, and Bernard Yeung, 2004, Value-enhancing capital budgeting and firm-specific stock return variation. Journal of Finance 59, 65-105.

Durnev, Art, Randall Morck, Bernard Yeung, and Paul Zarowin, 2003, Does greater firm-specific return variation mean more or less informed stock pricing? Journal of Accounting Research 41, 797-836.

Easley, David, Maureen O'Hara, and P.S. Srinivas, 1998, Option volume and stock prices: Evidence on where informed traders trade. Journal of Finance 53, 431-465.

Easley, David, Nicholas M. Kiefer, Maureen O'Hara, and Joseph B. Paperman, 1996, Liquidity, information, and infrequently traded stocks. Journal of Finance 51, 1405-1436.

Edmans, Alex, Itay Goldstein, and Wei Jiang, 2012, The real effects of financial markets: The impact of prices on takeovers. Journal of Finance 67, 933-971.

Edmans, Alex, Sudarshan Jayaraman, and Jan Schneemeier, 2016, The source of information in prices and investment-price sensitivity. Working paper.

Fama, Eugene F., 1970, Efficient capital market: A review of theory and empirical work. Journal of Finance 25, 28-30.

Fama, Eugene F., and Merton H. Miller, 1972, The theory of finance. Dryden Press, Hinsdale, Illinois.

Fang, Vivian W., Thomas H. Noe, and Sheri Tice, 2009, Stock market liquidity and firm value. Journal of Financial Economics 94, 150-169.

Faure-Grimaud, Antoine, and Denis Gromb, 2004, Public trading and private incentives. Review of Financial Studies 17, 985-1014.

Ferreira, Daniel, Miguel A. Ferreira, and Clara C. Raposo, 2011, Board structure and price informativeness. Journal of Financial Economics 99, 523-545.

Ferreira, Miguel A., and Paul A. Laux, 2007, Corporate governance, idiosyncratic risk, and information flow. Journal of Finance 62, 951-989.

Figlewski, Stephen, 1981, The informational effects of restrictions on short sales: Some empirical evidence. Journal of Financial and Quantitative Analysis 16, 463-476.

Foucault, Thierry, and Laurent Fresard, 2014, Learning from peers' stock prices and corporate investment. Journal of Financial Economics 111, 554-577.

Fresard, Laurent, 2012, Cash savings and stock price informativeness. Review of Finance 16, 985-1012.

Gao, Pengjie, Jia Hao, Ivalina Kalcheva, and Tongshu Ma, 2011, Short-selling, uptick rule, and market quality: Evidence from high-frequency data on Hong Kong stock exchange. Working paper.

Gompers, Paul, Joy Ishii, and Andrew Metrick, 2003, Corporate governance and equity prices. Quarterly Journal of Economics 118, 107-155.

Grullon, Gustavo, Sebastien Michenaud, and James P. Weston, 2015, The real effects of short-selling constraints. Review of Financial Studies 28, 1737-1767.

Habib, Michel A., and Alexander Ljungqvist, 2005, Firm value and managerial incentives: A stochastic frontier approach. Journal of Business 78, 2053-2093.

He, Jie, and Xuan Tian, 2014, Short sellers and innovation: Evidence from a quasi-natural experiment. Working paper.

Hirshleifer, Jack, 1971, The private and social value of information and the reward to inventive activity. American Economic Review 61, 561-574.

Holden, Craig W. and Leonard L. Lundstrum, 2009, Costly trade, managerial myopia, and long-term investment. Journal of Empirical Finance 16, 126-135.

Holden, Craig W., and Avanidhar Subrahmanyam, 1996, Risk aversion, liquidity, and endogenous short horizons. Review of Financial Studies 9, 691-722.

Holmstrom, Bengt, and Jean Tirole, 1993, Market liquidity and performance monitoring. Journal of Political Economy 101, 678-709.

Hong, Harrison, and Marcin Kacperczyk, 2010, Competition and bias. Quarterly Journal of Economics 125, 1683-1725.

Hou, Kewei, and Tobias J. Moskowitz, 2005, Market frictions, price delay, and the cross-section of expected returns. Review of Financial Studies 18, 981-1020.

Hu, Jianfeng, 2014, Does option trading convey stock price information? Journal of Financial Economics 111,625-645.

Huang, Shiyang, 2014, The effect of options on information acquisition and asset pricing. Working paper.

Huang, Shiyang, and Yao Zeng, 2015, Investment exuberance under cross learning. Working paper.

Hwang, Byoung-Hyoun, Baixiao Liu, and Wei Xu, 2015, How to help arbitrageurs correct under-pricing: Let them short! Working paper.

Jennings, Robert and Laura Starks, 1986, Earnings announcements, stock price adjustment, and the existence of option markets. Journal of Finance 41, 107-125.

Ke, Bin, Santhosh Ramalingegowda, and Yong Yu, 2006, The effect of investment horizon on institution investors' incentives to acquire private information on long term earnings. Working paper.

Leary, Mark, and Michael Roberts, 2014, Do peer firms affect corporate financial policy? Journal of Finance 69, 139-178.

Lundstrum, Leonard L. and Mark D. Walker, 2006, LEAPS introductions and the value of the underlying stocks. Journal of Financial Intermediation 15, 494-510.

Luo, Yuanzhi, 2005, Do insiders learn from outsiders? Evidence from mergers and acquisitions. Journal of Finance 60, 1951-1982.

Massa, Massimo, 2002, Financial innovation and information: The role of derivatives when a market for information exists. Review of Financial Studies 15, 927-957.

Massa, Massimo, Fei Wu, Bohui Zhang, and Hong Zhang, 2015, Saving long-term investment from short-termism: The surprising role of short selling. Working paper.

Massa, Massimo, Bohui Zhang, and Hong Zhang, 2015, The invisible hand of short selling: Does short selling discipline earnings management? Review of Financial Studies 28, 1701-1736.

Massoud, Nadia, Debarshi Nandy, Anthony Saunders, and Keke Song, 2011, Do hedge funds trade on private information? Evidence from syndicated lending and short-selling. Journal of Financial Economics 99, 477-499.

Mayhew Stewart, and Vassil T. Mihov, 2004, Short sale constraints, overvaluation, and the introduction of options. Working paper.

Mendenhall, Richard R. and Donald H. Fehrs, 1999, Option listing and the stock-price response to earnings announcements. Journal of Accounting and Economics 27, 57-87.

Miller, Edward M., 1977, Risk, uncertainty, and divergence of opinion. Journal of Finance 32, 1151-1168.

Morck, Randall, Bernard Yeung, and Wayne Yu, 2000, The information content of stock markets: Why do emerging markets have synchronous stock price movements? Journal of Financial Economics 58, 215-260.

Nezafat, Pedram, Tao Shen, and Qinghai Wang, 2014, The real effects of short selling. Working paper.

Nguyen, Giao X., and Peggy E. Swanson, 2009, Firm characteristics, relative efficiency, and equity returns. Journal of Financial and Quantitative Analysis 44, 213-236.

Ozoguz, Arzu, and Michael Rebello, 2015, Information, competition, and investment sensitivity to peer stock prices. Working paper.

Pan, Jun and Allen M. Poteshman, 2006, The information in option volume for future stock prices. Review of Financial Studies 19, 871-908.

Rajan, Raghuram G. and Luigi Zingales, 1998, Financial dependence and growth. American Economic Review 88, 559-586.

Roll, Richard, 1988, R2. Journal of Finance 43, 541-566.

Roll, Richard, Eduardo Schwartz, and Avanidhar Subrahmanyam, 2009, Options trading activity and firm valuation. Journal of Financial Economics 94, 345-360.

Shleifer, Andrei, and Robert Vishny, 1990, Equilibrium short horizons of investors and firms. American Economic Review 80, 148-153.

Skinner, Douglas J., 1990, Options markets and the information content of accounting earnings releases. Journal of Accounting and Economics 13, 191-211.

Stock, James H., and Motohiro Yogo, 2005, Testing for weak instruments in linear IV regression, in James Stock and Donald Andrews, eds. Identification and Inference for Econometric Models: A Festschrift in Honor of Thomas Rothenberg (Cambridge University Press, Cambridge).

Subrahmanyam, Avanidhar, and Sheridan Titman, 1999, The going-public decision and the development of financial markets. Journal of Finance 54, 1045-1082.

Vega, Clara, 2006, Stock price reaction to public and private information. Journal of Financial Economics 82, 103-133.

Veldkamp, Laura L., 2006, Information markets and the comovement of asset prices. Review of Financial Studies 73, 823-845.

Wurgler, Jeffrey, 2000, Financial markets and the allocation of capital. Journal of Financial Economics 58, 187-214.

Yan, Dong, 2016, Do private firms (mis)learn from the stock market? Working paper.

Résumé

Ce travail doctoral étudie l'effet « retour » de l'information financière liée aux prix des actions sur les décisions des dirigeants d'entreprise. Plus précisément, j'étudie si et comment les gestionnaires apprennent effectivement de nouvelles informations contenues dans les prix des actions pour guider leurs décisions d'entreprise. Cette thèse est composée de trois essais, abordant chacun un aspect différent de ce même sujet. Le premier essai étudie le lien entre l'efficacité informationnelle du marché d'actions et le niveau d'efficacité économique réelle de l'entreprise. Dans le premier essai, je montre que lorsque les prix des actions agrègent une quantité d'informations utile plus grande, les décisions d'entreprise prises par les gestionnaires devraient être encore plus efficaces. Le deuxième essai étudie si les gestionnaires cherchent à apprendre les informations utilisées par les vendeurs à découvert. L'étude des prix des actions en présence de vendeurs à découvert est-il utile pour les décisions de l'entreprise ? Dans le deuxième essai, j'ai surmonté les difficultés empiriques en exploitant une caractéristique institutionnelle du le marché des actions de Hong Kong. Je constate que les gestionnaires des entreprises « non-shortable » peuvent tirer profit des informations des vendeurs à découvert sur les conditions économiques sectorielles par l'intermédiaire des prix des actions d'autres entreprises « shortable » dans la même industrie et qu'ils les utilisent dans leurs décisions d'entreprise. Le troisième essai étudie les effets réels de la négociation d'options à long terme. Dans le troisième essai, je constate que l'introduction d'une catégorie spécifique d'options à long terme stimule la production d'informations privées à long terme et donc entraîne une augmentation de l'informativité des prix sur les fondamentaux à long terme des entreprises. Par conséquent, les dirigeants peuvent extraire davantage d'informations du prix de l'action pour guider leurs décisions

Mots Clés

Les effets réels des prix de l'action; l'informativité des prix; la sous-optimalité des choix managériaux dans l'entreprise; les décisions des enterprises; l'hypothèse de l'apprentissage; les vendeurs à découvert ;la négociation d'options à long terme

Abstract

In my doctoral thesis, I investigate the information feedback from stock prices to managers' decisions. More specifically, I study whether and how managers learn new information from stock prices to guide their corporate decisions. My doctoral thesis includes three essays focusing on this topic. The first essay studies the relationship between stock market informational efficiency and real economy efficiency at firm-level. In the first essay, I find that when stock prices reflect a greater amount of information that managers care about, corporate decisions made by managers become more efficient. The second essay studies whether managers seek to learn short sellers' information from stock prices and use it in corporate decisions. In the second essay, I overcome the empirical difficulties by exploiting a unique institutional feature in Hong Kong stock market that only stocks included in an official list are allowed for short sales. I find that that non-shortable firms' managers learn short sellers' information on external conditions from shortable peers' stock prices and use it in their corporate decisions. The third essay studies the real effects of long-term option trading. I find that long-term option trading stimulates the production of long-term information, which managers can use to guide their long-term investment decisions.

Keywords

Real effects of stock prices; stock price informativeness; managerial inefficiency; corporate decisions; managerial learning hypothesis, short sellers; long-term option trading