ESSAYS IN CORPORATE FINANCE AND BEHAVIORAL FINANCE

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Abstract

This thesis examines important topics in corporate cash holdings and forecaster overconfidence.

First, I provide an in-depth study of the interaction between intra-industry contagion risk and cash holdings. I develop a novel measure of a firm's exposure to contagion risk that builds on the firm's stock return comovement with other industry participants and separates contagion and competition effects caused by the expected financial distress of its industry peers. I show that high contagion-risk firms hold more cash because they face higher costs of external finance due to the potential decrease in their collateral values and the increased likelihood of their future financial distress caused by the net contagion effect.

Second, in a co-authored paper with Drs. Jiaping Qiu and Chi Wan, we conduct a cross-country analysis to examine how financial development affects the reliance of corporate liquidity management on tangible capital. We find that financial development and better institutions lower the cash-tangibility sensitivity. This supports the view that financial development reduces the collateral role of tangible assets, thereby relaxing financial constraints of firms with low asset tangibility. This provides further firm-level evidence and sheds new light on the link between financial development and economic growth, as financial development promotes more efficient allocations of economic resources and hence facilitates investments and economic growth.

Third, in a co-authored paper with Drs. Richard Deaves and Michael Schröder, we document using the ZEW panel of German stock market forecasters that weak forecasters tend to be overconfident in the sense that they provide extreme forecasts and their confidence intervals are less likely to contain eventual realizations. Moderate filters based on forecast

accuracy over short rolling windows are somewhat successful in improving predictability. While poor performance can be due to various factors, a filter based on a prior tendency to provide extreme forecasts also improves predictability.

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Chapter One: Introduction

The first two essays of this thesis examine two important topics in corporate finance: 1) the impact of a firm's exposure to contagion risk on its cash holding policy, and 2) the effect of financial development on the corporate liquidity reliance on tangible collateral, respectively. The third essay examines the effect of forecaster overconfidence on market survey performance using survey data and how forecast accuracy can be improved with filters based on forecasters' historical performance or characteristics such as overconfidence.

First, I provide an in depth study of the interaction between contagion risk and corporate cash holdings. This study highlights the importance of firm-level contagion risk in determining corporate cash holdings. I develop a novel measure of a firm's exposure to contagion risk that builds on the firm's stock return comovement with other industry participants and separates contagion and competition effects (Lang and Stulz, 1992) caused by the expected financial distress of industry peers. The baseline result indicates that intra-industry contagion risk exposure prompts firms to stockpile cash. I further explore the collateral and borrowing cost channels through which contagion risk affects cash holdings. The results show that contagion risk is amplified in industries with low asset specificity/tangibility and poor financing capacity, for which asset fire sales greatly reduce collateral values industry-wide. I also find that contagion risk increases a firm's cost of bank loans and probability of future financial distress. Further analysis suggests that equity holders assign a greater marginal value of cash to firms with high contagion risk.

Second, in a coauthored paper with Drs. Jiaping Qiu and Chi Wan, we conduct a cross-country analysis to examine how financial development affects the reliance of corporate liquidity management on tangible capital. We find that improvements in financial markets, which enable firms to access alternative financing sources and pledge a broader variety of assets as collateral, reduce the sensitivity of cash holdings to tangible assets. The results further suggest that the collateral role of tangibles is lessened by high quality institutions, proxied by creditor rights protection and accounting standards. Our findings are fully retained after a battery of robustness tests, including instrumental variable analysis that control for the endogeneity of asset tangibility and financial development, and employing alternative measures of financial development. Our study, focusing on corporate real decisions in cash holdings, extends the recent inquiries on the role of financial development in determining the value and specificity of collateral spread (Liberti and Mian, 2010). We also provide firm-level evidence that financial development contributes to economic growth (Rajan and Zingales, 1998) by easing precautionary savings for firms operating in industries with low asset tangibility and high external financing dependence, and hence promoting more efficient corporate liquidity allocation.

Third, in a coauthored paper with Drs. Richard Deaves and Michael Schröder, we document using the ZEW panel of German stock market forecasters that weak forecasters tend to be overconfident in the sense that they provide extreme forecasts and their confidence intervals are less likely to contain eventual realizations. Moderate filters based on forecast accuracy over short rolling windows are somewhat successful in improving predictability. While poor performance can be due to various factors, a filter based on a prior tendency to provide extreme forecasts also improves predictability.

The rest of the thesis proceeds as follows. Chapter 2 studies the effect of the intra-industry contagion risk on cash holdings. Chapter 3 conducts a cross-country analysis on the impact of financial development on the link between cash and asset tangibility. Chapter 4 focuses on the impact of forecaster overconfidence on market survey performance. Chapter 5 concludes by providing brief answers to the research questions raised in this thesis.

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Chapter Two: *Contagion Risk and Cash Holdings*

2.1 Introduction

Financial contagion is a phenomenon that a firm's financial distress spreads out and affects a large number of its peers or even the entire industry as a whole. Like species in biological ecosystems, firms interact with one another in complex ways, and their corporate policies often react to their peers' financial situations. This paper is among the first to identify firm-level contagion risk as a key determinant of corporate cash holdings. We demonstrate the robustness of the finding that firms adjust their cash reserves in response to the financial health of its industry participants in the presence of market frictions. Broadly speaking, our study fits into a growing body of literature that highlights the role of firm interdependence in influencing an individual firm's financial decisions (e.g., Leary and Roberts, 2014; Hoberg, Phillips, and Prabhala, 2014). It also sheds light on the documented upward trend in the cash holdings of public U.S. firms over the past three decades (Bates, Kahle, and Stulz, 2009).

Several recent studies highlight the importance of a firm's risk exposure in determining its liquidity policy. For example, Acharya, Almeida, and Campello (2013) show that firms with high aggregate risk rely more heavily on cash to hedge liquidity shocks and pay higher spreads on their bank loans. James and Kizilaslan (2014) document that, in addition to aggregate risk, a firm's exposure to industry downturns (i.e., industry risk) is a significant factor that affects the firm's loan pricing and cash reserves. Our study extends these investigations by focusing on a firm's exposure to the contagion of its peers' financial distress. This paper is further motivated by the empirical evidence on the intra-industry contagion. The work of Lang and Stulz (1992), for example, shows that other industry participants on average suffer negative stock price reactions around the time when a firm files for bankruptcy. Furthermore, Benmelech and Bergman (2011) and Hertzel and Officer (2012) provide *ex post* evidence that firms face high potential borrowing costs due to a drop in collateral value when their industry participants default. Consistent with the precautionary saving motive and in line with these findings in the contagion literature, we postulate and find strong evidence that firms with great contagion risk tend to hoard cash to cope with the increased external financing cost and other negative externalities generated by its distressed industry peers. In addition, we provide confirmatory results by exploring the impact of contagion on a firm's likelihood of future distress and its bank loan contracting.

The intra-industry contagion may influence a firm's cash balance both directly through various business ties and indirectly through revealing valuation-relevant information about the firm (i.e., information contagion). First, peer firms' distress may aggravate the default risk of a related firm and intensify its cash flow uncertainty. In particular, contagion risk could manifest itself through economic linkages along the supply chain (Hertzel, Li, Officer, and Rodgers, 2008), and directly impact counterparties with close business ties (Jarrow and Yu, 2001; Jorion and Zhang, 2007, 2009) and partner firms in strategic alliance or joint ventures (Boone and Ivanov, 2012). Second, distressed firms also reveal negative information to investors of a non-distressed firm. This, in turn, prompts the reassessment of the firm's risk and could bear upon its cash policy. For instance, Benmelech and Bergman (2011) show that bankrupt firms reduce the perceived collateral values of other solvent industry participants, thereby making others worse off by raising the cost of external finance across the entire industry. In addition, given the common notion that a firm's dismay makes customers and suppliers wary of other related non-distressed firms, such a negative wealth effect would motivate others to build up cash reserves. Therefore, a firm's cash and related financial policies could be greatly affected by financial distress of directly related firms and others for which the connection might not be so apparent.

The empirical identification of the firm-level contagion effect is difficult as the deterioration of some peer firms' financial health needs not convey only bad news for a firm. The reason is that their downfall may strengthen the competitive position of other firms in the same industry by reallocating market share (referred to as the competition effect by Lang and Stulz (1992)), and thus even potentially ease others' demand for liquidity. For instance, while Blackberry's financial position has been greatly undermined by a huge demand shift of the industry output toward popular smartphones and tablets, some industry rivals have enjoyed fast growth by delivering attractive substitutes. Furthermore, others may benefit from some firms' human capital loss and weakened intellectual property (e.g., patents and copyrights) protection as they fall into financial hardships. However, in line with Bates, Kahle, and Stulz (2009) who underscore the essential role of the precautionary motive for cash holdings, we expect that this competition effect is dominated by the effect of a firm's exposure to contagion in shaping its cash policy. Nonetheless, to gauge the overall contagion effect of peers' dismal financial status, we propose a novel measure that aims to capture the competing competition effect and contagion effect, and appraise the overall effect of a firm's *net* exposure to contagion risk.

In a nutshell, the interdependence of two firms is measured by the comovement of their equity prices. Drawn on studies of comovement in asset returns (Durnev, Morck, and Yeung, 2004; Jorion and Zhang, 2007), a positive correlation of firm-specific returns (i.e., positive comovement) indicates the existence of strong common factors that drive two firms' performance and their fundamental values simultaneously. Therefore, an increase in a firm's default risk would raise the discount factor applied to the other's future cash flows and hence adversely affect peer firms' financial health – the contagion effect. On the contrary, a negative pairwise return comovement suggests that a firm is more likely to benefit from the potential exit of its industry competitors. It is also noteworthy that our comovement measure teases out the effects of market and industry common shocks to avoid contamination of systematic risk. Next, for an individual firm, the net contagion effect is measured by the (signed) comovement-weighted average of its peers' distress risk. This aggregated measure intends to assess how a firm is affected by the expected financial distress of all other industry participants. We find that the proposed measure is positively related to a few firm and industry key characteristics that are known to affect a firm's proneness to financial contagion. Its usefulness is further substantiated as we find strong evidence that the *ex ante* comovement captures the spillover effect of bankruptcy filings by distress peers.

Our baseline result shows that firms with high contagion risk exposure hold more cash. The estimates suggest that, all else equal, a one standard deviation increase in the contagion measure boosts the cash-to-assets ratio by 1.50%, a sizable impact compared to the sample average of 14.6%. Thus, the results strongly indicate that firms that are susceptible to negative shocks originated by peers' financial distress build up cash reserves to mitigate potential contagion. Our results are also robust to the inclusion of firm fixed effects, and the use of various accounting- and market-based measures of expected default risk in the calculation of the contagion proxy.

After documenting a positive and significant association between contagion risk and cash, we then turn to explore possible mechanisms through which contagion risk could impinge on a firm's liquidity management. First, many studies (Shleifer and Vishny 1992; Asquith, Gertner and Scharfstein, 1994; Benmelech, Garmaise, and Moskowitz, 2005; Benmelech and Bergman, 2009) report that asset fire sales of distressed firms' tangible assets lead to an industry-wide drop in collateral and liquidation tangible values, which lowers the borrowing base and debt capacity of non-distressed firms. Therefore, we expect that contagion could propagate through the collateral channel and these non-distressed firms that face higher borrowing costs tend to accumulate cash as alternative financing resources. Our analysis provides strong support to this conjecture. For instance, we find that the positive contagion effect on cash holdings is more pronounced when industry participants have similar collateralizable assets (i.e., low asset specificity), and when firms have limited choices of collaterals (e.g., innovative firms and firms with very few tangible capital). In addition, the fire-sale liquidation notion also suggests that the prices at which assets of the distressed or in default firm can be sold depends on the financial condition of the potential buyers in the same industry. Consistent with this notion, we find that when other industry participants experience unfavorable financial conditions (i.e., high external financing needs and constraints), it further dampens the redeployability and liquidation value of collaterizable assets in the market, magnifying the contagion effect through the collateral channel.

Second, motived by our investigation of the collateral channel, we further examine the impact of contagion risk on firms' access to bank loans – the primary source of external credit (Chava, Livdan, and Purnanandam, 2009; Graham, Li, and Qiu, 2008).[1] The analysis reveals

[1] The flow of funds data from the Federal Reserve System indicates that, over the past decade, there have been $780 billion in net debt security issuances and only $2 billion for equities. Among the debt issues, bank loans play a significant role – about 54% of total debt since 1980.

that firms with greater contagion risk have higher loan spreads and more restrictive non-price terms, namely shorter maturity and a greater likelihood of collateral requirements and covenant usage. Furthermore, we find that intra-industry contagion directly increases a firm's propensity of becoming financially distressed. This finding supports the idea that banks charge higher interest or even decline loans to high contagion-risk firms because banks are concerned about the increased probability of distress of these high risk borrowers and the low expected recovery rates on their loans. Overall, our results suggest that contagion risk diminishes the pledgeability of assets and exacerbates financing costs. Therefore, high-contagion risk firms tend to hold higher cash balances to mitigate such potential costs.

To further gauge the role of intra-industry contagion in shaping a firm's demand for liquidity, we examine how contagion affects the market value of cash held by the firm using the methodology developed in Faulkender and Wang (2006). We show that contagion risk increases the marginal benefit of cash retention. That is, investors assign a large value of cash to firms with high contagion risk.

This paper advances the growing literature on firm-level financial contagion. Previous research mainly relies on event studies to examine *ex post* stock return reactions of solvent firms to competitors' bankruptcy announcements. The present study is the first to explore how a firm's financial policies is driven by expected distress of peer firms. Specifically, we employ return comovement that reflects the dynamic interdependence of firms' fundamentals, and construct a novel measure to capture the net financial contagion. The metric aims to paint a general picture of the overall effect of competitors' misfortune on a firm's financial well-being. Our research also adds to the cash holding literature. We highlight that both the level and value of a firm's cash holdings are influenced by financial conditions of its related industry participants through contagion. In addition, our empirical results complement the findings of Acharya, Almeida, and Campello (2013) and James and Kizilaslan (2014) by showing that a firm's exposure to aggregate risk and industry risk has a significant impact on cash holdings.

The remainder of the paper is structured as follows. Section 2.2 motivates and develops our testable hypotheses regarding the effect of contagion on cash holdings. Section 2.3 briefly describes the data as well as the construction and properties of the intra-industry contagion risk measure. Section 2.4 presents empirical analysis of the contagion effect on cash holdings. Finally, Section 2.5 concludes.

2.2 Literature review

Many studies document that the dissemination of information about competitors' extreme credit events closely affects other firms' performance and capital structures. For example, early work by Lang and Stulz (1992) demonstrates that, on average, the equity value of other participants experiences sizable decline at the time of a competitor' bankruptcy announcement. This finding is interpreted as strong evidence of financial contagion. The contagion effect is more pronounced among industries where the stock returns of the non-bankrupt and bankrupt firms are highly correlated. However, for a subset of highly concentrated low-leverage industries, they show that rivals' stock prices actually increase. This is referred to as the competition effect of peers' bankruptcy, which could be attributed to the redistribution of bankrupt firms' wealth and increased market power of the surviving firms. To further motivate our contagion proxy and subsequent analysis, we next briefly discuss the related literature of these contrasting types of information transfers stemming from others' financial distress.

An adverse credit event of one firm may be contagious through a worsening of the financial soundness of directly related firms. For example, Hertzel, Li, Officer, and Rodgers (2008) show that suppliers and customers of a Chapter 11 filing firm experience large negative stock price reactions around filing and pre-filing distress dates. Jorion and Zhang (2009) point out that counterparty credit risk is a channel of contagion. They find that a firm's bankruptcy announcement causes negative abnormal equity returns and increases in CDS spreads for its creditors, industry competitors, and suppliers. In a similar vein, Boone and Ivanov (2012) show that the stock of a non-bankrupt party tumbles when its partner firm in an alliance or joint venture goes bankrupt.

The destructive ripples of a firm entering financial distress also convey information that may falter business confidence and impel a re-evaluation of other firms' value. In this way, a firm's succumbing to financial ills generates far-reaching externalities that affect not only economically related peers, but also industry participants without direct relationships. Specifically, Das, Duffie, Kapadia, and Saita (2007) report that the event of default has detrimental consequences on the default probabilities of other firms through learning and signaling contagion. In particular, financial distress can be contagious and affect indirectly related firms that engage in similar business transactions and those that adopt similar accounting practices (Palmrose, Richardson, and Scholz, 2004; Gleason, Jenkins, and Johnson, 2008). The spillovers of peers' distress are further facilitated by information transfers via board interlocks (Chiu, Teoh, and Tian, 2013) and by similar religious and social norms shared among firms in a common geographic location (McGuire, Omer, and Sharp, 2012). Moreover, accusations of financial misrepresentation and earnings restatements of some firms, such as Enron and WorldCom, could also call other firms into question (Karpoff, Lee, and Martin, 2008a, b).

Collectively, witnessing the financial distress of some firms, investors would reassess their perception of the creditworthiness and market value of non-distressed firms in the same industry. As a result, contagion implies that stock returns of distressed and non-distressed industry peers would co-move in the same direction. The return correlation is greater especially between those bonded by various business ties and having common components in operations. The aforementioned studies also suggest that entering financial distress by a firm has important implications on others' liquidity management. We expect that firms with high positive return comovement with their financially distressed industry peers suffer more from contagion risk. Consequently, high contagion-risk firms increase their cash holdings to mitigate the adverse contagion effects on their stock and operating performance.

The competition effect, however, indicates a competitive shift in the structure of the industry; a non-distressed firm could actually benefit from the downfall of its industry competitors. However, its implication on cash holdings is not clear. While the eased competitive pressure is likely to decrease the need for precautionary cash holdings, the non-distressed firms could build up cash reserves to seize investment opportunities and acquire others' assets and intellectual property that could be later put up for sale.

This paper aims to gauge the *net* effect of peers' expected defaults on cash holdings of other industry participants. To this end, in the next section we construct a measure based on the pairwise return comovement to differentiate financial contagion effect from the potential competition effect.

2.3 Key variables and summary statistics

In this section, we detail the identification of a firm's exposure of contagion risk, and then describe the data used in our empirical analysis.

2.3.1 Measuring intra-industry firm-level contagion risk

We collect daily stock return data for all common stocks listed on NYSE, AMEX and NASDAQ from the Center for Research in Security Prices (CRSP). The sample stocks are restricted to ordinary common stocks with share codes 10 and 11. ADRs, shares of beneficial interest, companies incorporated outside the U.S., Americus Trust components, close-ended funds, preferred stocks, and REITs are excluded.

We use a two-step procedure to construct a measure of intra-industry contagion risk. First, we compute annual comovement for each pair of industry participants by running the following augmented two-factor market model regression:[2]

$$r_{i,w} = a_i + b_i^M \times r_{M,-I,w} + c_i^I \times r_{I,-i,-j,w} + d_i^j \times r_{j,w} + \varepsilon_{i,w}, \qquad (2.1)$$

where $r_{i,w}$ and $r_{j,w}$ are the stock return of firms i and j in week w, respectively. Both firms i and j operate in the same Fama-French's (1997) 48-industry I. $r_{M,-I,w}$ represents the weekly value-weighted market return, excluding the return on industry I. $r_{I,-i,-j,w}$ denotes a value-weighted return of all industry I stocks, where both firms i and j are excluded from the industry portfolio. The inclusion of $r_{M,-I,w}$ and $r_{I,-i,-j,w}$ partials out common market and

[2] Since Roll's (1988) seminal work that formalizes the notion of stock return synchronicity, the association between a firm's stock returns and market and industry returns, several studies have adopted a two-factor market model for their interpretation of stock return synchronicity (e.g., Durnev, Morck, and Yeung, 2004; Piotroski and Roulstone, 2004; Chun, Kim, Morck, and Yeung, 2008; Chun, Kim, and Morck, 2011; Panousi and Papanikilaou, 2012).

industry effects that drive return correlations. d_i^j captures the pairwise firm-specific return comovement.[3] Equation (2.1) is estimated for each pair of firms using weekly stock returns over the past year.[4]

A large positive value of d_i^j indicates that the deterioration of firm j's financial health is highly contagious to firm i as their equity prices tend to co-move in the same direction. A negative d_i^j, on the contrary, suggests that firm i is likely to benefit from j's misfortunes, reflecting at a competitive relation between the two. We note that the measure of d aims to serve as a general assessment of the overall interdependence between the pair of firms, and in this paper we do not intend to determine the underling factors that might drive the common pattern of returns (or the lack of that).

In the second step, we take the pair-wise return comovement measure, d, as building blocks to gauge a firm's net contagion risk exposure as follows:

$$Net\ contagion_{i,t} = \sum_{\forall j \neq i} d_{i,t}^j \times EDP_{j,t}, \tag{2.2}$$

where $EDP_{j,t}$ (expected default probability) represents the probability of firm j becoming financially distressed in year t. Essentially, $Net\ contagion$ is the (signed) comovement-weighted sum of peers' *ex ante* distress probabilities. The contagion proxy defined in equation (2.2) can be rewritten as the difference of the two terms shown below:

[3] As argued in Roll (1988), stock price changes or synchronicity should be explainable by not only general market systematic influences, but also industry influences and events unique to the firm. Roll (1992) further shows that industry influences capture a large portion of correlations in returns. Equity return incorporates changes in expected future cash flows and shifts in investors' risk preferences.

[4] In unreported results, pairwise comovements calculated using quarterly cash flows over the past five years generate similar results.

$$Raw\ contagion_{i,t} - Competition_{i,t} = \sum_{\forall j \neq i} 1(d_{i,t}^{j} > 0) \times d_{i,t}^{j} \times EDP_{j,t} - \sum_{\forall j \neq i} 1(d_{i,t}^{j} < 0) \times |d_{i,t}^{j}| \times EDP_{j,t}, \quad (2.3)$$

where $1(\cdot)$ is an indicator function that takes a value of one if the statement is true and zero otherwise. The first term is the comovement-weighted sum of expected distress probabilities of all firm i's industry peers whose stocks are positively correlated with firm i's (i.e., $d_{i,t}^{j} > 0$). It reflects the overall negative externalities caused by other industry peers' financial distress, and is expected to intensify firm i's liquidity needs. The second term aggregates the default risk of firm i's rivals (with $d_{i,t}^{j} < 0$) and captures the potential benefits derived from their defaults. For ease interpretation of regression estimates, we use the absolute value of return comovement to capture the competition effect.

Regarding the calculation of the expected default probability (EDP), our primary measure is a normal transformation of Altman's (1968) *Z*-score, a leading accounting-based estimate of financial distress.[5]

2.3.2 Contagion risk: Examples and further illustrations

The contagion measure defined in equations (2.2) and (2.3) allows different patterns of firm interdependence during others' credit events. For instance, the return comovement between the stock returns of Microsoft and IBM is 0.55 in 1990 (i.e., $d_{MS}^{IBM} = 0.55$).[6] This

[5] In unreported results (available upon request), we also complement this measure with the market-based alternative, Merton's (1974) probability expected default frequency (*EDF*). Specifically, we estimate a firm's implied default probability along the lines of Bharath and Shumway (2008). Our empirical findings are fully retained with *EDF*.

[6] An alternative metric to measure the return comovement between two stocks is the partial stock returns correlation after controlling for market and industry risks. The partial stock returns correlation between Microsoft and IBM shares is 0.245 in 1990. The partial correlation is calculated as $d_{MS}^{IBM} \times \frac{\sigma_{IBM}}{\sigma_{MS}}$, where σ_{IBM}

suggests a high level of contagion as the two companies jointly developed operation systems in 1980s and formed a partnership that bundled Microsoft's OS with IBM computers. More recently, given Microsoft's effort to edge in the mobile market and IBM's exit from the personal computer business in 2005, the contagion effect dropped to 0.15 in 2010.

Another example to illustrate the competition effect involves Apple Inc. and Hewlett-Packard (HP) Company. In 1980s, the two companies competed fiercely in the market for computers and printers. This is evidenced by a large negative value of stock comovement between the two was -0.43 in 1990, ($d_{APPLE}^{HP} = -0.43$), which suggests that one would greatly benefit from the other's withdrawal due to financial distress.[7] However, thirty years later, both companies' product lines have experienced dramatic changes. In particular, Apple had no long marked itself as a computer company. In 2010, iPhone and tablets brought in more than 75% of Apple's total revenue, and Macs accounted for only 10% of its sales. As a result, the competition effect between the two has ebbed away ($d_{APPLE}^{HP} = 0.03$).

In addition, the pairwise return comovement also captures the dynamics of the relationship between two companies in the same industry through strategic alliances. For example, SymmetriCom Inc. announced a broad technology strategic alliance with IMP Inc. on July 21, 1997. SymmetriCom specializes in designing and manufacturing a wide variety of next-generation portable power, desktop power, and data communications analog, and mixed-signal integrated circuit (IC) solutions. IMP specializes in high-volume manufacturing of analog and mixed-signal process technologies. Under this alliance, IMP and

and σ_{MS} are the respective standard deviation of IBM and Microsoft shares in 1990. The partial correlation value drops to 0.09 in 2010.

[7] The partial stock returns correlation between Apple Inc. and Hewlett-Packard (HP) Company is -0.282 in 1990 and 0.028 in 2010.

SymmetriCom will share marketing knowledge, and establish a long-term technical development program for the licensing, product designs, and production. In 1996, before the strategic alliance, the value of stock comovement between the two was -0.57, ($d_{IMP}^{SymmetriCom} = -0.57$), which suggests that IMP would greatly benefit from SymmetriCom's financial distress. However, after the alliance, the value of stock comovement changed to 0.82 in 1997, suggesting a strong contagion effect. Therefore, we believe the pairwise return comovement is useful in capturing the externalities triggered by peers' liquidity shortfall.

2.3.2.1 The relation with certain firm and industry characteristics

To gain additional insights on the properties of the proposed contagion risk measure, we look at the average net comovement across groups of firms formed based on a few key factors that are known to greatly influence a firm's susceptibility to others' financial health.

Results presented in Table 2.1, Panels A through C indicate that smaller, younger, and less profitable firms have higher exposure to contagion risk, measured by *Net Contagion*. Panels D and E further demonstrate that firms operating in competitive industries, and those facing tight bank lending standards (e.g., high Commercial and Industrial loan rates) are more vulnerable to financial contagion. Across panels, the difference in *Net Contagion* is positive and highly significant between the extreme quartile groups of firms (Q4-Q1). This result is consistent with the notion that small, newly established firms, industry followers, and those facing stiff rivalry are vulnerable to contagion as they lack the capacity to take full advantage of others' failure and tend to be greatly undermined by weakened industry conditions. Thus,

Table 2.1 shows that the proposed contagion risk measure is positively related to several firm- and industry-specific indicators of firms' vulnerability to financial contagion.

[Table 2.1 about here]

To explore how our contagion risk measure varies over time and across industries, in Appendix 2.B, we list the top (bottom) five industries with the highest (lowest) industry median levels of net contagion along with raw contagion and competition in 1990, 2000 and 2010. Industries are based on the Fama-French's (1997) 48-industry classification. We find that firms facing the largest net contagion shift from entertainment to computers and electronic equipment over time. Particularly, firms operating in pharmaceutical products and business services industries face very high contagion risk. Therefore, the result shows significant variations in contagion risk across industries and over time.

2.3.2.2 Contagion of peers' bankruptcy-related financial distress

The contagion literature shows that a firm's bankruptcy-related financial distress has important valuation implications on its customers, suppliers, and other related firms. Thus, it provides a clear setting to further evaluate the usefulness of the proposed contagion proxy. As defined in equation (2.3), our contagion proxy has two components, *Raw contagion* and *Competition*, which are designed to capture the contrasting spillover effects of peers' distress. We expect that the equity price of a firm with a large value of *Raw contagion* (*Competition*) drops (rises) significantly and the firm incurs bigger losses (gains) when its competitors experience severe financial deterioration.

Real wealth effects are discernable at the onset of financial distress, often widely known in advance of the initial bankruptcy event. Following Hertzel, Li, Officer, and Rogers

(2008), we first identify the date with the largest negative abnormal return of the filing firm and use it as the distress date (i.e., the event day).[8] Then, on the event day, non-distressed firms are sorted into tercile portfolios based on their *Raw contagion* (*Competition*) levels. Table 2.2 reports those firms' average cumulative abnormal returns (CARs) around the peer's distress date.

[Table 2.2 about here]

Panel A shows that, on the distress date (event window [0, 0]), non-distress firms, of which stock prices positively co-move with the distressed firm, experience large negative return reactions. The average AR for the highest contagion portfolio is -0.210% (*t*-statistic = -5.37). More importantly, the magnitude of the average abnormal return monotonically decreases with the value of *Raw contagion*. The same patterns of price reactions are observed over both the 3-day and 11-day windows around the event.

In Panel B, stocks that have a negative value of comovement (i.e., $d < 0$) with the distressed firms are sorted into tercile portfolios. The results show that, for firms that benefit from competition effects of peers' failure, their stock prices enjoy significant cumulative abnormal returns. Again, on the event day and over a 3-day window, the return reaction monotonically increases with the magnitude of *Competition*.

The finding clearly demonstrates that, a firm with high contagion (competition) exposure, as indicated by our measure, experiences sizable negative (positive) return shocks

[8] We identify 421 Chapter 11 distress dates from 1981 to 2012 using the data from the UCLA-LoPucki Bankruptcy Research Database (BRD). We thank Lynn M. LoPucki, founder of the BRD, for providing his Bankruptcy Research Database, available at http://lopucki.law.ucla.edu/index.htm.

when its peer firm enters financial distress.[9] It also demonstrates the usefulness of our measures in capturing the different spillover effects of industry participants' potential exit.[10]

Overall, our contagion risk measure may not be perfect but it does capture some key features of contagion and competition effects of related industry peer firms' financial distress.

2.3.3 Data and summary statistics

Data used in this study mainly come from two sources, the CRSP-Compustat merged database and the Dealscan database. To estimate the relation between cash holdings and contagion risk, we draw firm-level data for publicly traded non-financial non-utility U.S. firms from the merged CRSP-Compustat database for the period from 1980 to 2013. The sample contents 10,743 unique firms representing 113,832 firm-year observations. Missing explanatory values reduce the panel used in our baseline model to 90,364 firm-year observations for 10,608 unique firms.

To further shed light on the impact of contagion on the cost of bank debt, we merge the CRSP-Compustat database with the Loan Pricing Corporation's (LPC) Dealscan database.[11] After removing observations with incomplete DealScan or Compustat information, we obtain

[9] These mean CARs are also economically significant in terms of the Mean Dollar Loss (Gain), which is the product of the average market value of firms in each portfolio in the month prior to the distress day and the changes in the mean AR and CAR over the event period. Using the average market value of the non-distressed firms in the high positive-comovement portfolio, the 0.320% drop translates into a \$5.13 (= -0.320%*1,604) million (U.S.) dollar loss. Similarly, using the average market value of the non-distressed firms in the low negative-comovement portfolio, the 0.395% rise translates into a \$9.92 (=0.395%*2,511) million dollar gain.

[10] In untabulated results, we conduct difference test between High minus Low groups in average CARs for each event window. The results show that the constructed contagion (competition) measure does capture the downward (positive) price impact from bankrupt peer firms.

[11] Borrowing firms are matched to CRSP and Compustat using the Michael Roberts Dealscan-Compustat link file (See, Chava and Roberts, 2008). We then hand-match the remaining firms to CRSP and Compustat based on their names and ticker symbols. We are grateful to Michael Roberts and Sudheer Chava for generously providing Dealscan-Compustat Link File.

a final sample of 23,398 loan-facilities for 4,338 unique borrowing firms for the period 1987–2012.

Table 2.3 provides the descriptive statistics of the sample. Details on the construction of all variables are provided in the Appendix. All the continuous variables are winsorized at the 1st and 99th percentiles to remove outliers. The average and median cash ratio is 14.6% and 8.4%, respectively. *Net contagion* calculated according to equation (2.3) averages 1.681, suggesting that the contagion effect dominates the competition effect. Statistics of other variables are similar to those reported in previous empirical studies of cash holdings, such as Bates, Kahle, and Stulz (2009). Turning to loan facilities, the average loan spread and loan size are 197 basis points and $318 million, respectively. The average maturity is about 45 months. About 30.7% (56.0%) of the sample loans have a collateral (covenant) requirement. These loan characteristics in line with those reported in Graham, Li, and Qiu (2008) and Li, Qiu, and Wan (2011).

[Table 2.3 about here]

2.4 Empirical analysis: Contagion risk and cash holdings

Our preliminary analysis in Section 2.3.2 suggests that high net contagion risk firms are often more easily affected by other industry participants and sensitive to uncertainty about future financing frictions. Thus, financial contagion could escalate "liquidity hoarding," wherein firms are motivated to maintain financial flexibility to hedge future liquidity shortage. In this section, we provide evidence on the link between contagion risk and cash. Then, we investigate potential channels through which intra-industry contagion could be transmitted.

2.4.1 Baseline results

Our baseline econometric model is line with Bates, Kahle, and Stulz (2009) and specified as follows:

$$Cash_{i,t} = \delta\left(Net\ Contagion_{i,t-1}\right) + \beta' X_{i,t-1} + \sum_j \gamma_j Industry\ dummy_j + \sum_t \theta_t Year\ dummy_t + \varepsilon_{i,t}, \tag{2.4}$$

where i, j and t denote firm, industry, and year subscripts, respectively, and $\varepsilon_{i,t}$ is the error term. The dependent variable is cash plus equivalents deflated by total book assets. The primary interest is in the marginal effect of (lagged) $Net\ Contagion$ on cash holdings (denoted as δ). The vector $X_{i,t-1}$ is a comprehensive set of firm-level controls, including a constant term and firm i's exposure to industry and market aggregate risks (proxied by industry asset beta and market asset beta), own default probability (calculated based on Altman's (1968) Z-score), industry cash flow volatility, market to book, log of real book assets, cash flow, net working capital, capital expenditures, total book leverage, R&D expenditures, dividend payout dummy, acquisition expenditures, net equity issuance, and net debt issuance. We also include year dummies and industry dummies. Standard errors are adjusted for heteroscedasticity and serial correlation within firms.

Table 2.4 presents our baseline results. Specifically, column (1) reports the coefficient estimates of equation (2.4). We find that the coefficient of $Net\ contagion$ is positive and statistically significant at the 1% level. This strongly indicates a positive relation between a firm's cash holdings and its exposure to intra-industry contagion risk. The effect is also economically large. All else equal, a one standard deviation increase in $Net\ contagion$

(3.485) on average increases the cash-to-assets ratio by 1.50% (=0.0043×3.485), which is approximately 10.03% of the sample average value of the cash-to-assets ratio.

Column (2) confirms that the positive contagion effect on cash holdings is retained after controlling for firm fixed effects. Nonetheless, since contagion risk is closely related to several firm-specific traits that are rather stable over time (e.g., firm size and market share), the contagion effect is smaller in the fixed effects regression.

Moreover, column (3) shows that the baseline result is robust to the Fama-MacBeth (FM) technique, which further mitigates the problem of serial correlation in a panel regression. The positive average coefficient of $Net\ contagion$ obtained from annual cross-sectional regressions (1980-2013) attests that the degree of contagion risk accounts for a significant portion of the variability of cash holdings across firms.

[Table 2.4 about here]

In column (4), we re-estimate the baseline regression by replacing $Net\ contagion$ with its two components (defined in equation (2.3)) separately. $Raw\ contagion$ captures the raw detrimental impact caused by other firms' financial dread, and $Competition$ reflects the possible benefits driven by shifts in market share among a small set of non-distressed firms. As shown in column (4), the sign of the raw contagion effect is positive and significant, consistent with our finding about the contagion effect. This also asserts that firms, whose stock returns positively co-move with those of distressed industry participants, tend to hold more cash to cope with contagion risk. The second component, $Competition$ has a negative coefficient with a smaller magnitude, suggesting an eased liquidity demand by increased market power. Nonetheless, the overall result corroborates that the firm piles up cash as a cushion against serious ramifications of peers' distress, which dominates the competition effect in shaping a firm's cash policy.

Here, we also expand the set of controls normally included in related research on corporate cash holdings. In particular, we include lagged industry and market asset betas to absorb other sources of risk that could affect a firm's liquidity management. For example, Acharya, Almeida, and Campello (2013) find that firms with greater aggregate risk exposure choose to hoard cash rather than lines of credit as aggregate risk tightens banks' liquidity constraints. In addition, James and Kizilaslan (2014) report a positive link between cash holdings and industry asset beta. They argue that industry risk is associated with lower expected loan recovery rates, which in turn limits external financing and stimulates cash accumulation. The estimation results are consistent with Acharya, Almeida, and Campello (2013) and James and Kizilaslan (2014) as we find cash reserves increase with both the market and industry betas.

Overall, the findings in this section demonstrate the usefulness of our net contagion measures (and its two components) in appraising the effects of financial contagion and support the view that firms with large exposures to intra-industry contagion risk tend to stockpile cash.

2.4.2 Suggestive evidence for potential channels

In this section, we further the argument presented in Section 2.2 and explore potential channels that could mediate the contagion effect on cash holdings. The analysis also provides further identifications of our baseline findings. We acknowledge that those channels clearly are not mutually exclusive and our result is not to rule out other possible mechanisms.

2.4.2.1 The collateral channel: Industry asset specificity/tangibility and financial conditions

A firm's financial distress could cause asset liquidation to improve operating efficiencies and/or avoid impending bankruptcy as a central part of the restructuring process (Shleifer and Vishny 1992; Asquith, Gertner, and Scharfstein, 1994). Such fire sales greatly lower the prices of similar assets held by other industry participants. Consequently, the collateral value of remaining firms is unavoidably dropped industry-wide, which substantially impairs their borrowing capacity and prompts precautionary savings.

Hence, we expect that the contagion effect on cash holdings to be strengthened when distressed firms' assets and those of non-distressed are highly correlated. To the opposite, if industry assets are firm-specific and cannot not be easily redeployed to others, non-distressed firms' assets are not likely to be significantly undermined by distressed firms' asset fire sales. As a result, a high degree of industry asset specificity, or in other words, the lack of redeployability would confine the spread of financial disturbances across firms through the collateral channel.

Following Strömberg (2000) and Acharya, Bharath, and Srinivasan (2007), we measure the industry asset specificity by the median ratio of the book value of machinery and equipment relative to that of total assets in each industry every year (denoted as *Ind_Spec*). Compared with other assets such as land and buildings, machinery and equipment are less redeployable because they are tailored to meet specific production needs.

Moreover, the importance of the collateral channel of tangibles in determining financial policies has been greatly emphasized by recent studies that mainly focus on U.S. firms (e.g., Almeida and Campello, 2007; Falato, Kadyrzhanova, and Sim, 2014). As argued by Falato, Kadyrzhanova, and Sim (2014), the declining asset tangibility shrinks firms' debt capability and boosts firms' precautionary demand for cash because conventionally only tangibles can be pledged as collateral. Therefore, we posit that a high level of industry median tangibility (denoted as *Ind_Tang*) allows non-distressed firms to better cope with negative shocks on their collaterals, and hence alleviates the spillover effect of asset fire sales triggered by peers' financial distress.[12]

To summarize, we expect that the impact of contagion on cash holdings to be diminished in industries with a high degree of asset specificity or tangibility. To gain insights into the collateral channel of contagion, in Table 2.5, columns (1) and (2), we interact our contagion proxy with *Ind_Spec* and *Ind_Tang*, respectively. Our baseline result is fully retained as the coefficient of *Net contagion* remains positive and highly significant. The interaction terms in both columns also bear an expected sign ("-"). Concretely, estimates shown in column (1) suggest that a one-standard deviation increase in *Ind_Spec* (0.136) reduces the marginal impact of contagion by 16%.[13] Similarly, a one-standard deviation increase in *Ind_Tang* (0.103) reduces the marginal impact of contagion by 23.3%. Thus, we find strong support that the positive link between contagion and cash holdings could partly stem from reduced collateral value of remaining non-distressed firms. In addition, we find the coefficients of *Ind_Spec* and *Ind_Tang* are positive and statistically significant. This

[12] Following Berger, Ofek, and Swary (1996), we measure asset tangibility by using the liquidation value of tangible assets, which is calculated as the industry-median proportion of 0.715*receivables plus 0.547*inventories plus 0.535*fixed capital, deflated by book assets.

[13] Given the estimates shown in column (1), the marginal effect of $Net\ contagion$ equals 0.005 (= $0.006 - 0.007 \times 0.136$) for a one one-standard deviation increase in *Ind_Spec* (0.136).

highlights the important role of collateralizable assets in determining a firm's cash policy (Falato, Kadyrzhanova, and Sim, 2014).

[Table 2.5 about here]

In addition, the lack of potential buyers (e.g., non-distress industry competitors) forces a distressed firm to liquidate assets at a heavy discount, which amplifies the negative shocks of a fire sale on industry-wide collateral value. In particular, Shleifer and Vishny (1992) stress that liquidation value of a firm's assets depends on the financial condition of peer firms.

We construct two industry-level proxies for the overall financial conditions of industry participants. The first is the industry financing gap (*Ind_Fingap*), measured as the industry-median proportion of investment not financed by cash flow from operations divided by book assets (Klapper, Laeven, and Rajan, 2006). The second is the interest coverage ratio (denoted as *Ind_Intcov*), defined as the industry-median of operating income before depreciation divided by interest expenses (Acharya, Bharath, and Srinivasan, 2007). *Ind_Fingap* gauges how difficult it is for an industry to raise funds to meet investment shortfall, while *Ind_Intcov* quantifies the burden of debt expenses in an industry. A large financing wedge or a small coverage ratio suggests that the industry as a whole is financially constrained.

Table 2.5, columns (3) and (4) provide evidence that the sensitivity of cash to contagion risk is heightened in industries with poor financing capacity, indicated by the significant interaction terms *Asset Tangibility* × *Ind_Fingap* and *Asset Tangibility* × *Ind_Intcov*. This finding suggests that, as a constrained financing environment depresses other firms' collateral values in the event of fire sales of distress assets, firms with high threats of contagion risk rely more on cash for their further liquidity needs.

Overall, our results in this section suggest that financial contagion could influence cash policies of the non-distressed industry peers by affecting their collateral values. The finding also underlines the robustness of our baseline result and the importance of certain industry attributes (such as high asset specificity/tangibility and financial strength) in curbing the spread of financial contagion through the collateral channel.

2.4.2.2 Contagion risk and the cost of borrowing

In this subsection, we examine how a firm's contagion risk affects its cost of borrowing. Directly motivated by our previous analysis on the collateral channel and the argument that a firm's distress prompts valuation reassessment of its industry competitors, we conjecture that contagion risk could lead to cash stockpiling due to the rise in the cost of external capital. Specifically, we investigate the impact of contagion on a firm's bank loan contracting.

We focus on bank loans for two primary reasons. First, bank loans are the key source of external credit (Chava, Livdan, and Purnanandam, 2009; Graham, Li, and Qiu, 2008). The flow of funds data from the Federal Reserve System indicate that, over the past decade, there have been $780 billion from the issuance of debt securities but only $2 billion from equities. Among the debt issues, bank loans play a significant role – about 54% of total debt since 1980. Second, banks rely on both the price (i.e., loan spreads) and non-price terms (e.g., maturity and security requirement) as complements in managing borrowers' risk (Strahan, 1999). Therefore, loan contracts provide a rich and unified context to reveal creditors' assessment and valuation of a firm's contagion risk exposure.

Table 2.6 presents coefficient estimates of regressions that examine the impact of a borrower's exposure to intra-industry contagion risk on its cost of bank loans. Our regression specification is akin to Chava, Livdan, and Purnanandam (2009), Graham, Li, and Qiu (2008), and Li, Qiu, and Wan (2011). Specifically, the dependent variable is the natural logarithm of the all-in-drawn spread, which is the amount that the borrower pays in basis points over LIBOR for each dollar drawn down. Independent variables include the lagged contagion risk proxy, industry and market systematic risk (betas), various firm and loan characteristics, and macroeconomic factors. We also control for the fixed effects of different loan types and purposes, and industries. All variables are defined in the Appendix.

Column (1) reveals that contagion risk is significantly and positively related to loan cost at the 1% level. After further controlling for firms' exposure to industry and market aggregate risk in column (2), the impact of contagion risk on the cost of debt slightly drops but remains significant at the 1% level. Economically, a one standard deviation increase in *Net contagion* (2.475) increases the average loan cost by 2.31% (=0.0093×2.475). This marginal impact is greater than that induced by exposure to industry risk (2.03%) and market risk (2.11%).

[Table 2.6 about here]

Next, we investigate the effect of contagion on the non-price loan terms. The strict non-price terms, such as short maturity or collateral requirements, impose significant indirect costs on the borrowing firms (Graham, Li, and Qiu (2008); Smith and Warner, 1979). In addition to maturity and security, banks adopt a host of loan covenants to maintain their control rights and bargaining power in influencing corporate activities. Specifically, John, Lynch, and Puri (2003) show that loans extended to riskier borrowers generally carry a number of covenants, whereas creditworthy firms are able to borrow with fewer or even no covenants. Therefore one cannot fully appraise the impact of contagion on cost of bank loans without examining its role in determining non-price terms.

Table 2.7, column (1) shows that banks shorten loan maturity for high contagion-risk borrowers. For the collateral requirement, we estimate a multivariate probit regression model where the dependent variable is a dummy variable that takes a value of one if the loan is secured and zero otherwise. As reported in column (2), all else equal, the probability of a loan being secured increases with a firms' susceptibility to contagion. Column (3) suggests that a firm's likelihood of having covenants attached to its bank loans is positively associated with its contagion risk exposure.

[Table 2.7 about here]

Overall, our analysis in this subsection suggests that the financial distress of industry participants has a sizeable impact on peers' cost of debt financing. These findings are in line with the notion that shorter maturity, collateral requirements, and the use of covenants can mitigate a bank's concerns about potential losses when a firm succumb to financial contagion. Therefore, we provide support for the conjecture that firms manage contagion risk, which tends to escalate borrowing costs, by building up their cash reserves.

The empirical results also suggest that banks may be specialized in lending in certain industries through for example relationship lending and cannot sufficiently diversify their portfolios in reality by lending in different broadly defined Fama-French 48 industries due to information asymmetry and monitoring costs. Therefore, they set stricter loan terms and charge higher loan spreads to recover their potential losses due to borrowers' default. The finding also demonstrates that analyzing the ex ante response of banks to effects of borrowers' exposure to contagion risk may be important.

2.4.2.3 Contagion and the likelihood of distress

Ultimately, through various channels, the spread of financial woes may have a direct bearing on a non-distressed firm's financial health and long-term survival. We next examine whether contagion is related to the likelihood that a firm will be in financial distress using multivariate probit regressions.

In Table 2.8, columns (1) and (2), the dependent variable is binary, equal to one if the firm experiences extreme negative returns ($\leq 30\%$) in a year (indicating financial distress), and zero otherwise. In columns (3) and (4), the distress dummy takes a value of one if the firm's sales growth is negative in past two consecutive years, and zero otherwise. Following the literature on financial distress (see, e.g., Gilson, John and Lang, 1990; Opler and Titman, 1994; Shumway 2001; Acharya, Bharath, and Srinivasan, 2007), we adopt the full set of firm-level controls, and year and industry fixed effects. In addition, we also control for market and industry betas. All independent variables are measured at the beginning of the year (properly lagged).

Table 2.8 shows that the likelihood of a firm's financial distress is positively related to its exposure to contagion risk.[14] The results are qualitatively unchanged after controlling for both industry and market betas (columns (2) and (4)). This empirical finding supports the view that contagion leads to higher precautionary savings by directly jeopardizing the very survival of solvent firms.[15]

[Table 2.8 about here]

[14] In untabulated results, we show the usefulness of increasing liquidity to offset the negative impact of contagion to firms' future performance by adding cash ratio and its interaction with net contagion.
[15] Following Sufi (2009), we also find that high contagion risk increases the likelihood of covenant violations due to the weakening operating performance. The results are available upon request.

To summarize, we find strong evidence that financial contagion impinges on corporate cash holdings by reducing industry-wide collateral values, raising borrowing costs, and intensifying firms' distress likelihood.

2.4.3 Further analysis: Contagion risk and the market valuation of cash

Thus far, we find that firms stockpile cash to hedge their exposure to the contagion of others' distress. In this section, we evaluate how equity investors value corporate cash holdings in anticipation that the firm can use them to offset intra-industry contagion risk.

Hoarding cash is not costless. In particular, it aggravates agency costs and managerial myopia, which often destroy shareholder value (Jensen and Meckling, 1976). Thus, we delve deeper into the contagion effect by examining what value shareholders assign to the cash held to fend off the negative shocks introduced by others' distress.

We adopt the methodology developed by Faulkender and Wang (2006) to estimate the influence of contagion risk on the value of an additional dollar of cash to equity holders. Specifically, we regress the excess stock return on changes in firm characteristics over the fiscal year. We first estimate the benchmark regression which is in line with Model II, Table II of Faulkender and Wang (2006). The benchmark specification is then augmented by including *Net contagion* as follows:

$$
\begin{aligned}
r_{i,t} - R^B_{r,t} = \alpha &+ \delta_1 Net\ contagion_{i,t-1} + \delta_2 Net\ contagion_{i,t-1} \times \frac{\Delta Cash_{i,t}}{MV_{i,t-1}} \\
&+ \delta_3 \frac{\Delta Cash_{i,t}}{MV_{i,t-1}} + \beta_1 \frac{\Delta Earnings_{i,t}}{MV_{i,t-1}} + \beta_2 \frac{\Delta Net\ Assets_{i,t}}{MV_{i,t-1}} + \beta_3 \frac{\Delta R\&D_{i,t}}{MV_{i,t-1}} \\
&+ \beta_4 \frac{\Delta Interests\ Expenses_{i,t}}{MV_{i,t-1}} + \beta_5 \frac{\Delta Dividends_{i,t}}{MV_{i,t-1}} + \beta_6 \frac{Cash_{i,t-1}}{MV_{i,t-1}} \\
&+ \beta_7 Leverage_{i,t} + \beta_8 \frac{New\ Financing_{i,t}}{MV_{i,t-1}} + \beta_9 \frac{Cash_{i,t}}{MV_{i,t-1}} \times \frac{\Delta Cash_{i,t}}{MV_{i,t-1}} \\
&+ \beta_{10} Leverage_{i,t} \times \frac{\Delta Cash_{i,t}}{MV_{i,t-1}} + \varepsilon_{i,t},
\end{aligned} \tag{2.5}
$$

where $MV_{i,t-1}$ is the one-year lagged market value of equity. The dependent variable is calculated as the annual stock return of firm i minus its matched Fama and French 5×5 size and book-to-market portfolio return. This methodology can be viewed as a long-run event study. The event is the unexpected change in cash holdings, and the event window is a fiscal year.

The estimation results are reported in Table 2.9. Column (1) suggests that the average marginal value of an extra dollar of cash to shareholders equals $0.83.[16] In column (2), we introduce the net contagion effect into the specification, and the positive interaction term *Net contagion* × Δ*Cash* indicates that the contribution of cash holdings to market value is larger for high contagion-risk firms. The estimates suggest that, ceteris paribus, a one standard deviation increase in *Net contagion* (2.949) increases the marginal value of an extra dollar of cash to shareholders by 5.9 cents.

[Table 2.9 about here]

Overall, the finding in Table 2.9 confirms that additional cash holdings are greatly valued by shareholders of firms with high contagion risk and the market rewards these firms that retain liquidity with higher valuations.

2.5 Conclusions

Little is known about how the externalities of corporate financial distress affect corporate cash policies. This paper is among the first to provide evidence on whether and how intra-

[16] The marginal value of cash of $0.83 is calculated as (1.047+ (-0.098*0.166) + (-0.922*0.217)), where the lagged cash holdings as a percentage of market value of equity is equal to 0.166 and the mean value of market leverage is equal to 0.217.

industry contagion drives cash holdings. In particular, we introduce a novel measure of a firm's exposure to contagion risk. This general measure builds on return comovement and unravels contagion and competition effects caused by the financial distress of industry peers.

Our baseline results indicate that cash holdings are positively driven by a firm's net exposure of contagion risk. We further explore a few potential mechanisms that may mediate the contagion effect. The results suggest that contagion risk is amplified in industries with low asset specificity/tangibility and poor financing capacity, for which fire sales of distressed assets greatly reduce industry-wide collateral values. We also show that contagion directly impinges upon a firm's cost of borrowing and future distress likelihood. Further analysis also highlights the greater marginal value of cash perceived by equity holders of firms with high contagion risk.

Taken together, our findings are consistent with the precautionary cash holding motive underscored in Bates, Kahle, and Stulz (2009), and highlight the advantage of maintaining a solid balance sheet for high contagion-risk firms to avoid liquidity shortfalls.

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Appendix 2.A: Variable Definitions

This table provides the definition of variables used in the study.

Variable	Definitions with corresponding Compustat item names
Firm-level variables	
Cash/Assets	Cash plus marketable securities (CHE) divided by book value of total assets (AT).
Market and industry asset beta	The asset (unlevered) market and industry beta, calculated from the equity (levered) market and industry beta, respectively. Equity market beta and industry beta are obtained from a two-factor model in which firm return is regressed on market return and industry return: $r_{i,t} = a_i + \beta_{Equity}^{MKT} b_i r_{M,-I,\,t} + \beta_{Equity}^{IND} r_{I,-i,t} + \varepsilon_{i,t}$, where $r_{i,t}$ is the stock return in week *t* for firm *i*. $r_{M,-I,\,t}$ is the weekly value-weighted CRSP market index return, excluding the return on industry I, and $r_{I,-i,t}$ is a value-weighted return of all industry *I* stocks, where firm *i* is excluded from the industry portfolio. Industries are defined according to Fama-French's (1997) 48-industry classification. Since high leverage firms tend to have larger betas, we unlever equity betas as follows: $\beta_{Asset} = \beta_{Equity}\frac{E}{V}$, where *E* is the market value of a firm's equity and *V* is the underlying value of the firm, or market value of asset.
Altman's default probability	The normal density function is used to map a modified Altman's (1968) *Z*-score on to its implied probability of default.
Industry cash flow volatility	The average of prior 10 year standard deviations of cash flow/assets for firms in the same industry, as defined by the Fama-French's (1997) 48-industry classification.
Market-to-Book	The market value of common equity (fiscal year end price (PRCC_F) times shares outstanding (CSHO), plus total assets (AT) minus book value of common equity (CEQ)) divided by book value of total assets (AT).
Ln(real book assets)	Natural logarithm of book value of total assets (AT) in millions of 2006 U.S. dollars.
Cash flow	operating income before depreciation (OIBDP), less interest and related expense (XINT), income taxes (TXT), and dividends (DVC), divided by book value of total assets (AT) over year *t*.
Net working capital	Working capital (WCAP) minus cash (CHE) divided by total assets (AT).
Asset tangibility	Net property, plant, and equipment (PPENT) divided by total assets (AT).

Capital expenditures	The ratio of capital expenditures (CAPX) to the book value of total assets (AT). The capital expenditure from the statement of cash flows is often missing. Following Dittmar and Mahrt-Smith (2007), I impute any missing CAPX from the change in net fixed assets plus depreciation and amortization over the year.
Total book leverage	The ratio of long-term debt (DLTT) plus debt in current liabilities (DLC) to total assets (AT).
R&D expenditures	The ratio of R&D expenditure (XRD) to sales (SALE). If R&D expenditure is missing, I follow the tradition to set the missing value to zero, over year *t*.
Dividend payout dummy	A dummy variable equal to one in years in which a firm pays a common dividend (DVC). Otherwise, the dummy equals zero.
Acquisition expenditures	Acquisition activity is defined as acquisitions (AQC) divided by book assets (AT).
Net equity issuance	Sale of common and preferred stock (SSTK) minus the purchase of common and preferred stock (PRSTKC), divided by the book value of total assets (AT).
Net debt issuance	Annual total long-term debt issuance (DLTIS) minus long-term debt reduction (DLTR), scaled by the book value of total assets (AT).
Return on Assets	Income before extraordinary items (NI) divided by total assets (AT) at the beginning of the fiscal year.
Market share	Sales (SALE) as a fraction of industry sales.
Stock return	Stock return in annual frequency.
Altman's (1968) *Z*-score	(3.3*EBIT (OIBDP) + 1.0*Net Sales (SALE) + 1.4*Retained Earnings (RE) + 1.2*Working Capital (WCAP))/Total Assets (AT) + 0.6*Market Value of Equity (PRCC*CSHO)/Total Liabilities (DLTT+DLC).
Modified Altman's (1968) *Z*-score	(3.3*EBIT (OIBDP) + 1.0*Net Sales (SALE) + 1.4*Retained Earnings (RE) + 1.2*Working Capital (WCAP))/Total Assets (AT), as used in MacKie-Mason (1990).
Stock return volatility	Standard deviation of the quarterly stock return over the 20 quarters before the quarter containing the loan origination date.
Cash flow volatility	Standard deviation of operating income before depreciation (OIBDPQ) divided by total assets (ATQ) over the 20 quarters before the quarter containing the loan origination date.
ΔNetWorkingCapital	The change in the ratio of noncash net working capital (WCAP-CHE) to total assets (AT) between year t and $t-1$.
ΔShortDebt	The change in the ratio of short-term debt (DLC) to total assets (AT) between

	year *t* and *t*−1.
Industry-level variables	
Herfindahl-Hirschman Index (HHI)	Herfindahl-Hirschman Index is defined as the sum of squared market shares index at the three-digit SIC code industry level. Market shares are computed using firms' sales (SALE).
Asset specificity (SPEC)	Industry-median of the book value of machinery and equipment (PPEME) divided by the book value of total assets (AT) in each Fama-French's (1997) industry each year, following Strömberg (2000) and Acharya, Bharath, and Srinivasan (2007).
Asset tangibility (TANG)	Industry-median proportion of 0.715*receivables (RECT) + 0.547*inventories (INVT) + 0.535*fixed capital (PPENT), deflated by book assets (AT), similar to Berger, Ofek, and Swary (1996).
Financing gap (FGAP)	Industry-median proportion of investment not financed by cash flow from operations (IVNCF-OANCF), deflated by book assets (AT).
Interest coverage ratio (INTCOV)	Industry-median of the operating income before depreciation (OIBDP) divided by interest expenses (XINT).
Loan variables	
Ln (loan spreads)	Natural logarithm of loan all-in-drawn spread above the LIBOR rate, including any annual fee paid to the bank group. The "All-in-Drawn" variable in the DealScan database describes the amount the borrower pays in basis points over LIBOR for each dollar drawn down. It also adds the spread of the loan with any annual (or facility) fee paid to the bank or bank group.
Ln (loan amount)	Natural logarithm of the loan facility amount. Loan amount is measured in millions of U.S. dollars.
Ln (loan maturity)	Natural logarithm of the loan maturity measured in months.
Security dummy	An indicator variable equal to one if the loan facility is secured, and zero otherwise.
Financial covenants dummy	An indicator variable equal to one if a facility has financial covenants, and zero otherwise.
Sole lender dummy	An indicator variable equal to one if the loan has a sole lender, and zero otherwise.
Performance pricing dummy	An indicator variable equal to one if the loan contains a performance pricing feature (either interest-increasing or interest-decreasing), and zero otherwise.
Loan type dummies	Dummy variable for loan types, including 364-day facility, revolver less than 1 year, revolver/term loan, term loan, acquisition facility, bridge loan, demand loan, limited line, and others.

Loan purpose dummies	Dummy variable for loan purposes, including corporate purposes, debt repayment, working capital, takeover, CP backup, acquisition line, LBO/MBO, debtor-in-possession, recapitalization, and others.
Macroeconomic variables	
Credit market conditions	The average commercial and industrial (C&I) loan rate spread (the spread of the average C&I loan rate over the federal funds rate) over a particular year. (data source: Federal Reserve Board Statistical Release E.2: Survey of Terms of Business Lending (for commercial and industrial loan rate))
Credit spread	The difference between the monthly yields of BAA and AAA rated corporate bonds (data source: Federal Reserve Board of Governors).
Term spread	The difference between the 10-year Treasury yield and the 2-year Treasury yield (data source: Federal Reserve Board of Governors).

Appendix 2.B: Industries with Extreme Contagion Risk

This table provides a list of top (bottom) five industries with the highest (lowest) industry median levels of net contagion along with raw contagion and competition in 1990, 2000 and 2010.

Highest net contagion				Lowest net contagion			
1990							
Industry	Net Contagion	Raw Contagion	Competition	Industry	Net Contagion	Raw Contagion	Competition
Petroleum and Natural Gas	2.323	5.151	-2.289	Shipping Containers	0.039	0.126	-0.072
Communication	1.246	3.544	-2.208	Business Supplies	0.014	0.452	-0.387
Pharmaceutical Products	1.088	4.349	-3.103	Defense	-0.005	0.008	-0.013
Business Services	0.696	3.748	-2.866	Beer & Liquor	-0.052	0.138	-0.134
Entertainment	0.540	1.228	-0.576	Apparel	-0.060	0.198	-0.214
2000							
Industry	Net Contagion	Raw Contagion	Competition	Industry	Net Contagion	Raw Contagion	Competition
Pharmaceutical Products	29.857	33.827	-3.424	Meals	0.041	1.601	-1.460
Business Services	18.620	35.521	-16.214	Mines	0.035	0.176	-0.191
Computers	6.140	9.173	-3.004	Ships	0.025	0.052	-0.036
Communication	5.915	11.912	-5.539	Candy & Soda	-0.013	0.132	-0.099
Electronic Equipment	4.926	8.042	-2.666	Construction	-0.028	0.245	-0.276
2010							
Industry	Net Contagion	Raw Contagion	Competition	Industry	Net Contagion	Raw Contagion	Competition
Pharmaceutical Products	4.854	12.047	-6.447	Defense	0.081	0.140	-0.068
Business Services	4.496	12.086	-6.820	Textiles	0.069	0.085	-0.015
Petroleum and Natural Gas	2.972	5.770	-2.160	Candy & Soda	0.063	0.186	-0.040
Electronic Equipment	2.212	5.822	-3.422	Fabricated Products	0.062	0.076	-0.010
Computers	1.477	3.264	-1.909	Beer & Liquor	0.049	0.184	-0.058

Table 2.1
Contagion risk measure and industry and firm characteristics

Panels A through E of this table present mean and median net comovement with industry peers or rivals for quartile portfolios based on real firm size, age, profitability, sales-based Herfindahl-Hirschman Index (HHI), and the average C&I loan rate spread which proxies for credit market conditions, respectively. The last column reports the time-series averaging of annual difference in means and medians of net comovement between high and low quartiles with *t*-test and Wilcoxon *Z*-test for equality, respectively.

Panel A: Quartiles based on firm size

		Small	Q2	Q3	Large	Difference (Large - Small)
Net contagion	mean	2.021	2.294	1.764	1.076	-0.945***
	median	0.609	0.626	0.464	0.289	-0.320***

Panel B: Quartiles based on firm age

		Young	Q2	Q3	Old	Difference (Old - Young)
Net contagion	mean	2.484	2.209	1.662	0.812	-1.672***
	median	0.737	0.604	0.457	0.242	-0.494***

Panel C: Quartiles based on profitability

		Unprofitable	Q2	Q3	Profitable	Difference (Profitable - Unprofitable)
Net contagion	mean	1.961	1.975	1.708	1.354	-0.607***
	median	0.495	0.494	0.426	0.360	-0.135***

Panel D: Quartile based on the industry concentration

		Competitive	Q2	Q3	Concentrated	Difference (Concentrated - Competitive)
Net contagion	mean	1.671	2.111	1.665	0.365	-1.306***
	median	0.446	0.482	0.470	0.150	-0.295***

Panel E: Quartile based on credit market conditions

		Strong	Q2	Q3	Weak	Difference (Weak - Strong)
Net contagion	mean	1.386	1.652	2.056	1.934	0.549***
	median	0.384	0.448	0.418	0.533	0.149***

Table 2.2

Raw Contagion versus Competition around Peers' Pre-Chapter 11 Bankruptcy Distress Date

The table presents the mean abnormal stock returns of non-bankrupt firms on the pre-bankruptcy distress date as well as the mean cumulative abnormal stock returns of non-bankrupt firms surrounding the pre-bankruptcy distress date. The sample contains 421 Chapter 11 distress dates from 1981 to 2012 and 56,702 firm-year observations. The distress dates are identified using the approach of Hertzel, Li, Officer, and Rogers (2008). Specifically, it is the day with the largest decrease in abnormal returns within the year prior to the bankruptcy announcement. Following Brown and Warner (1985), the abnormal return on stock *i* over day *t* is calculated by using the market-adjusted returns method, $AR_{i,t} = r_{i,t} - r_{m,t}$, where $r_{i,t}$ and $r_{m,t}$ are the returns for stock *i* and the market portfolio *m* (CRSP's value-weighted index) on day *t*, respectively. *Raw contagion* and *Competition* for firm *i* is measured by $\sum_{\forall j \neq i} 1\left(d_{i,t}^{j} > 0\right) \times d_{i,t}^{j} \times EDP_{j,t}$ and $\sum_{\forall j \neq i} 1\left(d_{i,t}^{j} < 0\right) \times \left|d_{i,t}^{j}\right| \times EDP_{j,t}$, respectively. $d_{i,t}^{j}$ is the pair-wise comovement of stock returns between non-bankrupt firm *i* and bankrupt industry peer firm *j*. $EDP_{j,t} = 1$ for all firms *j* that turn out to experience financial distress on day *t* and operate in the same industry as firm *i*. High, medium, and low portfolios are formed based on positive and negative comovement between filing firms and non-bankrupt firms within the same Fama-French's (1997) 48-industry over the year prior to the distress date, respectively. Distress period CAR is the cumulative abnormal returns centered on the distress date (day 0) for both 3-day (-1, +1) and 11-day (-5, +5) windows.

Panel A: Sorting based on *Raw contagion* ($d > 0$)

Event window	Tercile Portfolio	Average CAR (%)	*t*-statistic Avg. CAR=0	N
[0, 0]	High	-0.210***	-5.37	11,158
	Medium	-0.149***	-4.28	11,314
	Low	-0.012	-0.38	10,810
[-1, +1]	High	-0.187***	-2.91	11,165
	Medium	-0.129**	-2.22	11,032
	Low	-0.061	-1.16	11,152
[-5, +5]	High	-0.320***	-2.79	11,212
	Medium	-0.274***	-2.62	11,079
	Low	0.100	1.06	11,196

Panel B: Sorting based on *Competition* ($d < 0$)

Event window	Tercile Portfolio	Average CAR (%)	*t*-statistic Avg. CAR=0	N
[0, 0]	High	0.230***	3.51	7,733
	Medium	0.148**	2.47	7,561
	Low	0.131*	1.76	7,743
[-1, +1]	High	0.187*	1.88	7,748
	Medium	0.135	1.35	7,572
	Low	0.062	0.52	7,767
[-5, +5]	High	0.395***	2.53	7,790
	Medium	0.092	0.60	7,613
	Low	0.316*	1.68	7,812

Table 2.3
Summary Statistics

This table provides summary statistics of key variables employed in the analysis. Data on firm characteristics are collected from the merged Compustat-CRSP database for the years 1980 to 2013. Loan data come from the Loan Pricing Corporation's (LPC) Dealscan database for the period 1987–2012. The table provides mean, median, standard deviations, 25th and 75th percentiles, and the number of observations. *Raw Contagion* is defined for firm i as $\sum_{\forall j \neq i} 1\left(d_{i,t}^{j} > 0\right) \times d_{i,t}^{j} \times EDP_{j,t}$, which is the sum of the pair-wise stock return comovement times the respective expected default probability of industry peer *j* over all firm i's industry peers that have positive pair-wise stock return comovement with firm i (i.e., $d_{i,t}^{j} > 0$). $EDP_{j,t}$, the expected default probability of firm *j*, is computed from Altman's (1968) *Z*-score. *Competition* is defined as $\sum_{\forall j \neq i} 1\left(d_{i,t}^{j} < 0\right) \times \left|d_{i,t}^{j}\right| \times EDP_{j,t}$, where $d_{i,t}^{j}$ is the pair-wise stock return comovement between firm i and firm j, and $EDP_{j,t}$ is expected default probability of other industry participants *j* computed from Altman's (1968) *Z*-score. *Net Contagion* is the sum of *Raw Contagion* and *Competition*. Variables are winsorized at the 1% and 99% levels. Details on the construction of all variables are provided in the Appendix.

Variable	Mean	Median	Std. Dev.	25%	75%	N
Firm characteristics						
Net contagion	1.681	0.420	3.485	0.019	1.624	90,364
Raw contagion	4.225	1.715	5.926	0.704	4.884	90,362
Competition	-2.504	-1.173	3.301	-3.000	-0.471	90,263
Cash/Assets	0.146	0.084	0.198	0.024	0.235	90,364
Industry asset beta	0.337	0.284	0.648	-0.053	0.711	90,364
Market asset beta	0.454	0.366	0.808	-0.031	0.886	90,364
Altman's default probability	0.274	0.123	0.324	0.024	0.427	90,364
Industry cash flow volatility	0.136	0.105	0.094	0.067	0.184	90,364
Market to book	1.967	1.398	1.911	1.053	2.115	90,364
Book assets ($ million)	1,344	187	3,660	52	767	90,364
Cash flow	0.024	0.068	0.213	0.019	0.108	90,364
Net working capital	0.121	0.112	0.201	-0.007	0.252	90,364
Capital expenditures	0.067	0.046	0.069	0.023	0.085	90,364
Total book leverage	0.221	0.188	0.204	0.035	0.341	90,364
R&D expenditures	0.209	0.000	1.155	0.000	0.054	90,364
Dividend payout dummy	0.351	0.000	0.477	0.000	1.000	90,364
Acquisition expenditures	0.022	0.000	0.058	0.000	0.007	90,364
Net equity issuance	0.035	0.001	0.148	-0.001	0.011	90,364
Net debt issuance	0.012	0.000	0.097	-0.017	0.021	90,364
Loan characteristics						
Spreads (basis points)	197	175	140	88	275	23,398
Loan size ($ million)	318	100	787	25	300	23,398
Loan maturity (month)	45	48	25	24	60	23,398
Security dummy	0.307	0.000	0.461	0.000	1.000	23,398
Covenants dummy	0.560	1.000	0.496	0.000	1.000	23,398

Table 2.4
Baseline Results: Intra-industry Contagion Risk and Cash Holdings

This table shows how a firm's liquidity policy reacts to its intra-industry contagion risk exposure. The dependent variable is the ratio of cash plus marketable securities to total book assets. Column (2) reports firm fixed effects estimates. The Fama-MacBeth model in column (3) uses Newey and West (1987) standard errors. Values of *t*-statistics based on standard errors robust to heteroscedasticity and clustering by firm are reported in parentheses. All independent variables are measured at the beginning of the year.

Dependent variable: Cash/Assets	(1) OLS	(2) FE	(3) F-M	(4) OLS
Net contagion	0.004***	0.001***	0.003***	
	(13.63)	(2.63)	(2.93)	
Raw contagion				0.004***
				(13.25)
Competition				-0.003***
				(-5.52)
Industry asset beta	0.027***	0.005***	0.028***	0.027***
	(16.47)	(4.01)	(7.77)	(16.18)
Market asset beta	0.017***	0.004***	0.019***	0.017***
	(13.73)	(4.94)	(8.54)	(13.34)
Altman's default probability	0.039***	-0.027***	0.028***	0.038***
	(6.47)	(-4.20)	(3.08)	(6.24)
Industry cash flow volatility	0.176***	0.027	0.365***	0.166***
	(6.88)	(1.01)	(8.46)	(6.41)
Market to book	0.009***	0.005***	0.012***	0.009***
	(12.02)	(8.56)	(6.89)	(12.11)
Ln (real book assets)	-0.011***	-0.016***	-0.012***	-0.011***
	(-14.54)	(-10.09)	(-14.54)	(-13.87)
Cash flow	0.036***	0.006	0.025**	0.036***
	(5.24)	(0.86)	(2.61)	(5.30)
Net working capital	-0.244***	-0.145***	-0.224***	-0.243***
	(-27.08)	(-18.44)	(-33.13)	(-26.89)
Capital expenditures	-0.490***	-0.302***	-0.584***	-0.487***
	(-31.30)	(-24.51)	(-12.68)	(-30.98)
Total book leverage	-0.311***	-0.162***	-0.308***	-0.312***
	(-45.47)	(-23.73)	(-38.65)	(-45.51)
R&D expenditures	0.024***	0.007***	0.031***	0.024***
	(18.74)	(4.87)	(5.12)	(18.58)
Dividend payout dummy	-0.019***	-0.004*	-0.026***	-0.019***
	(-7.40)	(-1.73)	(-9.26)	(-7.37)
Acquisition expenditures	-0.365***	-0.197***	-0.356***	-0.364***
	(-33.61)	(-24.90)	(-11.72)	(-33.43)
Net equity issuance	0.026***	0.052***	0.020**	0.025***
	(3.77)	(9.11)	(2.08)	(3.70)
Net debt issuance	0.205***	0.102***	0.206***	0.205***
	(26.23)	(17.09)	(23.70)	(26.20)
Constant	0.251***	0.315***	0.268***	0.257***
	(9.32)	(36.83)	(31.70)	(8.89)
Year fixed effects	Yes	Yes	No	Yes
Industry fixed effects	Yes	Yes	No	Yes
Firm fixed effects	No	Yes	No	No
Number of observations	90,364	90,364	90,364	90,261
Adj. (Avg./within) R-squared	0.49	0.10	0.44	0.49

Table 2.5
Asset Redeployability and the Correlation of Collateral Assets

This table examines how industry-level asset specificity, asset tangibility, financing gap, and interest coverage ratio affect the relation between cash holdings and contagion risk through the collateral channel of intra-industry contagion. The dependent variable is the ratio of cash plus marketable securities (CHE) to total book assets (AT). *IND_SPEC* is asset specificity which is defined as the industry-median of the book value of machinery and equipment divided by the book value of total assets in each Fama-French's (1997) industry each year, following Strömberg (2000) and Acharya, Bharath, and Srinivasan (2007). The higher the asset specificity, the less the correlation of the redeployability and liquidation value of collateral assets within the industry. The higher the asset specificity, the less the liquidation value of collateral assets within the industry. *IND_TANG* is asset tangibility which is defined as the industry-median of 0.715*receivables (RECT) + 0.547*inventories (INVT) + 0.535*fixed capital (PPENT), deflated by book assets (AT), following Berger, Ofek, and Swary (1996). *IND_FINGAP* is financing gap which is the industry-median proportion of investment not financed by cash flow from operations (IVNCF-OANCF) divided by book assets (AT). It is a proxy for external finance dependence and financial constraints according to Rajan and Zingales (1998). Higher the industry financing gap indicates a more constrained financing environment. *IND_INTCOV* is the interest coverage ratio which is defined as the industry-median of the operating income before depreciation (OIBDP) divided by interest expenses (XINT). Values of *t*-statistics based on standard errors robust to heteroscedasticity and clustering by firm are reported in parentheses. Variables are winsorized at the 1% and 99% levels.

Dependent variable: Cash/Assets	Industry asset redeployability		Industry financing friction	
	(1)	(2)	(3)	(4)
Net contagion	0.006***	0.009***	0.005***	0.004***
	(11.23)	(11.44)	(14.25)	(13.72)
Net contagion × Ind_Spec	-0.007***			
	(-4.17)			
Net contagion × Ind_Tang		-0.021***		
		(-8.00)		
Net contagion × Ind_Fingap			0.021***	
			(8.20)	
Net contagion × Ind_Intcov				-0.0004***
				(-6.88)
Ind_Spec	-0.027**			
	(-2.01)			
Ind_Tang		-0.205***		
		(-6.90)		
Ind_Fingap			0.003	
			(0.12)	
Ind_Intcov				-0.0001
				(-0.31)
Control variables	Same as in the baseline Model 1, Table 2.4			
Year fixed effects	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes
Number of observations	90,215	90,364	72,263	90,364
Adj. R-squared	0.49	0.49	0.51	0.49

Table 2.6
The Effect of Contagion Risk on the Price Term of Bank Debt

This table presents coefficient estimates of regressions which examine the impact of borrowing firms' exposure to intra-industry contagion risk on their cost of bank debt. The sample period is from 1987 to 2012. Heteroskedasticity-robust *t*-statistics are in parentheses. Details on the construction of all variables are provided in Appendix.

Dependent variable: Ln(spreads)	(1)	(2)
Net contagion	0.010***	0.009***
	(5.92)	(5.27)
Industry asset beta		0.037***
		(4.16)
Market asset beta		0.032***
		(4.63)
Firm characteristics		
Ln (real book assets)	-0.141***	-0.143***
	(-33.12)	(-33.28)
Market to book	-0.101***	-0.104***
	(-20.62)	(-21.09)
Total book leverage	0.661***	0.685***
	(31.70)	(31.93)
Profitability	-0.755***	-0.759***
	(-13.59)	(-13.66)
Tangibility	-0.274***	-0.273***
	(-11.85)	(-11.81)
Stock return volatility	0.123***	0.121***
	(10.20)	(10.01)
Cash flow volatility	2.861***	2.809***
	(11.79)	(11.58)
Borrower modified Altman's (1968) *Z*-score	-0.051***	-0.050***
	(-11.47)	(-11.16)
Loan characteristics		
Ln (loan amount)	-0.049***	-0.050***
	(-10.89)	(-11.07)
Ln (loan maturity)	-0.047***	-0.047***
	(-5.19)	(-5.26)
Security dummy	0.297***	0.296***
	(34.65)	(34.55)
Financial covenants dummy	0.111***	0.112***
	(11.52)	(11.61)
Sole lender dummy	-0.006	-0.007
	(-0.47)	(-0.54)
Performance pricing dummy	-0.130***	-0.130***
	(-14.60)	(-14.60)
Macroeconomic factors		
Credit spread	0.314***	0.313***
	(24.52)	(24.37)
Term spread	0.079***	0.080***
	(22.34)	(22.55)
Constant	6.653***	6.648***
	(60.29)	(60.93)
Loan type and purpose fixed effects	Yes	Yes
Industry fixed effects	Yes	Yes
Number of observations	23,398	23,398
Adj. R-squared	0.61	0.61

Table 2.7
The Effect of Contagion Risk on the Non-price Terms of Bank Debt

This table presents coefficient estimates of regressions which examine the impact of borrowing firms' exposure to intra-industry contagion risk on their non-price contract terms of bank loans. The sample period is from 1987 to 2012. Heteroskedasticity-robust *t*-statistics are in parentheses.

Dependent variable	Ln(maturity)	Security dummy	Covenants dummy
	(1)	(2)	(3)
	OLS	Probit	Probit
Net contagion	-0.004***	0.017***	0.006***
	(-2.78)	(14.08)	(5.13)
Firm characteristics			
Ln (real book assets)	-0.017***	-0.038***	-0.020***
	(-4.75)	(-13.82)	(-7.57)
Market to book	0.004	-0.018***	0.006*
	(1.06)	(-5.21)	(1.89)
Total book leverage	0.034*	0.128***	-0.115***
	(1.92)	(9.25)	(-8.17)
Profitability	0.297***	-0.245***	0.214***
	(5.91)	(-6.20)	(5.52)
Tangibility	0.016	-0.078***	-0.048***
	(0.85)	(-5.07)	(-3.16)
Stock return volatility	0.018*	0.075***	0.005
	(1.95)	(8.63)	(0.58)
Cash flow volatility	-2.148***	0.162	-0.317*
	(-9.54)	(0.94)	(-1.93)
Borrower modified *Z*-score	-0.009**	-0.022***	-0.011***
	(-2.16)	(-6.92)	(-3.36)
Loan characteristics			
Ln (loan amount)	0.090***	0.013***	0.002
	(23.52)	(4.30)	(0.69)
Ln (loan maturity)		0.059***	-0.024***
		(10.20)	(-4.65)
Security dummy	0.077***		0.292***
	(10.84)		(43.41)
Financial covenants dummy	-0.041***	0.291***	
	(-5.08)	(46.28)	
Sole lender dummy	-0.105***	-0.173***	-0.088***
	(-8.01)	(-21.79)	(-10.25)
Performance pricing dummy	0.096***	0.003	0.475***
	(13.17)	(0.49)	(79.91)
Macroeconomic factors			
Credit spread	-0.094***	0.172***	0.010
	(-9.00)	(17.83)	(1.19)
Term spread	-0.010***	0.032***	-0.020***
	(-3.43)	(12.87)	(-8.67)
Constant	2.990***		
	(20.71)		
Loan type and purpose fixed effects	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes
Number of observations	23,398	23,359	23,372
Adj. R-squared	0.63	0.32	0.40

Table 2.8
The Impact of Contagion on the Likelihood of Firm Distress

This table presents marginal effects of multivariate probit regressions examining whether the contagion risk measure is related to the probability that a firm will be in distress after controlling for market and industry risks. In columns (1) and (2), the dependent variable is equal to one if the stock return of the firm is less than -30% in a given year, and zero otherwise. In columns (3) and (4), the dependent variable is equal to one if the sales growth of the firm is negative in any two consecutive years, and zero otherwise. Similar to Shumway (2001), additional firm-level controls include EBITDA/total assets, total liabilities/total assets, current asset/current liabilities, working capital/total assets, sales/total assets, retained earnings/total assets, net worth/total assets, market to book, the natural log of firm size, and year and industry fixed effects. All independent variables are measured at the beginning of the year. The estimations correct the error structure for heteroskedasticity and within-firm error clustering. Robust *t*-statistics are shown in parentheses. ***, **, and * indicate significance at equal to or less than the 1%, 5%, and 10% levels, respectively.

Dependent variable	Distress dummy based on stock returns		Distress dummy based on sales growth	
	(1)	(2)	(3)	(4)
Net contagion	0.009***	0.007***	0.004***	0.003***
	(17.68)	(13.49)	(6.97)	(5.85)
Industry asset beta		0.062***		0.016***
		(20.28)		(4.93)
Market asset beta		0.048***		0.005*
		(20.32)		(1.84)
EBITDA/book assets	-0.012	-0.023**	-0.200***	-0.202***
	(-1.25)	(-2.49)	(-20.36)	(-20.56)
Total book leverage	0.103***	0.136***	0.107***	0.113***
	(10.73)	(14.09)	(9.97)	(10.39)
Current ratio	-0.001	-0.001	0.003***	0.003***
	(-1.53)	(-1.13)	(4.33)	(4.43)
Working capital/book assets	0.034***	0.018*	0.005	0.003
	(3.50)	(1.91)	(0.51)	(0.27)
Sales/total assets	-0.024***	-0.021***	-0.007***	-0.006**
	(-10.28)	(-9.17)	(-2.91)	(-2.53)
Retained earnings/book assets	0.004***	0.005***	0.005***	0.005***
	(2.74)	(3.36)	(3.17)	(3.23)
Net worth/book assets	0.015**	0.020***	0.072***	0.073***
	(1.99)	(2.78)	(8.22)	(8.26)
Market to book	0.018***	0.015***	-0.016***	-0.016***
	(16.77)	(14.96)	(-15.34)	(-15.29)
Ln(real book assets)	-0.013***	-0.017***	0.000	-0.001
	(-14.29)	(-18.70)	(0.01)	(-1.10)
Year fixed effects	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes
Number of observations	93,329	92,641	90,622	89,962
Adj. R-squared	0.10	0.10	0.05	0.05

Table 2.9
The Effect of Contagion Risk on the Market Valuation of Cash Holdings

This table tests the hypothesis whether high comovement firms hold more cash to offset the larger intra-industry contagion risk. We use the methodology developed in Faulkender and Wang (2006) to estimate the influence of contagion risk on the value of an additional dollar of cash to equity holders. Specifically, we regress the excess stock return $r_{i,t} - R^B_{r,t}$ (the firm's annual stock return minus the firm's matched Fama and French 5×5 size and book-to-market portfolio return) on changes in firm characteristics over the fiscal year. Column (1) of this table reports a regression similar to Model II in Table II of Faulkender and Wang (2006). In column (2), we estimate the benchmark Faulkender and Wang regression augmented to include net contagion.

Dependent variable: Excess stock return	(1)	(2)
Net contagion		-0.006***
		(-8.71)
Net contagion × Δ Cash holdings		0.020***
		(3.60)
Δ Cash holdings	1.047***	1.004***
	(31.65)	(28.91)
Δ Earnings	0.470***	0.471***
	(37.27)	(37.35)
Δ Net assets	0.196***	0.193***
	(26.22)	(25.78)
Δ Research and development expenses	0.683***	0.667***
	(6.31)	(6.13)
Δ Interest expenses	-1.706***	-1.690***
	(-16.64)	(-16.50)
Δ Dividends	2.156***	2.151***
	(10.31)	(10.32)
Cash holdings$_{t-1}$	0.229***	0.239***
	(19.58)	(19.88)
Market leverage	-0.353***	-0.364***
	(-44.40)	(-44.99)
Net financing	-0.033**	-0.026*
	(-2.47)	(-1.96)
Cash holdings$_{t-1}$ × Δ Cash holdings	-0.098***	-0.113***
	(-2.75)	(-3.20)
Market leverage × Δ Cash holdings	-0.922***	-0.865***
	(-15.47)	(-14.27)
Constant	0.015***	0.024***
	(5.25)	(8.02)
Number of observations	78,968	78,968
Adj. R-squared	0.16	0.16

Chapter Three: *Financial Development, Asset Tangibility and Cash Holdings: A Cross-Country Analysis*

3.1 Introduction

The rapid development of financial markets has continuously shaped the environment in which firms operate. Financial development is partly prompted by facilitated creditor rights, contract enforcement, and accounting standards which provide accurate information about corporations and hence improve financial contacting and intermediation (Levine, 1999). Recent work by Liberti and Mian (2010), for example, finds that financial development driven by strong institutions eases borrowing constraints by lowering the collateral spread and expanding the scope of collateralizable assets. Clearly, one would expect that financial development could also impinge upon a firm's cash and other financial policies by affecting the collateral value of its tangibles and its access to alternative financing sources. Yet, there is still surprisingly little empirical work on this important issue. The objective of this paper is to conduct a cross-country analysis to examine how financial market development affects the reliance of corporate liquidity management on tangible capital.

A developed financial market reduces the demand for collateralizable tangibles, and thus lowers the collateral cost of capital. However, how the reduced reliance on tangibles affects corporate real decisions is unclear. In particular, financial development may affect the role of tangibles in determining cash holdings (i.e., the cash-tangibility sensitivity) through two important yet potentially countervailing dimensions.

On the one hand, it is associated with enhanced creditor rights protection and the quality of accounting standards which reflects the quality of information available to creditors and hence the costs of monitoring and screening. Therefore, financial development may improve loan availability and lower the cost of debt financing (Qian and Strahan, 2007). More importantly, it reduces collateral haircuts, and, correspondingly, increases a firm's borrowing capacity given the same stock of tangibles. Therefore, as financial development allows tangible assets to be pledged as collateral with a smaller markdown, it may strengthen the "collateral channel" and heighten the reliance of cash reserves on asset tangibility.[17]

One the other hand, however, the rapid growth of financial intermediaries increases the pledgeability of intangible assets such as intellectual property, or even goodwill and reputation of borrowers, and thus could effectively lessen the marginal impact of asset tangibility on cash balances. Given the rising importance of intangible assets as a percentage of the market capitalization of U.S. firms, there has been growing attention to the innovations of financial market that facilitate the use of intangible assets as security to lenders, thereby allowing firms, particularly R&D intensive ones, to tap additional sources of funding and lower precautionary cash reserves. Specifically, Loumioti (2014) finds that, during 1996 to 2005, about a quarter of U.S. originated secured syndicated loans have been collateralized by intangibles, and probably more importantly, the collateralization of intangibles has significantly increased near the end of the period. Therefore, the overall effect of financial development on corporate liquidity management remains a major question mark. Thus, we are motivated to study this important issue by conducting a cross-country analysis that exploits variations in countries' level of financial development.

It is also of great political importance to determine the effect of financial development on the reliance of cash holdings on tangibles. In the case that financial development

[17] Throughout the paper, we use the collateral channel to refer the link between the diminishing proportion of tangibles and the rising corporate savings as documented by Falato, Kadyrzhanova, and Sim (2014).

ultimately reinforces the role of tangibles as a leading determinant of cash holdings, financial development may particularly benefit tangible asset rich firms by facilitating their external finance. Firms with limited tangibles, however, are less likely to take advantage of this fortified "collateral channel" and hence have to resort more to their savings for future investment. Thus, policymakers would have to bear this potential repercussion of financial development as it strengthens the impact of tangibles-based financing in shaping corporate cash holdings. It would fail to alleviate financing frictions for innovative firms and essentially could be viewed as a sign of credit market imperfections since ideally lending should be based on expected cash flows.

On the contrary, an overall weakened role of tangibles by financial development, which facilitates the collateralization of intangibles and provides alternative financing sources, helps innovative firms partly overcome their collateral constraints in external finance and better allocate their excessive cash reserves with low productivity to physical and intellectual assets with high productivity. The flux of legal and financial reforms following the recent global economic crisis has further ignited interests in understanding how the quality of institutions affects the reliance of cash holdings on asset tangibility.

The importance of the collateral channel of tangibles in determining financial policies has been greatly emphasized by recent studies that mainly focus on U.S. firms (e.g., Almeida and Campello, 2007; Falato, Kadyrzhanova, and Sim, 2014). Falato, Kadyrzhanova, and Sim (2014), argue that the decline in asset tangibility shrinks firms' debt capability and hence boosts firms' precautionary demand for cash because conventionally only tangibles can be pledged as collateral. They further document theoretical and empirical evidence that a strong and negative sensitivity of cash holdings to tangibles helps explain the secular trend in corporate cash holdings over the last decades.[18] Our study bridges this line of inquiry with another growing strand of literature that examines how the development of a country's financial sector affects economic outcome at the firm level (e.g., Liberti and Mian, 2010; Beck, Lin and Ma, 2014). First, we show that, at a multi-country level, the cash-tangibility sensitivity is negative and statistically significant. Economically, our estimate suggests that increasing in one unit in tangibility, on average, leads to a decrease in cash holdings of 23% $(= e^{-0.260\times 1} - 1)$, all else equal. This result implies that technological advances, which increase the share of intangible capital in production, contribute substantially to the dramatic increase in cash holdings. This result also extends the key finding of Falato, Kadyrzhanova, and Sim (2014) to a global economy.

Second, we find that the cash-tangibility sensitivity is decreased by the ratio of private credit to gross domestic product, a leading proxy of financial development. Concretely, our results indicate that for a country with the median level of economic development, an interquartile range (IQR) increase in financial development leads to a 48% reduction in the cash-tangibility sensitivity. This provides strongly supportive evidence that the improvement in financial markets, which enable firms to pledge a variety of assets as collateral and broaden their financing sources, actually reduces the reliance of corporate cash holdings on tangibles. The result is also consistent with Liberti and Mian (2010), who show that financial development enhances the debt capacity of firms by lessening the reliance on the

[18] Falato, Kadyrzhanova and Sim (2014) show that a one standard deviation decrease in tangible capital is associated with about 8.5% increase in the cash ratio, which is equal to about half the mean value of the cash ratio (15%) in their sample.

conventional collateral-based lending. The eased borrowing constraints consequently moderate the precautionary motive to hoard cash.

Third, having shown that financial development attenuates the cash-tangibility sensitivity, we next turn to further explore the role of legal and information environment that promotes a country's financial market development. Djankov, McLiesh, and Shleifer (2007) conduct a cross-country study and find that the degree of a country's financial development is positively related to strong creditor rights and availability of information about borrowers to creditors. Haselmann, Pistor, and Vig (2010) show that strong creditor protection spurs credit market development. A stream of studies on corporate disclosure quality further suggests that detailed disclosures decrease creditors' perception of default risk for the disclosing firm, reducing its cost of debt (Sengupta, 1998). In addition, Francis, Khurana, and Pereira (2005) find cross-country evidence that a higher disclosure level lowers cost external financing by mitigating information asymmetry. A closely related strand of literature on creditor information sharing also suggests that information availability regarding borrowers' creditworthiness improves credit availability (Pagano and Jappelli, 1993; Padilla and Pagano, 2000), lowers the cost of borrowing (Brown, Jappelli and Pagano, 2009), motivates loan repayments (Brown and Zehnder, 2007), and reduces default rates (Jappelli and Pagano, 2002).

We broaden this body of literature by showing that, strong creditor rights and accounting standards incrementally weaken the impact of asset tangibility on cash balances. These findings provide strong confirmatory evidence for our main result that financial development, partly driven by effective legal institutions and great information availability, loosens the grip of tangibility on cash reserves. The results are also consistent with the seminal work of (La Porta, Lopez-de-Silanes, Shleifer, and Vishny, 1997, 1998, hereafter LLSV), who demonstrate the important connections between creditor protections, information about borrowers, and the development of financial markets. Moreover, our split-sample estimates suggest that 1) creditor rights weaken the cash-tangibility sensitivity more in countries with a high level of legal enforceability of contracts that better protects the rights of creditors in reorganizations and defaults; and 2) young, high-growth opportunities, and high R&D intensity firms, which arguably suffer most from asymmetric information and hence more costly external financing, benefit more from the improvement in accounting standards.

Fourth, we relate the cash-tangibility sensitivity differential between high and low risk borrowers to improvements in the quality of institutions. Liberti and Mian (2010) define the collateral spread as the difference in collateralization rates between high and low risk borrowers. A large spread implies that, compared with financially sounded borrowers, risky ones need to pledge more assets as collateral to obtain the same amount of loans. They find that the spread declines rapidly with improvements in financial development, which allow risky firms to access credit by pledging a lower amount of collateral. In our study, the cash-tangibility sensitivity can be interpreted as the collateral cost of liquidity. For instance, a sensitivity of -0.26 (the baseline result shown in Table 3.2, column (3)) suggests that a unit increase in tangibles can lower the precautionary liquidity demand of the firm by reducing the optimal cash holdings of about 23%. We find that the differential cash-tangibility sensitivity between high and low risk borrowers is positive. This suggests that, compared with a creditworthy borrower, a riskier firm has to deposit significantly more tangibles to secure external finance so that its liquidity demand can be lowered by the same amount. Put it differently, the value of a less creditworthy firm's tangible assets is more heavily discounted by external liquidity providers, which is in line with Berger and Udell (1990). More importantly, we demonstrate that the cash-tangibility sensitivity differential declines with improvements in the quality of institutions. This result highlights the role of financial development in closing the wedge in the collateral cost of capital between high- and low-risk borrowers and complements the findings of Liberti and Mian (2010).

Last, based on the methodology developed in Rajan and Zingales (1998), we find that industries that are naturally heavy users of external finance grow faster in economies with better developed financial systems consistent with Rajan and Zingales (1998), and industries that have low tangible assets grow faster in economies with better developed financial systems. This finding implies that firms operating in industries such as high-tech industries with fewer tangible assets as collateral actually benefit more from financial development. We further provide firm-level evidence that, on average, firms that operate in external finance dependent industries or low asset tangibility industries perform better (in terms of return on assets (ROA) and return on sales (ROS)) in economies with better developed financial systems.

Taken together, our results highlight the important role of financial development in shaping cash policy through a collateral channel. We provide strong evidence that a high level of financial development substantially lowers the reliance of corporate cash holdings on tangibles, hence allowing more efficient allocation of capital from low productivity assets (cash) to high productivity assets (physical or intangible capital) within firms. Our findings are also robust to a battery of robustness tests, including instrumental variable analysis that control for the endogeneity of tangibility and financial development, employing alternative measures of cash, tangibility and financial development, and using weighted least squares regressions where each country receives equal weight in the estimation.

This paper makes three contributions. First, recent studies document strong evidence for the importance of financial development in lowering interest rates and contracting costs of financing (Qian and Strahan, 2007; Lerner and Schoar, 2005), easing collateral spreads (Liberti and Mian, 2010) and affecting technological innovation (Hsu, Tian, and Xu, 2014) and corporate tax evasion (Beck, Lin, and Ma, 2014). Our paper provides new insights into the real effects of financial development on corporate cash policy through asset tangibility. To the best of our knowledge, this study is the first to explore how financial development affects a firm's cash-tangibility sensitivity. Second, we provide strong evidence for the collateral channel, through which the composition of asset classes exerts a great impact on firm performance and financial policies (e.g., Falato, Kadyrzhanova and Sim, 2014; Gan, 2007). We extend this line of work and the cash holding literature (e.g., Bates, Kahle, and Stulz, 2009) by showing that asset tangibility is a key determinant of corporate cash holdings at a multi-country level and underscoring the important role of the quality of institutions in mitigating the precautionary motive for holding cash.[19] Last, this study contributes to the literature on the link between financial development and economic growth (Rajan and Zingales, 1998; Beck, Levine, and Loayza, 2000; Aghion, Hemous, and Kharroubi, 2014). We provide both industry- and firm-level evidence that industries with lower asset tangibility tend to grow faster (in terms of real value-added growth) in countries with better financial

[19] We also note that our study shows that financial development reduces the reliance of cash holdings on tangibles. Certainly, the development of a country's financial market does not overturn the negative cash-tangibility linkage (e.g., Falato, Kadyrzhanova, and Sim, 2014).

development, and firms operating in industries with low asset tangibility perform better in countries with developed financial systems. These findings imply that financial development may benefit firms with low asset tangibility by reducing the collateral role of tangibles and hence relaxing their financial constraints. This supports the view that better financial institutions enhance firms' economic resource allocation, and hence promote real investments, innovation, and eventually economic growth.

The rest of the paper proceeds as follows. Section 3.2 provides an illustrative example to further motivate our study. In Section 3.3, we describe the data and report summary statistics. Section 3.4 presents the results of our empirical analysis. We conclude in Section 3.5.

3.2 An illustration: The cash-tangibility sensitivity and the role of financial development

In this section, we further motivate our study by providing a simple illustration of the aforementioned two channels through which financial development could bear upon the cash-tangibility sensitivity. Suppose that a firm anticipates an investment need I in the next period (time 1). The investment is supported by the firm's current cash reserves C and its external financing capacity B at time 1. That is, $I = C + B$. The firm's total asset value A consists of tangibles, T and intangibles, $A - T$. The firm could potentially pledge both of its tangible and intangible assets as collateral for borrowing. The loan-to-value ratio of its tangibles is L_{Tang}. A close-to-one L_{Tang} reflects a low perceived credit risk associated with the firm's tangibles. Therefore, the market value of these assets is discounted less when these assets are used as collateral. The borrowing capacity of tangible assets is $T \times L_{Tang}$. Similarly, the borrowing capacity based on the firm's intangibles is $(A - T) \times L_{Intang}$, where L_{Intang} is the loan-to-value ratio of the firm's intangibles. Thus, the total borrowing capacity of the firm is $T \times L_{Tang} + (A - T) \times L_{Intang}$. Since physical capital generally receives a lower haircut, naturally, we assume that $L_{Tang} > L_{Intang}$. In the case where intangibles cannot be pledged as collateral, L_{Intang} takes a value of zero.

The firm's optimal cash holdings, C^*, is equal to $I - B$, which is $I - (L_{Tang} - L_{Intang}) \times T - A \times L_{Intang}$. The cash-tangibility sensitivity (i.e., $\partial C^*/\partial T$) is $-(L_{Tang} - L_{Intang})$, which is less than zero given $L_{Tang} > L_{Intang}$. Therefore, as a firm's asset tangibility declines, the firm would raise its cash holdings.

Institutions that promote financial development ease borrowing constraints by increasing L_{Tang} as tangibles receive a smaller haircut when being pledged as collateral. However, in the meanwhile, innovations in loan markets also raise L_{Intang} by enabling the use of intangibles as collateral because of enhanced protection of creditors' rights and reduced information asymmetry between borrowers and creditors. Therefore, the overall impact of financial development on the cash-tangibility sensitivity remains ambiguous and demands further empirical investigation.

3.3 Data and summary statistics

In this section, we describe the data used in our analysis and the construction of key variables. Appendix details variable definitions.

3.3.1 Data sources of the key variables

We draw firm-level data for U.S. and non-U.S. firms from the Compustat North America and Compustat Global Fundamentals Annual databases for the period 1990-2013.

We remove the following sets of firms from the sample: 1) financial firms (SIC code 6000-6999) and utility firms (SIC codes 4900-4999); 2) firms missing the 48 Fama-French industry dummies constructed by using the firm's four-digit SIC industry code; 3) firms for which cash and equivalents, asset tangibility, and/or total assets are missing; and 4) all firm-year observations with negative cash holdings, total assets and sales revenue, values for cash less than total assets, and values for the book value of total assets less than $5 million, inflation-adjusted in 2006 U.S. dollars. Finally, missing explanatory values reduce the panel to 294,520 firm-year observations covering 29,422 unique firms from 45 countries.

In this study, the dependent variable is the natural logarithm of the ratio of cash and equivalents divided by assets, where assets are the book value of total assets net of cash, following Dittmar, Mahrt-Smith, and Servaes (2003). Our primary proxy for the firm-level asset tangibility is computed as the expected liquidation values of firm assets in discontinued operations and asset fire sales, following Berger, Ofek, and Swary (1996) and Almeida and Campello (2007). This value represents the expected liquidation (resale) value of a firm's main categories of operating assets. Specifically, *Asset Tangibility* is defined as 0.715 × receivables + 0.547 × inventories + 0.535 × fixed capital, deflated by the book value of total assets net of cash. By construction, *Asset Tangibility* captures a firm's overall tangible capital composition.**[20]** For brevity, we include the construction of other control variables in the Appendix.

[20] One assumption of our baseline asset tangibility measure is that the weight for each component of operating assets applies to other countries. This baseline asset tangibility metric represents the expected liquidation (resale) value of a firm's operating assets, which are the key assets that creditors could seize in bankruptcy. The weight drops as the liquidity of collateral assets decreases. However, our baseline results continue to hold after using fixed assets as the asset tangibility measure, after controlling for net working capital as an independent variable.

3.3.2 Summary statistics

Table 3.1 presents country medians of key variables employed in our analysis. In column (2), we observe that Japan behind the U.S. has the second largest total firm-year observations and number of unique firms, while Venezuela has the smallest. There is a wide variation in the cash ratios as displayed in column (5). For instance, the median cash ratio of firms in Israel and Hong Kong is 19.9% and 17.8%, respectively; while that in New Zealand, Pakistan, and Peru has a value of only 3.1%, 4.0%, and 4.0%, respectively. In contrast, as shown in column (6), the median asset tangibility of firms in Israel and Hong Kong is relatively low (merely 47.3% and 42.2%, respectively); whereas the share of tangibles assets is 47.3%, 52.8% and 50.4% for firms in New Zealand, Pakistan, and Peru, respectively. Thus, the summary statistics hint a negative relation between cash holdings and asset tangibility in worldwide data.

[Table 3.1 about here]

Financial development is measured using the ratio of private credit to GDP (*Private credit to GDP*), which is the most commonly used measure of financial development in the existing literature (e.g., Rajan and Zingales, 1998). In Section 3.4.5.2, for robustness checks, we consider the financial intermediary development index that equals the sum of (standardized indices of) the ratio of liquid liabilities to the GDP and the total amount of credit by deposit money banks and other financial institutions going to the private sector over the GDP, from 1990 to 2011, following Khurana, Martin, and Pereira (2006).

Because financial development (institutional variables) tends to be positively correlated with general economic development, we use *GDP per capita* to control for the impact of factors related to economic development. We gather aggregate country-specific data on *Private credit to GDP* and *GDP per capita* from the World Bank's World Development Indicators (WDI) database. *GDP per capita* is converted to constant 2011 international dollars using purchasing power parity (PPP) rates.

The last two columns of Table 3.1 report the country median of private credit to GDP and real per capita GDP. In particular, the data reveal substantial variability in private credit creation and the wealth of nations. The median private credit over the period 1990–2013 ranges from 302.5% in Japan, 199.9% in the United States, and 162.8% in Switzerland to values below 30% as in Peru, Venezuela, and Argentina. Similarly, as our sample covers both developing and developed countries, the median gross national income level per capita varies from well above \$50,000 to as low as about \$3,000 per annum. The substantial cross-country variations in financial and economic development help us identify the role of financial development in sharing the reliance of cash holdings on asset tangibility.

3.4 Empirical analysis

3.4.1 Baseline results: Asset tangibility, financial development, and cash holdings

We conduct a cross-country analysis to study how asset tangibility and financial development shape corporate cash holdings. The baseline econometric model is as follows:

$$\begin{aligned} Cash_{i,t} = \alpha &+ \beta_1 Asset\ Tangibility_{i,t} \\ &+ \beta_2\, Asset\ Tangibility_{i,t} \times Finanical\ Development_{c,t} \\ &+ \beta_3\, Asset\ Tangibility_{i,t} \times log(GDP\ per\ capita)_{c,t} + \theta' X_{i,t} + \delta_c \\ &+ \eta_j + \phi_t + \varepsilon_{i,t}, \end{aligned} \tag{3.1}$$

where i, c, j and t denote firm, country, industry and year, respectively. *Cash* and *Asset Tangibility* are defined as in Section 3.3.1. *Financial Development* is measured by *Private credit to GDP*, a leading proxy for the development of financial intermediaries that captures the demand-side effect for collateralizable tangible assets in financial systems. As in Liberti and Mian (2010), we include the natural logarithm of income per capita (*log(GDP per capita*) as a control by interacting it with *Asset Tangibility* to capture other aspects of a country's economic growth other than financial development.[21] X is a vector of a constant term and other firm-level control variables that are similar to those used by Dittmar, Mahrt-Smith, and Servaes (2003), and Kalcheva and Lins (2007). Respectively, δ_c and η_j are the country and industry fixed effects, which absorb systematic differences in liquidity management across countries and industries. ϕ_t, the year effect, captures common macroeconomic shocks that might affect firms' cash decisions. Since we include country fixed effects, there is no need to control for country-specific variables.

The estimated coefficient on *Asset Tangibility* indicates the direct effect of tangibility on cash holdings, i.e., the collateral channel. Given the fact that generally only tangibles can be used as collateral to raise debt financing, firms that are rich in tangible capital would be less willing to hoard cash as a precaution. Therefore, we expect the marginal effect of *Asset Tangibility* on cash holdings to be negative (i.e., $\beta_1 < 0$). We are most interested in the estimate of β_2 , the coefficient of the interaction term *Asset Tangibility* × *Financial*

[21] To ease interpretation, we subtract the median from $\log(GDP\ per\ capita)$, so that the marginal effect (e.g., of $Asset\ Tangibility$) can be interpreted as its impact on a country with the median income level. This practice does not affect the statistical significance of coefficient estimates and our results fully sustain without this adjustment.

Development. A positive β_2 would partly offset the collateral channel and suggest that financial development could moderate a firm's precautionary motive of cash holdings by reducing the reliance of liquidity management on tangibles. Whereas, a negative β_2 would suggest that financial development further strengthens the cash-tangibility sensitivity by increasing the deployability of tangibles.

[Table 3.2 about here]

Table 3.2 reports the estimation results of equation (3.1) and its variations. As suggested by Petersen (2009) and Thompson (2011), standard errors are clustered at both the firm and year levels to obtain conservative statistical inference throughout our empirical analysis.[22] We begin our analysis by examining the impact of asset tangibility on cash holdings alone. Columns (1)-(3) report the estimation results of equation (3.1) without the two interaction terms. Column (1) shows the estimates using only U.S. firms. We observe that the coefficient estimate of *Asset Tangibility* (β_1) is negative and highly significant, which indicates that having high values of potential collateralizable tangibles substantially decreases corporate cash holdings. Economically, the estimate suggests that, ceteris paribus, one dollar's worth of tangible capital lowers cash balance by about 29%. It represents a 71% haircut that is subtracted from the liquidation value of tangibles when being pledged as collateral. Column (2) restricts to non-U.S. firms and, again, the estimate of β_1 remains negative and statistically significant at a 1% level. Compared with Column (1), the cash-tangibility sensitivity of foreign firms, however, is quantitatively smaller as the value of

[22] Following Bates, Kahle, and Stulz (2009), we use the double-clustered standard errors suggested by Petersen (2009), Moulton (1986) and Thompson (2011) to account for serial correlations of unobserved time and firm effects.

tangible assets is more heavily discounted in less development financial markets. Concretely, a one-dollar increase in tangibles can only release about 23% of cash reserves, representing a 77% haircut of its market value. These results imply that, across countries, foreign firms generally face higher collateral cost (a larger haircut). This might be partly attributed to the fact that with more sophisticated financial markets and better investor protection U.S. firms are under more stringent scrutiny and better monitoring by the financial sector. However, how financial development affects the cash-tangibility of a country's own firms still remains unclear. Column (3) shows the full sample result estimated with both U.S. and non-U.S. firms. Taken together, we find strong support to the importance of the collateral channel in determining cash policy, which support the findings of Falato, Kadyrzhanova, and Sim (2014). More importantly, we show the channel by demonstrating that the negative cash-tangibility sensitivity exists worldwide and its magnitude varies across countries.

Next, we turn to investigate the impact of financial development on the sensitivity of cash holdings to asset tangibility. Column (4) reports our baseline estimates of equation (3.1) with our full sample. We find that β_2 , the coefficient on the interaction of financial development with asset tangibility, is positive and statistically significant.[23] This indicates that the collateral role of tangible assets on cash holdings is weakened in countries with developed financial markets. In terms of economic significance, ceteris paribus, an

[23] Our results remain qualitatively unchanged when we use alternative definitions of the cash ratio, including cash to net assets, cash over sales, and cash to total assets, and when we replace asset tangibility by fixed assets or net tangibility, which is calculated as 0.715*Receivables plus 0.547*Inventories plus 0.535*Fixed Capital minus total current liabilities (LCT) and plus total debt in current liabilities (DLC), deflated by book assets net of cash.

interquartile range (IQR) increase in financial development leads to a 48% reduction in the cash-tangibility sensitivity.[24]

As robustness checks, column (5) shows that the results are also robust to instrumental variable estimation for private credit per GDP. Specifically, following Liberti and Mian (2010), we use legal origin, creditor rights, and information sharing as instruments for private credit per GDP. The instrumental variables pass underidentification, weak identification, and overidentification tests. Our IV estimation results remain broadly similar to our baseline results.

Column (6) shows that our main results are also robust to weighted least squares regressions where each country receives equal weight in the estimation (Dittmar, Mahrt-Smith, and Servaes, 2003; Khurana, Martin, and Pereira, 2006; Kyröläinen, Tan, Karjalainen, 2013).

To summarize, our baseline results provide strong evidence that, despite still being a key determinant of cash holdings, the overall impact of tangibility on corporate cash holdings is substantially lessened by the development of financial markets.

3.4.2 The quality of financial institutions: Creditor rights and accounting standards

Financial development is a multifaceted construct that is closely related to creditors' protection and the quality of financial reporting (the financial disclosure quality at the country level). For example, LLSV (1998) find that both creditor rights and information about

[24] The cash-tangibility sensitivity is equal to $\beta_1 + \beta_2 \times Finanical\ Development + \beta_3 \times log(GDP\ per\ capita)$. For a country with the median level of $log(GDP\ per\ capita)$, as $Finanical\ Development$ moves from its 1st quartile (0.496) to the 3rd (1.103), the sensitivity changes from -0.408 $(= -0.567 + 0.320 \times 0.496)$ to -0.214 $(= -0.567 + 0.320 \times 1.103)$, a 48% reduction in magnitude.

borrowers help promote capital market development. More specially, a strand of literature on creditor rights documents that strong creditor protection promotes financial market development (e.g., Djankov, McLiesh, and Shleifer, 2007; Haselmann, Pistor, and Vig, 2010).

Arguably, a well-functioning financial market is an outcome of the high quality of underlying institutions. To this extent, we employ two indices, namely *Creditor Rights* and *Accounting Standards*, to directly gauge the quality of a country's financial institutions, and anticipate to find both affect the cash-tangibility sensitivity. These two indices have been widely used in related studies as proxies for the quality of financial institutions (e.g., Rajan and Zingales, 1998; Fisman and Love, 2004; Liberti and Mian, 2010).

The index of creditor rights in bankruptcy, constructed by LLSV (1998), measures the ease with which creditors secure assets in the event of a borrower's default. *Accounting Standards* is an information disclosure intensity index created by examining and rating companies' 1995 annual reports on their inclusion or omission of 90 items. These items fall into seven categories: general information, income statements, balance sheets, funds flow statement, accounting standards, stock data, and special items. Accounting standards reflect the quality of information available to creditors and, therefore, the costs of monitoring and screening. High accounting standards help alleviate the costs of information asymmetries, and therefore promote more lending and weaken the role of tangible assets as collateral in lending.

3.4.2.1 Creditor rights and legal enforcement

Table 3.3, column (1), reports the regression estimates that evaluate the effect of creditor rights on the relationship between cash holdings and asset tangibility. The positive and significant estimate of the interaction term *Asset Tangibility* × *Creditor Rights* indicates that the cash-tangibility sensitivity is toned down in countries with effective institutional environment. This suggests that higher levels of creditor rights reduce the reliance of cash on tangibles.

In addition, we explore variations of legal enforceability across countries to further gauge the impact of creditor rights on the cash-tangibility sensitivity. LLSV (1998) document that the legal rules covering the protection of corporate shareholders and creditors and the quality of their enforcement vary considerably across countries. Bae and Goyal (2009) further call attention to the importance of contract enforceability and show that both the existence of strong creditor rights per se and their effective legal enforcement are important to bank lending. Motivated by their studies, we postulate that strong legal protection that better ensures creditors to repossess collateral would strongly facilitate the development of financial market. Thus, we expect the impact of *Creditor Rights* on the cash-tangibility sensitivity to be more pronounced (i.e., a larger estimate of β_2) in countries with strong legal enforcement.

To capture key aspects of a country's relevant legal environment, we use three proxies, namely, the duration of contract enforcement, legal formalism, and enforceability of contracts (See the Appendix for detailed description). We rank countries based on one of the enforcement proxies and partition the sample using the median of the proxy. This split sample analysis aims to differentiate the effect of legal enforcement.

Focusing on the coefficient of *Asset Tangibility* × *Creditor Rights*, we consistently find that a fundamental driver of financial development, creditors' rights, significantly weakens the underpin of cash on tangibility in countries with stronger enforceability (shown in even numbered columns (2), (4), and (6) as compared with corresponding odd numbered columns (3), (5), and (7)). The result confirms the idea that better institutions lower the reliance of cash holdings on tangibles as collateral by improving financial development in a country.

[Table 3.3 about here]

3.4.2.2 Information sharing and information asymmetry

In Table 3.4, we explore the effect of accounting standards as an institutional measure of financial development on the cash-tangibility sensitivity, and whether the effect varies with the opacity of a company.

Column (1) indicates that the estimated coefficient on *Asset Tangibility* × *Accounting Standards* is positive and significant. This suggests that accounting standards have a significant attenuating impact on the negative link between cash and tangibility. The finding confirms our earlier prediction that better institutions lower the importance of tangible assets and hence reduce a firm's financial constraint.

Next, we turn to find further evidence in support of our finding that better accounting standards lessen the cash-tangibility sensitivity. Creditors typically demand tangible assets as collateral to reduce their high risk exposure to relatively young and unfamiliar firms. Particularly, lenders can obtain useful information about a borrower by evaluating the quality and nature of the collateral (Picker, 1992) and assess repayment prospects. However, having an access to firm-specific information via improved institutional mechanisms decreases the importance of this information role of tangibles. For instance, creditors could consider other forms of intangible collateral or even provide unsecured loans based on borrowers' credit history and reputation. As a result, we anticipate that the benefit of better accounting standards or financial disclosures in general would be more significant in the presence of a high degree of information asymmetry between outside lenders and a firm.

To further investigate how the effect of accounting standards on the cash-tangibility sensitivity varies with the opacity of a firm, we carry out a subsample analysis and report the results in columns (2)-(7). Specifically, in every year for a country, we separate firms according to the median of firm age, growth opportunities measured by Tobin's *Q*, or firm's R&D intensity proxied by R&D expenditures divided by sales.

Throughout all subsamples, we find that the coefficient estimate of *Asset Tangibility* × *Accounting Standards* is persistently greater and statistically more significant among firms with a higher degree of information asymmetry (i.e., younger, with higher Tobin's *Q*, or R&D intensity shown in even numbered columns). This finding suggests that better accountings standards bring down the pressure of extra cash savings for opaque firms, which generally have a limited amount of tangible capital.

[Table 3.4 about here]

Taken together, these results presented in this section broadly confirm our main findings presented in Section 3.4.1, that better institutions weaken the role of tangible assets in determining corporate cash holdings.

3.4.3 Firm default risk, the sensitivity differential, and financial development

Thus far, we find strong evidence of negative cash-tangibility sensitivity. We also find that financial development, along with better institutions, limits the reliance of cash holdings on tangibles. In this section, we study the cash-tangibility sensitivity differential between high- and low-risk borrowers to shed more light on our main results.

The collateral cost of tangible capital is much higher for riskier borrowers than credit-worthy borrowers. Specifically, Liberti and Mian (2010) find that on average a 1% increase in the probability of default increases the collateralization rate by 2.1%. As high risk borrowers' tangible assets are heavily discounted, they are expected to face lower cash-tangibility sensitivity.

We construct a dummy variable (*High Credit Risk*) that is equal to one if a firm's Altman's (1968) *Z*-score is below the median value in each country and in each year, and zero otherwise.[25] Then, we interact *High Credit Risk* with *Asset Tangibility* to assess the cash-tangibility sensitivity differential and report the full sample estimates in Table 3.5, column (1). The sensitivity of the baseline group (firms with low credit risk) is -0.897, which suggests that one unit of tangibles can reduce cash holdings by 59% (a 41% markdown). However, for risky borrowers, the sensitivity is lowered by about two third to -0.301 ($= -0.897 + 0.596$). This implies that the value of tangibles held by less credit-worthy firms receives a 74% markdown by external liquidity providers. Thus, a sensitivity differential of 0.596, indicated by the estimated coefficient of *Asset Tangibility* × *High Credit Risk*, shows a sizable wedge in collateralization rates between high- and low-risk borrowers and essentially can be interpreted as the extra collateral cost of liquidity for riskier firms.

We are particularly interested in examining how the development of financial markets affects this sensitivity differential. Every year, we partition our whole sample into two based

[25] We find similar results by using Ohlson's (1980) *O*-score or the measure proposed by Zmijewski's (1984) as the distress proxy.

on the median level of financial development (proxied by *Private Credit per GDP*), or one of the two measures of institution quality, *Creditor Rights* and *Accounting Standards*. The subsample regression results are shown in Table 3.5, columns 2-7. We find that the sensitivity differential declines remarkably with improvements in a country's financial markets. For example, column (2) shows that the differential is 0.715 among countries with their *Private Credit per GDP* falls below the global median. The differential is cut to three-quarters (0.535 shown in column (3)) for countries with more developed financial markets. Consistently, we also find that the sensitivity differentials are much smaller in economies with stronger creditor rights (column (5) vs. (4)) and better accounting standards (column (7) vs. (6)).

[Table 3.5 about here]

To summarize, the finding in this subsection accentuates the role of financial development in closing the wedge in the collateral cost of liquidity between high- and low-risk borrowers and complements the findings of Liberti and Mian (2010).

3.4.4 Industry growth, industry asset tangibility, and financial development

In this subsection, using a similar methodology developed in Rajan and Zingales (1998) and later used in Braun and Larrain (2005), we study the differential impact of financial market development on the real value-added growth rate in industries that depend on external finance to different extents and have different degrees of asset tangibility. We expect that better developed financial markets should lead to greater growth in industries that 1) rely more on external finance, which is shown by Rajan and Zingales (1998), and 2) have less tangible assets to use as collateral, which reflects our earlier findings that financial development weakens the cash-tangibility sensitivity and hence the reliance of cash on tangible assets.

The model we estimate is as follows:

$$Growth_{i,c,t} = \beta_0 + \beta_1 Initial\ Share_{i,c} + \beta_2 Dependence_i \times FD_{c,t} + \beta_3 Tang_i \times FD_{c,t} + \beta_4 Dependence_i \times ED_{c,t} + \beta_5 Tang_i \times ED_{c,t} + \eta_i + \eta_c + \eta_t + \varepsilon_{i,c,t}, \quad (3.2)$$

where the dependent variable, $Growth_{i,c,t}$, is the annual real value-added growth rate in industry *i*, country *c*, and year *t*. $Initial\ Share_{i,c}$ denotes the industry *i*'s initial share of total value-added in manufacturing in country *c*. $Dependence_i$ is external finance dependence, which is calculated as the fraction of capital expenditures not financed with internal funds for U.S. firms in the industry *i* between 1990-2010, similar to Rajan and Zingales (1998). $FD_{c,t}$ is an indicator of financial development for country *i* in year *t* and is measured by the domestic credit provided to the private sector as a percent of GDP. $Tang_i$ denotes asset tangibility for U.S. firms in the industry *i* between 1990-2010, according to Berger, Ofek, and Swary (1996). $ED_{c,t}$ is an indicator of economic development for country *i* in year *t* and is measured by the natural logarithm of country real gross domestic product per capita in constant 2011 international dollars, PPP adjusted. η_i, η_c and η_t denotes the dummies for industry *i*, country *c* and year *t*, respectively. Our sample includes 55 ISIC industries at the three-digit level. The sample period is 1990-2010. The value-added data are from the UNIDO Industrial Statistics Database (INDSTAT4) at the 3- and 4-digit level of the International Standard Industrial Classification of All Economic Activities (ISIC) Revision 3 pertaining to the manufacturing sector. The standard errors are clustered by country.

The results are reported in Table 3.6. Column (1) confirms the key findings in Rajan and Zingales (1998) that external finance dependent industries grow faster in countries with more-developed financial markets, as indicated by the positive and significant interaction term *Dependence* × *FD*. The result is qualitatively similar after controlling the effect of a country's overall level of economic development through the interaction term *Dependence* × *ED*, as shown in column (2). Column (3) shows that industries with more tangible assets grow slower than industries with fewer tangible assets as collateral in economies with better developed financial systems, implying that industries with very limited tangible assets or high levels of intangible assets benefit from financial development. This can be seen from the negative and significant coefficient on the interaction term *Tang* × *FD*. Again, after controlling for the impact of economic development in column (4), the coefficient on this term is still negative, significant, and economically large.

As robustness checks, we re-estimate columns (3) and (4) by replacing asset tangibility with fixed assets. *Fixed Assets* is defined as the ratio of Property, Plant and Equipment (Compustat item PPENT) to total assets and it is a commonly used measure of asset tangibility in the finance literature (e.g., Campello and Giambona, 2013). We obtain similar results as with our primary measure of asset tangibility.

[Table 3.6 about here]

Next, in Table 3.7, we further provide firm-level evidence that firms that operate in industries that are naturally heavy users of external finance perform better in economies with better developed financial systems as shown in column (1), and firms that operate in industries with high asset tangibility perform worse than those that operate in industries with low asset tangibility in economies with better developed financial systems as shown in the remaining columns. Firm performance is measured by return on assets (ROA) and return on sales (ROS), and we use our primary measure of asset tangibility in columns (2) and (5) and fixed assets as an alternative one in columns (3) and (6).

[Table 3.7 about here]

Overall, in this subsection, we show industry- and firm-level evidence that firms operate in industries with low asset tangibility greatly benefit from financial development. These results echo our earlier findings that financial development relaxes liquidity constraints of firms such as start-up firms and high-tech firms with limited hard assets or liquid assets as collateral, and hence stimulate investments and growth.

3.4.5 Robustness checks

3.4.5.1 An instrumental analysis

While we control for full sets of country, industry, and year fixed effects throughout our analysis, we further conduct an instrumental variable regression to further alleviate the endogeneity concern of asset tangibility in determining cash holdings.[26]

We adopt manufacture structure (machinery and equipment) and labor configuration as our instruments for asset tangibility because they are correlated with a firm's tangibility. Following Schlingemann, Stulz, and Walkling (2002) and Campello and Giambona (2013), the first instrument for asset tangibility, *IndustryResale*, is a proxy for the liquidity of machinery and equipment in the industry in which a firm operates. It is calculated as the

[26] Similar to Table 3.2, legal origin (Djankov, McLiesh, and Shleifer, 2007), creditor rights, and information sharing are adopted as instruments for private credit to GDP, following Liberti and Mian (2010).

Fama-French's (1997) 48-industry-year median ratios of sales of PP&E to the sum of sales of PP&E and capital expenditures in each country.

The second instrument, *IndustryLabo*r, used by Garmaise (2008) and Campello and Giambona (2013), is defined as the Fama-French's (1997) 48-industry-year median ratios of the number of employees scaled by total assets as an additional instrument for fixed capital and captures variation that is not part of the individual firm's policy set. A firm's tangibility is closely related to industry production factors (e.g., machinery & equipment and labor). However, those average industry inputs are unlikely to directly affect an individual firm's cash reserves.

Table 3.8 reports estimates from instrumental variables (IV) regression exploring how the cash holding sensitivities to asset tangibility vary with financial development. The results show that our baseline regression results (Table 3.2, column 4, Table 3.3, column 1, and Table 3.4, column 1) presented in Sections 3.4.1 and 3.4.2 are fully retained. After controlling for potential endogeneity, the negative effect of financial development on the cash-tangibility sensitivity remains highly significant as shown in column (1). Columns (2) and (3) provide further confirmatory evidence that institutions that promote creditor rights and accounting standards ease the reliance of cash on tangibles.

[Table 3.8 about here]

The validity of the chosen IVs is closely examined. In order for a variable to qualify as a valid instrument, it must be both relevant (highly correlated with the endogenous explanatory variable) and exogenous (uncorrelated with the regression residuals). The relevance of instruments is confirmed by unreported first-stage regressions: both *IndustryResale* and *IndustryLabor* are statistically significantly related to asset tangibility, and further confirmed by the Angrist-Pischke's weak identification test. We also conduct Hansen's *J* overidentification test, which has a joint null hypothesis of valid IVs (relevance and exogeneity). The validity of IVs is substantiated by the fact that we cannot reject the null hypothesis at a conventional level of significance.

To summarize, after correcting the potential bias caused by the endogeneity of asset tangibility, our results are in line with the previous findings that the improvement of a country's financial market substantially weakens the linkage between cash holdings and asset tangibility.

3.4.5.2 Additional tests

In this subsection, we performance additional robustness tests to verify our key results presented thus far. The results are reported in Table 3.9.

In column (1), to measure the overall level of the financial intermediary development, we construct *FININT*, which is an index that equals the sum of (standardized indices of) the ratio of liquid liabilities to the GDP and the total amount of credit by deposit money banks and other financial institutions going to the private sector over the GDP, following Khurana, Martin, and Pereira (2006).[27] We find a positive and significant coefficient on *Asset Tangibility* × *FININT*. This suggests that the development of financial intermediaries contributes greatly to the easing of financing constraints due to limited tangible collaterals.

In column (2), we use *Financial Disclosure* as an alternative institutional measure of financial development. It captures the quality of a company's financial information available

[27] The two indices used to construct *FININT* are provided by Beck, Demirgüç-Kunt, and Levine (2010). Please refer to the appendix for variable definitions.

to outside investors, and is defined as an average ranking of the prevalence of disclosures concerning research and development expenses, capital expenditures, product and geographic segment data, subsidiary information, and accounting methods and policies. These disclosures are proprietary in nature and useful to creditors for evaluating borrowing firms' risks and creating loan contracts. The positive and significant coefficient on *Asset Tangibility* × *Financial Disclosure* indicates that better financial disclosures help creditors assess the creditworthiness of loan applicants. Therefore, this reduces the role of tangible collateral in reducing information asymmetry in loan contracting, and hence promotes non-collateral based lending and decreases the cash-tangibility sensitivity.

Columns (3) and (4) show the results using weighted least squares (WLS) estimates. The weights are the inverse of the number of observations for each country so that each country receives equal weight in the estimation. The results are very similar to those in columns (1) and (2).

Finally, columns (5) and (6) show that our baseline results in column (4) of Table 3.2 are robust to using cash and equivalents divided by sales as an alternative measure of the dependent variable. Estimates in columns (7) and (8) also show that financial development reduces not only the cash-tangibility sensitivity but also the excess-cash-tangibility sensitivity.[28]

[Table 3.9 about here]

[28] A firm's excess cash is calculated according to Opler, Pinkowitz, Stulz, Williamson (1999) and Dittmar and Mahrt-Smith (2007). A firm may hold excess cash because the management seeks for optionality and financial flexibility to remain independent from the capital markets when making investment policies.

Collectively, the additional analyses carried out in this subsection strongly indicate the robustness of our finding that financial development improves availability of liquidity and hence reduces the impact of tangibles on corporate cash policy.[29]

3.5 Conclusions

Our paper conducts a cross-country study to investigate the impact of asset tangibility on cash holdings and explore how the development of a country's financial market influences this important relationship. Using data on 45 countries over the period of 1990-2013, we find a negative relationship between cash holdings and asset tangibility at a multi-country level. Furthermore, we provide strong evidence that financial development subdues the cash-tangibility sensitivity and the sensitivity differential between firms with high vs. low credit risk.

Our results indicate that tangible capital plays an important role in determining corporate cash policy. We extend the main finding of Falato, Kadyrzhanova, and Sim (2014) to the global economy. We also reveal that improvements in financial market, which broaden asset pledgeability and expand alternative financing sources, reduce the reliance of corporate cash holdings on tangibles, and close the gap in the collateral cost of liquidity between high- and low-risk borrowers.

Liberti and Mian (2010) employ data on loans issued by a multinational bank and show that institutions that promote financial development ease borrowing constraints. From firms' perspective, our paper suggests that financial development contributes to economic growth

[29] In untabulated results, we show that our main results hold with country-level regressions where we run panel regressions of the country mean or median value of cash on the country-level mean or median value of asset tangibility and firm characteristics.

by lessening the reliance of cash holdings on tangibles and facilitating financial intermediaries to allocate resources more efficiently to, for instance, innovative firms that generally have less tangible capital. Therefore, this paper sheds new light on the implications of financial development and institutional environment on corporate liquidity management. Our results also furnish firm-level evidence that financial development contributes to economic growth by allowing more efficient corporate liquidity allocation.

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Appendix 3.A: Variable Definitions

This table provides the definition of variables used in the study and data sources.

Variable	**Definitions with corresponding Compustat item names**
Firm-level variables	
Ln(cash/assets)	The natural logarithm of the ratio of cash plus marketable securities (CHE) divided by assets. Assets are the book value of total assets (AT) net of cash (CHE).
Asset tangibility	Following Berger et al. (1996), asset tangibility is defined as 0.715*receivables (RECT) + 0.547* inventories (INVT) + 0.535*fixed capital (PPENT), deflated by book value of total assets (AT) net of cash (CHE).
Fixed assets	The net property, plant and equipment (PPENT) deflated by book value of total assets (AT) net of cash (CHE).
Cash flow	Cash flow is defined as operating income before depreciation (OIBDP), less interest and related expense (XINT), income taxes (TXT), and dividends (DVC), divided by book value of total assets (AT) net of cash (CHE) over year *t*.
Market-to-book	The ratio of market value of assets to book value of total assets (AT) net of cash (CHE). The market value of assets is equal to the market value of common equity (fiscal year end price (PRCC_F) times shares outstanding (CSHO), plus total assets (AT) minus book value of common equity (CEQ). Market value of equity for firms in Compustat Global database is calculated using December closing price (PRCCD) multiplied by the total number of common shares outstanding for the issue (CSHOC). If the current figure for common shares outstanding as of the company's fiscal year-end is missing, the previous year's value is used.
Log of real assets	The natural logarithm of book value of total assets (AT) net of cash (CHE) in millions of 2006 U.S. dollars.
Total capital expenditures	The ratio of capital expenditures (CAPX) to the book value of total assets (AT) net of cash (CHE). The capital expenditure from the statement of cash flows is often missing. Following Dittmar and Mahrt-Smith (2007), we impute any missing CAPX from the change in net fixed assets plus depreciation and amortization over the year. CAPX is replaced by zero if it is negative.
Total book leverage	The ratio of long-term debt (DLTT) plus debt in current liabilities (DLC) to total assets (AT) net of cash (CHE).
R&D expenditures	The ratio of R&D expenditure (XRD) to sales (SALE). If R&D expenditure is missing, we follow the tradition to set the missing value to zero, over year *t*.

High credit risk	A dummy variable equal to one if the firm's Altman's (1968) Z-score is below the median value in each country and in each year, and zero otherwise. Altman's Z-score is calculated as (3.3*EBIT (OIBDP) + 1.0*Sales(SALE) + 1.4*Retained Earnings (RE) + 1.2*Working Capital(WCAP))/Total assets (AT) + 0.6*PRCC_F*CSHO/(DLTT + DLC).
Assets in place	The ratio of inventories (INVT) plus gross plant and equipment (PPEGT) to assets (AT).
Dividend dummy	A dummy variable equal to one in years in which a firm pays a common dividend (DVC). Otherwise, the dummy equals zero.
Ln (firm age)	The natural logarithm of the number of years since the firm first appeared on Compustat Global or North America database.
Industry-level variables	
Growth	The annual real value-added growth rate for each three-digit level ISIC industry in each country and year. Authors' calculations using data from UNIDO Industrial Statistics Database (INDSTAT4) Revision 3.
Initial share	The three-digit level ISIC industry's initial share of total value-added in manufacturing in each country. Authors' calculations using data from UNIDO Industrial Statistics Database (INDSTAT4) Revision 3.
Dependence	External finance dependence, which is calculated as the fraction of capital expenditures not financed by cash flow from operations for U.S. firms in each three-digit level ISIC industry between 1990-2010, similar to Rajan and Zingales (1998). Authors' calculations using data from Compustat North America database.
Country-level variables	
Private credit per GDP	The domestic credit provided to the private sector as a percent of GDP from 1990 to 2013. Data source: World Bank's World Development Indicators (WDI) database.
Ln(GDP per capita)	The natural logarithm of country real gross domestic product per capita in constant 2011 international dollars, PPP adjusted, for the years 1990-2013. Data source: World Bank's World Development Indicators (WDI) database.
Creditor rights	An index aggregating four powers of secured lenders in bankruptcy. A score of one is added to the index when a country's laws and regulations provide each of these powers to secured creditors to arrive at the aggregate creditor rights index: (1) whether there are restrictions imposed, such as creditors' consent, when a debtor files for reorganization (restrictions on reorganization); (2) whether secured creditors have the ability to seize collateral after the petition for reorganization is approved (no automatic stay or asset freeze); (3) whether secured creditors are ranked first in the distribution of proceeds of liquidating a bankrupt firm as opposed to other creditors such as employees or

	government (secured creditor paid first); and (4) whether an administrator, rather than the incumbent management, is in control of property pending and responsible for running the business during the reorganization (no management stay). The aggregate creditor rights index ranges from zero to four, with higher values indicating stronger creditor rights. The index measures the ease with which creditors can secure the assets in the event of bankruptcy, and ranges between zero and four as of 2002. Data source: LLSV (1998), and Djankov, McLeish, and Shleifer (2007).
Accounting standards	A disclosure intensity index created by examining and rating companies' 1995 annual reports on their inclusion or omission of 90 items. These items fall into seven categories: general information, income statements, balance sheets, funds flow statement, accounting standards, stock data, and special items. A minimum of 3 companies in each country were studied. Data source: International Accounting and Auditing Trends, Center for Financial Analysis and Research (CIFAR).
Information sharing	A time-varying indicator variable equals one if either a public registry or a private bureau operates in the country, zero otherwise. Information sharing among creditors about clients' past (and possible subsequent) indebtedness helps alleviate the costs of information asymmetries, and therefore facilitate lending decisions and promote more lending. Data source: Djankov, McLiesh and Shleifer (2007).
Duration of enforcement	The number of days it takes to resolve a dispute counted from the moment the plaintiff files the lawsuit in court until payment is made. This includes both the days when actions take place and the waiting periods between. Data source: World Bank's World Development Indicators (WDI) database.
Legal formalism	An index of formalism in check collection. Based on extensive surveys of lawyers and judges, DLLS (2003) construct measures on how courts handle two types of cases: collection of a bounced check and eviction of a (nonpaying) tenant. A higher score in either category implies that the court system is slower (more bureaucracy) and less efficient. Although these measures are highly positively correlated across countries, I use the check-based formalism index because the process of collecting a check boils down to enforcement of a financial contract. The index measures substantive and procedural statutory intervention in judicial cases at lower-level civil trial courts, and equals the sum of the following categories (each takes on the value of one or zero): (1) professionals vs. laymen; (2) written vs. oral elements; (3) legal justification; (4) statutory regulation of evidence; (5) control of superior review; (6) engagement formalities; and (7) independent procedural actions. The index measures legal enforcement costs DLLS (2003). The more legal formalism, the higher enforcement costs in the courts. Data source: Survey of Lex Mundi/Lex Africa association of law firms.
Enforceability of contracts	An index ranging from zero to ten with higher scores indicating higher enforceability representing "The relative degree to which contractual agreements are honored and complications presented by language and

	mentality differences." Exact definition in Knack and Keefer (1995). Data source: Business Environmental Risk Intelligence; DLLS (2003).
FININT	The financial intermediary development index that equals the sum of (standardized indices of) the ratio of liquid liabilities to the GDP and the total amount of credit by deposit money banks and other financial institutions going to the private sector over the GDP, from 1990 to 2011, following Khurana, Martin, and Pereira (2006). Liquid liabilities of the financial system measured by currency plus demand and interest-bearing liabilities of banks and non-bank financial intermediaries, divided by GDP. It is a measure of financial depth. Data source: Beck, Demirgüç-Kunt, and Levine (2010).
Financial disclosure	Average ranking of the prevalence of disclosures concerning research and development (R&D) expenses, capital expenditures, product and geographic segment data, subsidiary information, and accounting methods and policies. These disclosures are proprietary in nature and useful to creditors for evaluating borrowing firms' risks and creating loan contracts. Data source: Bushman, Piotroski, and Smith (2004) using data contained in CIFAR.

Table 3.1
Summary Statistics

This table presents country medians of firm-specific characteristics (except for No. of Firm-Years, No. of Unique Firms, and No. of Firms). The firm-level data for U.S. and non-U.S. firms are drawn from the Compustat North America and Compustat Global Fundamentals Annual databases for the period 1990-2013. The following sets of firms are removed from the sample: 1) financial firms (SIC code 6000-6999) and utility firms (SIC codes 4900-4999); 2) firms missing the 48 Fama-French industry dummies constructed by using the firm's four-digit SIC industry code; 3) firms for which cash and equivalents, asset tangibility, and/or total assets are missing; and 4) all firm-year observations with negative cash holdings, total assets and sales revenue, values for cash less than total assets, and values for the book value of total assets less than $5 million, inflation-adjusted in 2006 U.S. dollars. Finally, missing explanatory values reduce the panel to 294,520 firm-year observations covering 29,422 unique firms from 45 countries. The definitions of all variables are provided in Appendix.

Country	No. of Firm-Years	No. of Unique Firms	Mean No. of Firms Per Year	Cash Equivalents/ Net Assets (%)	Asset Tangibility (%)	Private Credit/GDP (%)	Real GDP per Capita (constant 2011 international $)
Argentina	480	53	25	5.9	50.7	28.8	10,011
Australia	11,815	1,464	473	10.4	45.1	96.3	35,913
Austria	1,175	109	51	9.5	47.3	123.2	39,145
Belgium	1,454	129	58	8.6	48.7	113.5	37,828
Brazil	2,356	283	118	11.4	45.6	86.5	11,070
Canada	9,133	1,236	304	7.9	49.5	116.0	37,861
Chile	1,143	118	60	5.0	49.0	79.1	15,009
Colombia	221	26	13	5.9	36.1	41.1	8,692
Denmark	1,807	161	46	9.3	50.8	149.9	41,916
Egypt	486	83	29	12.5	50.2	83.9	7,988
Finland	1,895	145	68	9.0	46.0	76.7	35,580
France	8,848	821	268	11.3	46.6	102.2	35,265
Germany	9,343	820	275	9.7	45.4	127.2	37,312
Greece	2,285	226	120	5.2	52.8	91.9	25,010
Hong Kong, China	1,837	135	73	17.8	42.2	141.1	34,201
India	12,294	1,698	559	4.1	49.1	54.3	2,656
Indonesia	3,587	323	156	8.0	49.9	47.1	6,077
Ireland	903	83	38	11.0	48.4	105.6	43,273
Israel	1,446	225	85	19.9	47.3	78.0	24,908
Italy	3,036	277	117	8.3	48.7	96.3	35,126
Japan	42,332	3,534	1,693	15.9	48.2	302.5	32,319
Jordan	323	69	19	4.3	50.2	90.0	8,031
Korea, Rep.	9,391	1,240	348	12.3	47.3	123.4	22,272
Malaysia	11,127	932	397	9.2	51.9	127.8	15,849
Mexico	1,340	114	58	6.7	48.0	36.1	14,340
Netherlands	2,458	210	107	6.9	48.7	144.3	41,809
New Zealand	870	107	44	3.1	47.3	109.6	28,702
Norway	1,195	149	36	13.5	48.7	68.2	59,232
Pakistan	1,949	197	89	4.0	52.8	47.8	3,385
Peru	638	66	32	4.0	50.4	19.0	6,622
Philippines	1,305	129	59	7.7	44.1	51.4	4,307
Poland	2,593	332	74	6.0	51.6	37.2	14,842
Portugal	749	67	36	3.9	43.6	135.6	26,146
Singapore	6,941	642	267	16.9	51.7	72.6	51,378
South Africa	3,028	302	132	10.7	50.1	159.9	10,289
Spain	1,821	160	40	6.6	48.8	118.2	31,585
Sri Lanka	964	134	48	4.6	52.5	40.8	5,030
Sweden	4,035	414	139	10.7	42.7	116.4	37,616
Switzerland	3,101	238	129	13.4	49.3	162.8	49,130
Thailand	5,557	465	232	6.1	51.0	131.2	9,571
Turkey	1,531	173	55	7.3	51.4	42.1	13,016
United Kingdom	20,625	2,072	458	9.4	48.5	133.0	33,618
United States	93,859	9,017	3,754	10.6	44.9	199.9	46,177
Venezuela	153	16	9	6.0	49.5	20.1	15,497
Vietnam	1,091	228	136	9.8	48.3	48.0	2,849

Table 3.2
Baseline Results: Financial Development and the Cash-Tangibility Sensitivity

This table reports estimates from cross-country regression exploring how the cash holding sensitivities to asset tangibility vary with financial development. In all variables, assets are the book value of total assets net of cash. The dependent variable is the natural logarithm of the ratio of cash and equivalents divided by assets. *Asset Tangibility* is defined as the ratio of 0.715*Receivables plus 0.547*Inventories plus 0.535* Fixed Capital to Assets, according to Berger, Ofek, and Swary (1996). *Private Credit per GDP* is the domestic credit provided to the private sector as a percent of GDP from 1990 to 2013. Columns (1) through (4) report OLS estimates. Columns (1) and (2) show regression estimates using only U.S. firms and non-U.S. firms, respectively. The remaining columns show regression estimates using the entire sample. Column (5) reports instrumental variables (IV) estimates using Legal Origin (Djankov, McLiesh, and Shleifer, 2007), Creditor Rights, and Information Sharing as instruments for Private Credit to GDP, following Liberti and Mian (2010). Column (6) reports weighted least squares (WLS) estimates. The weights are the inverse of the number of observations for each country so that each country receives equal weight in the estimation. Values of *t*-statistics based on standard errors of the coefficients robust to heteroscedasticity are reported in parentheses. The standard errors also allow for correlations among different firms in the same year and different years in the same firm through clustering by firm and by year. Significance at the 1%, 5%, and 10% levels is represented by ***, **, and *, respectively. Details on the construction of all variables are provided in Appendix.

Dependent variable: Ln(Cash/Assets)	(1) OLS	(2) OLS	(3) OLS	(4) OLS	(5) IV	(6) WLS
Asset tangibility	-0.337***	-0.265***	-0.260***	-0.567***	-0.737***	-0.505***
	(-2.74)	(-2.62)	(-3.30)	(-5.00)	(-5.09)	(-15.36)
Asset tangibility × Private credit per GDP				0.320***	0.519***	0.255***
				(3.35)	(3.42)	(10.79)
Asset tangibility × Log of GDP per capita				-0.300***	-0.332***	-0.272***
				(-3.61)	(-4.09)	(-7.40)
Market to book	0.171***	0.123***	0.148***	0.149***	0.149***	0.142***
	(24.03)	(21.48)	(31.63)	(32.06)	(38.76)	(67.50)
Log of real assets	-0.150***	-0.086***	-0.102***	-0.103***	-0.103***	-0.096***
	(-13.95)	(-10.98)	(-16.61)	(-16.43)	(-26.41)	(-61.42)
Cash flow	-0.332***	-0.376***	-0.410***	-0.410***	-0.409***	-0.413***
	(-8.65)	(-5.89)	(-10.56)	(-10.59)	(-18.17)	(-29.69)
Total capital expenditures	2.505***	1.660***	1.938***	1.953***	1.958***	1.892***
	(13.95)	(15.20)	(21.09)	(21.22)	(28.57)	(47.12)
Total book leverage	-1.487***	-1.387***	-1.443***	-1.452***	-1.456***	-1.452***
	(-18.11)	(-26.45)	(-39.41)	(-40.84)	(-49.73)	(-105.86)
R&D expenditures	0.482***	0.632***	0.584***	0.578***	0.576***	0.597***
	(14.34)	(17.25)	(21.98)	(21.77)	(25.63)	(45.58)
Constant	-2.211***	-2.618***	-2.630***	-2.679***	-2.619***	-2.716***
	(-7.89)	(-13.87)	(-13.32)	(-13.28)	(-14.76)	(-37.33)
Country fixed effects	No	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Angrist-Pischke χ^2-statistic *p*-value (underidentification)					0.000	
Angrist-Pischke *F*-statistic *p*-value (weak identification)					0.000	
Hansen *J*-statistic *p*-value (overidentification)					0.475	
Number of observations	93,859	200,661	294,520	294,520	294,520	294,520
Adj. *R*-squared	0.39	0.26	0.30	0.30	0.30	0.29

Table 3.3
The Quality of Institutions: Creditor Rights and the Legal Enforcement of Creditors' Rights

This table reports estimates from cross-country ordinary least squares regression exploring the effect of creditor rights as an institutional measure of financial development on the cash-tangibility sensitivity, and whether the effect varies with the differences in laws and enforceability of contracts, in the spirit of Bae and Goyal (2009). In all variables, assets are the book value of total assets net of cash. The dependent variable is the natural logarithm of the ratio of cash and equivalents divided by assets. *Creditor Rights*, an index aggregating creditor rights, measures the ease with which creditors can secure the assets in the event of bankruptcy, and ranges between zero and four as of 2002. The degree of the legal enforcement of creditors' rights is measured by three proxies: duration of enforcement, legal formalism, and enforceability of contracts. Short enforcement time, low legal formalism, and high enforceability of contracts reflect a high degree of legal enforcement of creditor's rights, classified as such according to the sample median. *Duration of Enforcement* is the number of days it takes to resolve a dispute and eventually enforce a basic business contract. *Legal Formalism* is a check-based index which measures substantive and procedural statutory intervention in judicial cases at lower-level civil trial courts. A higher score of the index implies that the court system is slower (more bureaucracy) and less efficient. The index measures how efficiently the courts of the borrower's country enforce contracts. Court efficiency matters because the ability of lenders to enforce or to threaten to enforce specific clauses of a loan contract (e.g., covenants), or to seize collateral, depends on the costs of using the legal system. *Enforceability of Contracts* is an index ranging from zero to ten with higher scores indicating higher enforceability representing "The relative degree to which contractual agreements are honored and complications presented by language and mentality differences." Values of *t*-statistics based on standard errors of the coefficients robust to heteroscedasticity are reported in parentheses. The standard errors are clustered by firm and by year. Significance at the 1%, 5%, and 10% levels is represented by ***, **, and *, respectively. Details on the construction of all variables are provided in Appendix.

Legal enforcement proxy		Duration of enforcement		Legal formalism		Enforceability of contracts	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dependent variable: Ln(Cash/Assets)	Pooled	Short	Long	Low	High	High	Low
Asset tangibility	-0.543***	-0.915***	0.011	-0.950***	0.207	-0.491**	-0.366
	(-4.64)	(-6.21)	(0.04)	(-5.87)	(1.00)	(-2.44)	(-1.63)
Asset tangibility × Creditor rights	0.131**	0.236***	-0.078	0.392***	-0.501***	0.226***	-0.053
	(2.16)	(3.57)	(-0.59)	(5.36)	(-5.32)	(2.75)	(-0.62)
Asset tangibility × Log of GDP per capita	-0.225***	0.660***	-0.295**	0.365**	-0.386***	-0.038	-0.200*
	(-2.74)	(3.03)	(-2.35)	(1.96)	(-3.36)	(-0.08)	(-1.66)
Market to book	0.149***	0.173***	0.092***	0.176***	0.090***	0.176***	0.098***
	(31.64)	(30.86)	(12.41)	(29.97)	(12.66)	(30.83)	(12.79)
Log of real assets	-0.103***	-0.123***	-0.018	-0.127***	-0.078***	-0.113***	-0.098***
	(-16.93)	(-20.92)	(-1.45)	(-19.44)	(-9.89)	(-14.72)	(-13.38)
Cash flow	-0.411***	-0.446***	0.031	-0.471***	0.304**	-0.466***	-0.049
	(-10.53)	(-12.12)	(0.30)	(-13.98)	(2.22)	(-11.56)	(-0.95)
Total capital expenditures	1.945***	1.995***	1.517***	2.042***	1.434***	2.148***	1.815***
	(21.05)	(17.33)	(10.13)	(16.05)	(11.73)	(14.22)	(19.93)
Total book leverage	-1.446***	-1.405***	-1.571***	-1.588***	-1.183***	-1.533***	-1.326***
	(-39.71)	(-32.11)	(-21.18)	(-29.11)	(-18.03)	(-23.25)	(-19.46)
R&D expenditures	0.578***	0.491***	1.005***	0.433***	1.005***	0.450***	0.732***
	(21.92)	(16.58)	(13.00)	(14.37)	(13.18)	(15.14)	(15.96)
Constant	-2.696***	-1.248***	-3.487***	-3.539***	-2.396***	-1.573***	-2.631***
	(-13.51)	(-3.63)	(-16.03)	(-15.39)	(-10.89)	(-6.58)	(-13.33)
Country fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of observations	294,520	218,996	75,524	162,573	131,947	144,924	145,602
Adj. *R*-squared	0.30	0.33	0.21	0.34	0.28	0.34	0.27

Table 3.4

The Quality of Institutions: Accounting Standards and Firms' Information Asymmetry

This table reports estimates from cross-country ordinary least squares regression exploring the effect of accounting standards as an institutional measure of financial development on the cash-tangibility sensitivity, and whether the effect varies with the opacity of a company. In all variables, assets are the book value of total assets net of cash. The dependent variable is the natural logarithm of the ratio of cash and equivalents divided by assets. *Accounting Standards* is an information disclosure intensity index created by examining and rating companies' 1995 annual reports on their inclusion or omission of 90 items. These items fall into seven categories: general information, income statements, balance sheets, funds flow statement, accounting standards, stock data, and special items. Accounting standards reflects the quality of information available to creditors and therefore, the costs of monitoring and screening. High accounting standards helps alleviate the costs of information asymmetries, and therefore promotes more lending and weakens the role of tangible assets as collateral in lending. The degree of information asymmetry is measured by three proxies: firm age, firm's growth opportunities proxied by Tobin's *Q*, and firm's R&D intensity proxied by R&D expenditures divided by sales. Young, high-growth opportunities, and high R&D intensity firms usually exhibit a high degree of information asymmetry. Young, high Tobin's *Q* and high R&D intensity groups are classified according to the median value in each country and in each year. Values of *t*-statistics based on standard errors of the coefficients robust to heteroscedasticity are reported in parentheses. The standard errors are clustered by firm and by year. Significance at the 1%, 5%, and 10% levels is represented by ***, **, and *, respectively. Details on the construction of all variables are provided in Appendix.

Information asymmetry proxy		Firm age		Tobin's *Q*		R&D intensity	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dependent variable: Ln(Cash/Assets)	Pooled	Young	Mature	High	Low	High	Low
Asset tangibility	-3.778***	-5.348***	-1.500	-4.614***	-2.824***	-7.190***	-2.056**
	(-4.32)	(-5.30)	(-1.31)	(-4.65)	(-2.75)	(-6.37)	(-2.21)
Asset tangibility × Accounting standards	4.627***	6.992***	1.342	6.024***	3.169**	9.862***	2.228*
	(3.92)	(5.19)	(0.88)	(4.54)	(2.32)	(6.49)	(1.79)
Asset tangibility × Log of GDP per capita	-0.458***	-0.518***	-0.352**	-0.126	-0.625***	-0.676***	-0.346***
	(-4.01)	(-3.63)	(-2.45)	(-0.89)	(-4.55)	(-4.11)	(-2.80)
Market to book	0.154***	0.144***	0.160***	0.111***	0.282***	0.131***	0.148***
	(31.38)	(22.31)	(24.29)	(23.44)	(5.01)	(19.51)	(24.60)
Log of real assets	-0.104***	-0.124***	-0.096***	-0.125***	-0.085***	-0.101***	-0.115***
	(-17.05)	(-12.71)	(-12.21)	(-19.17)	(-11.67)	(-15.18)	(-16.25)
Cash flow	-0.429***	-0.483***	-0.178***	-0.263***	-0.943***	-0.430***	-0.357***
	(-11.35)	(-11.94)	(-3.55)	(-9.09)	(-15.99)	(-13.81)	(-5.77)
Total capital expenditures	1.914***	1.993***	1.700***	1.653***	1.878***	2.645***	1.721***
	(19.67)	(16.70)	(13.88)	(15.80)	(14.71)	(13.76)	(15.74)
Total book leverage	-1.462***	-1.483***	-1.403***	-1.317***	-1.657***	-1.283***	-1.449***
	(-39.64)	(-31.74)	(-28.00)	(-31.20)	(-35.66)	(-19.54)	(-35.98)
R&D expenditures	0.564***	0.515***	0.708***	0.551***	0.662***	0.434***	7.985
	(21.46)	(17.73)	(15.16)	(21.47)	(14.41)	(16.64)	(1.36)
Constant	-2.752***	-2.548***	-2.685***	-2.446***	-2.879***	-3.150***	-2.489***
	(-12.93)	(-7.87)	(-10.63)	(-9.82)	(-12.03)	(-8.68)	(-11.12)
Country fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of observations	284,685	134,049	150,636	142,730	141,955	102,357	182,328
Adj. *R*-squared	0.31	0.35	0.26	0.33	0.25	0.40	0.22

Table 3.5
Firm Default Risk, Collateral Spread, and Financial Development

This table reports estimates from cross-country ordinary least squares regression exploring the differential effect of firm's credit risk on the cash-tangibility sensitivity and assessing whether the average collateral spread, measured by the differential cash-tangibility sensitivity between high- and low-risk borrowers, declines with a country's degree of financial development and its improvements in the quality of institutions, proxied by creditor's rights and accounting standards. In all variables, assets are the book value of total assets net of cash. The dependent variable is the natural logarithm of the ratio of cash and equivalents divided by assets. *High Credit Risk* is a dummy variable equal to one if the firm's Altman's (1968) Z-score is below the median value in each country and in each year, and zero otherwise. Altman's Z-score is a proxy for the financial distress costs or probability of bankruptcy of a firm. The lower the likelihood of bankruptcy, the higher the Z-score. The degree of financial development is measured by three proxies: a country's private credit per GDP, creditor rights index, and accounting standards index. High private credit per GDP, high creditor rights, and high accounting standards reflect a high degree of financial development, classified as such according to the median value in each country and in each year. *Creditor Rights*, an index aggregating creditor rights, measures the ease with which creditors can secure the assets in the event of bankruptcy, and ranges between zero and four as of 2002. *Accounting Standards* is an information disclosure intensity index created by examining and rating companies' 1995 annual reports on their inclusion or omission of 90 items. Values of *t*-statistics based on standard errors of the coefficients robust to heteroscedasticity are reported in parentheses. The standard errors are clustered by firm and by year. Significance at the 1%, 5%, and 10% levels is represented by ***, **, and *, respectively. Details on the construction of all variables are provided in Appendix.

Financial development proxy		Private credit per GDP		Creditor rights		Accounting standards	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dependent variable: Ln(Cash/Assets)	Pooled	Low	High	Low	High	Low	High
Asset tangibility	-0.897***	-0.902***	-0.950***	-0.975***	-0.752***	-1.916***	-0.402***
	(-9.18)	(-6.63)	(-6.52)	(-8.47)	(-4.25)	(-14.29)	(-2.96)
High credit risk	-0.527***	-0.527***	-0.590***	-0.540***	-0.559***	-0.888***	-0.303***
	(-11.22)	(-8.10)	(-10.48)	(-8.73)	(-8.62)	(-11.88)	(-5.46)
Asset tangibility × High credit risk	0.596***	0.715***	0.535***	0.716***	0.492***	1.052***	0.388***
	(6.12)	(5.12)	(4.68)	(5.83)	(3.48)	(7.16)	(3.25)
Asset tangibility × Log of GDP per capita	-0.207**	-0.419***	1.001***	-0.331***	0.288	-0.488***	-0.269
	(-2.53)	(-4.10)	(5.63)	(-3.49)	(1.61)	(-4.19)	(-1.56)
Market to book	0.142***	0.133***	0.164***	0.140***	0.148***	0.099***	0.167***
	(29.69)	(21.62)	(22.87)	(23.42)	(18.74)	(12.26)	(31.21)
Log of real assets	-0.106***	-0.122***	-0.105***	-0.116***	-0.100***	-0.093***	-0.111***
	(-18.17)	(-12.32)	(-10.08)	(-14.48)	(-8.61)	(-10.93)	(-17.14)
Cash flow	-0.535***	-0.385***	-0.758***	-0.406***	-0.776***	-0.284***	-0.536***
	(-15.66)	(-9.74)	(-16.55)	(-11.02)	(-16.21)	(-2.89)	(-14.62)
Total capital expenditures	2.017***	2.352***	1.503***	2.164***	1.747***	1.302***	2.240***
	(22.57)	(17.70)	(11.89)	(19.89)	(14.01)	(9.03)	(17.02)
Total book leverage	-1.317***	-1.359***	-1.212***	-1.333***	-1.298***	-0.955***	-1.554***
	(-30.58)	(-19.14)	(-18.04)	(-19.84)	(-13.25)	(-16.72)	(-26.79)
R&D expenditures	0.562***	0.619***	0.459***	0.625***	0.401***	0.877***	0.454***
	(21.56)	(18.95)	(12.21)	(20.56)	(9.96)	(14.29)	(14.69)
Constant	-2.257***	-2.393***	-0.359	-2.231***	-2.319***	-1.769***	-1.506***
	(-12.05)	(-10.88)	(-0.76)	(-10.24)	(-3.71)	(-8.18)	(-4.94)
Country fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of observations	291,310	160,125	131,185	198,379	92,931	114,431	167,044
Adj. R-squared	0.31	0.35	0.28	0.34	0.26	0.31	0.33

Table 3.6
Industry Growth, Industry Asset Tangibility, and Financial Development

This table presents the results from the following ordinary least squares regression which tests whether, on average, industries that are naturally heavy users of external finance grow faster in economies with better developed financial systems, and industries that have fewer tangible assets as collateral grow faster in economies with better developed financial systems:

$$Growth_{i,c,t} = \beta_0 + \beta_1 Initial\ Share_{i,c} + \beta_2 Dependence_i \times FD_{c,t} + \beta_3 Tang_i \times FD_{c,t} + \beta_4 Dependence_i \times ED_{c,t} + \beta_5 Tang_i \times ED_{c,t} + \eta_i + \eta_c + \eta_t + \varepsilon_{i,c,t},$$

where the dependent variable, $Growth_{i,c,t}$, is the annual real value-added growth rate in industry i, country c, and year t. $Initial\ Share_{i,c}$ denotes the industry i's initial share of total value-added in manufacturing in country c. $Dependence_i$ is external finance dependence, which is calculated as the fraction of capital expenditures not financed with internal funds for U.S. firms in the industry i between 1990-2010, similar to Rajan and Zingales (1998). $FD_{c,t}$ is an indicator of financial development for country i in year t and is measured by the domestic credit provided to the private sector as a percent of GDP. $Tang_i$ denotes asset tangibility for U.S. firms in the industry i between 1990-2010, according to Berger, Ofek, and Swary (1996). $ED_{c,t}$ is an indicator of economic development for country i in year t and is measured by the natural logarithm of country real gross domestic product per capita in constant 2011 international dollars, PPP adjusted. η_i, η_c and η_t denotes the dummies for industry i, country c and year t, respectively. *Fixed Assets* is the ratio of Property, Plant and Equipment (Compustat item PPENT) to total assets as an alternative measure of asset tangibility. Our sample includes 55 ISIC industries at the three-digit level. The sample period is 1990-2010. The value-added data are from the UNIDO Industrial Statistics Database (INDSTAT4) at the 3- and 4-digit level of the International Standard Industrial Classification of All Economic Activities (ISIC) Revision 3 pertaining to the manufacturing sector. Values of *t*-statistics based on standard errors of the coefficients robust to heteroscedasticity are reported in parentheses. The standard errors are clustered by country. Significance at the 1%, 5%, and 10% levels is represented by ***, **, and *, respectively.

Dependent variable: Growth	(1)	(2)	(3)	(4)	(5)	(6)
Initial share	-0.381**	-0.391**	-0.397**	-0.399**	-0.414**	-0.406**
	(-2.37)	(-2.40)	(-2.43)	(-2.43)	(-2.46)	(-2.42)
Dependence × FD	0.018**	0.027**	0.017***	0.015***	0.028***	0.028***
	(2.21)	(2.64)	(2.88)	(2.98)	(3.73)	(3.87)
Tang × FD			-0.211***	-0.238***		
			(-3.39)	(-3.58)		
Tang × ED				0.284*		
				(1.85)		
Fixed assets × FD					-0.160***	-0.191***
					(-3.32)	(-3.52)
Fixed assets × ED						0.157**
						(2.51)
Dependence × ED		-0.023***	-0.017***	-0.024***	-0.019***	-0.031***
		(-3.60)	(-2.90)	(-2.99)	(-3.22)	(-3.42)
Constant	-0.165*	-0.447***	-0.333***	-1.620**	-0.368***	-1.027***
	(-1.83)	(-3.69)	(-2.94)	(-2.21)	(-3.21)	(-3.24)
Country fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Number of observations	23,032	23,032	23,032	23,032	23,032	23,032
Adj. *R*-squared	0.01	0.01	0.01	0.01	0.01	0.01

Table 3.7
Firm Performance, Industry Asset Tangibility, and Financial Development

This table presents the results from ordinary least squares regression which tests whether, on average, firms that operate in industries that are naturally heavy users of external finance perform better in economies with better developed financial systems, and firms that operate in industries that have more tangible assets benefit less than those operate in industries with fewer tangible assets in economies with better developed financial systems. In columns (1) through (3), the dependent variable is return on assets (*ROA*), which is defined as operating income before depreciation (OIBDP) divided by the book value of total assets (AT). The ROA is operating cash flow return and reflects the firm's operating performance. In columns (4) through (6), the dependent variable is return on sales (*ROS*), which equals operating income before depreciation (OIBDP) divided by sales (SALE). It is the sales margin and measures operating profit margin before depreciation. Independent variables include proxies for growth opportunities, assets in place, debt ratio, business risk, size, payout, and firm age, similar to Mehran (1995). *Fixed Assets* is the ratio of Property, Plant and Equipment (Compustat item PPENT) to total assets as an alternative measure of asset tangibility. All regressions contain country, industry, and year fixed effects. Industry dummies are defined according to the Fama and French (1997) 48-industry classification. The sample period is 1990-2013. All ratios are winsorized at the 1% and 99% levels. Values of *t*-statistics based on standard errors of the coefficients robust to heteroscedasticity are reported in parentheses. The standard errors are clustered by firm and by year. Significance at the 1%, 5%, and 10% levels is represented by ***, **, and *, respectively. Details on the construction of all variables are provided in Appendix.

Dependent variable	ROA			ROS		
	(1)	(2)	(3)	(4)	(5)	(6)
External finance dependence × Private credit per GDP	0.002***	0.000	0.005***	0.019***	0.005	0.064***
	(2.79)	(0.34)	(6.89)	(2.99)	(0.60)	(6.84)
Industry asset tangibility × Private credit per GDP		-0.072***			-0.695***	
		(-8.01)			(-5.28)	
Industry asset tangibility × Log of GDP per capita		0.037**			0.782***	
		(2.22)			(3.92)	
Industry fixed assets × Private credit per GDP			-0.048***			-0.644***
			(-6.58)			(-5.07)
Industry fixed assets × Log of GDP per capita			-0.023**			-0.661***
			(-2.03)			(-3.91)
External finance dependence × Log of GDP per capita	-0.003***	-0.002**	0.000	-0.088***	-0.082***	-0.011
	(-3.47)	(-2.56)	(0.19)	(-7.94)	(-7.59)	(-0.89)
Market to book	-0.010***	-0.010***	-0.010***	-0.083***	-0.083***	-0.083***
	(-11.77)	(-11.87)	(-11.81)	(-9.33)	(-9.45)	(-9.45)
Log of real assets	0.030***	0.030***	0.030***	0.228***	0.227***	0.228***
	(20.80)	(20.80)	(20.84)	(17.83)	(17.68)	(17.71)
R&D expenditures	-1.074***	-1.067***	-1.080***	-8.759***	-8.611***	-8.878***
	(-18.70)	(-18.92)	(-19.03)	(-14.92)	(-14.92)	(-15.17)
Total capital expenditures	0.069***	0.069***	0.070***	-1.297***	-1.309***	-1.254***
	(4.66)	(4.64)	(4.76)	(-6.77)	(-6.83)	(-6.65)
Assets in place	0.047***	0.047***	0.047***	0.619***	0.614***	0.622***
	(16.33)	(16.32)	(16.45)	(18.46)	(18.41)	(18.66)
Total book leverage	-0.132***	-0.131***	-0.132***	0.084*	0.101**	0.090*
	(-21.69)	(-21.23)	(-21.50)	(1.66)	(1.99)	(1.78)
Dividend dummy	0.070***	0.070***	0.070***	0.387***	0.382***	0.380***
	(41.21)	(41.48)	(41.04)	(22.90)	(22.43)	(22.57)
Ln (firm age)	-0.014***	-0.014***	-0.014***	-0.099***	-0.087***	-0.100***
	(-5.27)	(-5.00)	(-5.24)	(-4.97)	(-4.36)	(-5.04)
Constant	-0.056**	-0.190***	0.056	-2.612***	-5.516***	0.488
	(-2.55)	(-3.10)	(1.17)	(-10.58)	(-7.47)	(0.72)
Country fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Number of observations	217,619	217,619	217,619	211,097	211,097	211,097
Adj. *R*-squared	0.37	0.38	0.38	0.25	0.25	0.26

Table 3.8
Robustness: Endogeneity of Asset Tangibility

This table reports estimates from instrumental variables (IV) regression exploring how the cash holding sensitivities to asset tangibility vary with financial development. In all variables, assets are the book value of total assets net of cash. The dependent variable is the natural logarithm of the ratio of cash and equivalents divided by assets. Legal Origin (Djankov, McLiesh, and Shleifer, 2007), Creditor Rights, and Information Sharing are adopted as instruments for Private Credit to GDP, following Liberti and Mian (2010). IndustryResale and IndustryLabor are used as instruments for Asset Tangibility, following Campello and Giambona (2013). IndustryResale is the Fama-French's (1997) 48-industry-year median ratios of sales of PP&E to the sum of sales of PP&E and capital expenditures (Compustat items SPPE/(SPPE + CAPX)) in each country as a proxy for the liquidity of machinery and equipment in the industry in which a firm operates. IndustryLabor is the Fama-French's (1997) 48-industry-year median ratios of the number of employees (EMP) scaled by total assets (AT) as an additional instrument for fixed capital and captures variation that is not part of the individual firm's policy set. Values of *t*-statistics based on standard errors of the coefficients robust to heteroscedasticity are reported in parentheses. Significance at the 1%, 5%, and 10% levels is represented by ***, **, and *, respectively. Details on the construction of all variables are provided in Appendix.

Dependent variable: Ln(Cash/Assets)	(1)	(2)	(3)
Asset tangibility	-6.608***	-8.452***	-18.465***
	(-7.90)	(-8.46)	(-7.71)
Asset tangibility × Private credit per GDP	3.974***		
	(8.63)		
Asset tangibility × Creditor rights		0.899***	
		(7.35)	
Asset tangibility × Accounting standards			14.866***
			(5.52)
Asset tangibility × Log of GDP per capita	0.335	1.241***	0.954***
	(1.37)	(4.71)	(3.56)
Market to book	0.150***	0.144***	0.150***
	(34.43)	(30.56)	(30.32)
Log of real assets	-0.155***	-0.195***	-0.196***
	(-13.81)	(-16.44)	(-16.01)
Cash flow	-0.330***	-0.273***	-0.286***
	(-11.16)	(-8.39)	(-8.71)
Total capital expenditures	3.088***	4.202***	4.320***
	(9.66)	(12.67)	(12.34)
Total book leverage	-1.547***	-1.523***	-1.527***
	(-48.37)	(-44.41)	(-43.31)
R&D expenditures	0.399***	0.259***	0.248***
	(8.72)	(5.17)	(4.79)
Constant	1.298**	2.895***	3.056***
	(1.96)	(3.84)	(3.90)
Country fixed effects	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
Angrist-Pischke χ^2-statistic *p*-value (underidentification)	0.000	0.000	0.000
Angrist-Pischke *F*-statistic *p*-value (weak identification)	0.000	0.000	0.000
Hansen *J*-statistic *p*-value (overidentification)	0.143	0.708	0.968
Number of observations	253,755	253,755	246,951
Adj. *R*-squared	0.24	0.11	0.09

Table 3.9
Additional Robustness: Cash Holdings and Asset Tangibility

This table reports estimates from cross-country regression showing the robustness of the effect of financial development on the cash-tangibility sensitivity. The dependent variable in columns (1) through (4) is the logarithm of cash and equivalents divided by net assets. Net Assets are total assets minus cash and equivalents. The dependent variable in columns (5) and (6) is cash and equivalents divided by sales. The dependent variable in columns (7) and (8) is excess cash, which is calculated according to Opler, Pinkowitz, Stulz, Williamson (1999) and Dittmar and Mahrt-Smith (2007). *FININT* is the financial intermediary development index that equals the sum of (standardized indices of) the ratio of liquid liabilities to the GDP and the total amount of credit by deposit money banks and other financial institutions going to the private sector over the GDP, following Khurana, Martin, and Pereira (2006). *Financial Disclosure* is an average ranking of the prevalence of disclosures concerning research and development expenses, capital expenditures, product and geographic segment data, subsidiary information, and accounting methods and policies. These disclosures are proprietary in nature and useful to creditors for evaluating borrowing firms' risks and creating loan contracts. *Private Credit per GDP* is the domestic credit provided to the private sector as a percent of GDP from 1990 to 2013. Values of *t*-statistics based on standard errors of the coefficients robust to heteroscedasticity are reported in parentheses. The standard errors are clustered by firm and by year. Significance at the 1%, 5%, and 10% levels is represented by ***, **, and *, respectively.

Dependent variable	Ln(Cash/Assets)				Cash/sales		Excess cash	
	(1) OLS	(2) OLS	(3) WLS	(4) WLS	(5) OLS	(6) WLS	(7) OLS	(8) WLS
Asset tangibility	-0.324***	-1.612***	-0.307***	-1.506***	-2.311***	-2.304***	-1.546***	-1.537***
	(-4.27)	(-3.23)	(-11.27)	(-7.79)	(-18.60)	(-34.70)	(-13.14)	(-30.28)
Asset tangibility × FININT	0.130***		0.111***					
	(3.23)		(12.13)					
Asset tangibility × Financial disclosure		1.456**		1.355***				
		(2.57)		(6.51)				
Asset tangibility × Private credit per GDP					0.649***	0.667***	0.234***	0.234***
					(9.22)	(18.13)	(4.73)	(13.73)
Asset Tangibility × Log of GDP per Capita	-0.407***	-0.332***	-0.370***	-0.310***	-0.114	-0.093	-0.097***	-0.094***
	(-4.28)	(-3.57)	(-8.91)	(-7.65)	(-0.95)	(-1.43)	(-3.36)	(-10.94)
Market to book	0.151***	0.155***	0.145***	0.148***	0.005	-0.001		
	(30.32)	(31.40)	(64.13)	(68.46)	(0.55)	(-0.20)		
Log of real assets	-0.108***	-0.104***	-0.101***	-0.097***	-0.111***	-0.102***		
	(-17.25)	(-17.01)	(-60.47)	(-61.36)	(-17.28)	(-43.41)		
Cash flow	-0.414***	-0.426***	-0.422***	-0.434***	-1.571***	-1.367***		
	(-10.48)	(-11.15)	(-29.16)	(-31.11)	(-10.26)	(-29.17)		
Total capital expenditures	1.966***	1.929***	1.893***	1.862***	2.923***	2.863***		
	(20.32)	(19.99)	(44.58)	(45.49)	(13.36)	(26.89)		
Total book leverage	-1.459***	-1.462***	-1.455***	-1.467***	-0.649***	-0.570***		
	(-38.95)	(-39.53)	(-99.49)	(-105.35)	(-9.46)	(-21.55)		
R&D expenditures	0.571***	0.565***	0.587***	0.581***	3.508***	3.642***		
	(20.87)	(21.45)	(42.96)	(44.27)	(28.97)	(64.06)		
Constant	-2.484***	-2.702***	-2.540***	-2.739***	1.812***	1.768***	0.580***	0.579***
	(-11.11)	(-12.98)	(-32.90)	(-36.31)	(9.85)	(23.10)	(11.85)	(25.04)
Country fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	No	No
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	No	No
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	No	No
Number of observations	259,485	285,323	259,485	285,323	294,520	294,520	294,520	294,520
Adj. *R*-squared	0.31	0.31	0.29	0.30	0.44	0.47	0.01	0.01

Chapter Four: *Forecaster Overconfidence and Market Survey Performance*

4.1 Introduction

Abundant research has documented the pitfalls of overconfidence in financial decision-making. For example, investors so affected are likely to trade too much (e.g., Barber and Odean (2000)) and under-diversify (Goetzmann and Kumar (2008)), while susceptible managers are prone to excessive M&A activity (Malmendier and Tate (2008)) and market entry (Camerer and Lovallo (1999)). Daniel Kahneman, in his recent bestseller *Thinking, Fast and Slow* (2011), argues that professional forecasters are often bested by simple algorithms because they "try to be too clever, think outside the box, and consider complex combinations of features in making their predictions (p. 224)." This is another way of saying that they are overconfident: they believe they know more than they actually do.

While forecast disagreement can occur because of heterogeneity in information, information-updating frequency and model choice (Capistran and Timmermann (2009a)), behavioral bias might also contribute. The purpose of this paper is to explore the impact of overconfidence on forecasting stock market returns in the context of surveys of professional forecasters. The questions we ask ourselves are these. Does overconfidence weaken forecast accuracy? And, given that there is heterogeneity in performance in part induced by heterogeneity in overconfidence, is there a payoff to filtering out weaker forecasters to improve survey accuracy, where weakness is based either on past performance or the tendency to exhibit markers of overconfidence?

Excess market returns have proved to be notoriously difficult to predict out of sample. While there is an extensive literature documenting return predictability within sample using such fundamental variables as dividend yields, interest rates and term spreads, as pointed out by Goyal and Welch (2008), this has not translated into out-of-sample performance as (typically) measured by out-of-sample R^2 (OS-R^2) relative to a naïve benchmark such as the historical average equity premium.[30] Nevertheless Rapach, Strauss and Zhou (2010) have shown that a combination forecast methodology whereby several predictive variables are optimally combined can lead to a modicum of out-of-sample success. The same holds in Ferreira and Santa-Clara (2011) where the components of stock market returns are predicted separately. Nevertheless predictability is modest, in the former case being less than 4% (using quarterly data) and in the latter case less than 2% (using monthly).

While it is logical to expect that panels of professional forecasters, not only with such predictive variables at their disposal but also armed with experiential judgment, should easily be able to outperform naïve benchmarks, the Kahneman perspective encourages skepticism in this regard. Take the ZEW survey in Germany, which since February 2003 has solicited point forecasts for the DAX.[31] While the mean forecast of the excess market return coming from this survey produces OS-R^2 of 6.19% (with p-value=0.073) for March 2003-June 2010, success is concentrated in the first year as OS-R^2 = 1.09% (p-value=0.239) during February 2004-June 2010.[32]

Some forecasters are weaker than others and these may skew the consensus. We conjecture that weak forecasters may be weak in part because they are more overconfident than other forecasters. One possibility is that, relying too much on intuition, they have a

[30] See Neely, Rapach, Tu and Zhou (2014) for many references on return predictability.
[31] The DAX is an index composed of the 30 largest and most important German companies traded on the German Stock Exchange in Frankfurt.
[32] The ZEW survey actually requests six-month DAX forecasts. The reported OS-R^2s are based on imputed one-month forecasts (as described below) so (given this imputation) the February 2003 survey solicits forecasts for March 2003.

tendency to make extreme forecasts. Denrell and Fang (2010) document that those who have made a very accurate recent prediction – since markets are volatile this often implies an extreme prediction – are likely to be inferior forecasters going forward. Indeed our data indicate that survey respondents with higher forecast standard deviations have higher mean squared prediction errors (*MSPE*s).

Overconfidence can also manifest itself in the tendency to be too sure of one's views, leading to overly narrow confidence intervals.[33] This tendency is echoed in the model of Daniel, Hirshleifer and Subrahmanyam (1998), where overconfident investors put too much stock in private information and exert pressure on prices in the direction of their information, with the result that if such investors dominate markets overreaction and eventual reversal in security prices can ensue. We further document that forecasters whose confidence intervals are wide enough to contain the eventual DAX realization more often than other forecasters are better forecasters in the sense that they have lower *MSPE*s. This is not tautological because better forecasters actually have *narrower* confidence bounds.

Next consensus forecast improvement is considered. We show that filtering out from the survey inferior forecasters can lead to modest but statistically significant improvements in accuracy. For example, if we drop the 30% of forecasters whose prior *MSPE*s over the preceding three forecasts was highest, OS-R^2 reaches 4.18%, which is significant at 2%. It is not obvious that this should be so since one might expect that inferior forecasts would be as likely to be too high (relative to the realization) as too low. Evidently, some error clustering

[33] Deaves, Lüders and Schröder (2010) have previously documented that the ZEW forecasters are overconfident in this sense. Ben-David, Graham and Harvey (2013) have performed a similar exercise using a U.S. panel of market forecasts.

is occurring, consistent with what has been found for analysts (Hirshleifer and Teoh (2003)). We also document that there is a payoff to dropping forecasters without regard to past performance but who exhibit one marker of overconfidence, namely the tendency to make extreme forecasts. For example, if we drop the 70% of forecasters whose prior forecast volatility is highest over the preceding 12 months, OS-R^2 reaches 4.43%, which is significant at 3%.

In what follows, we begin by providing appropriate background on the ZEW DAX survey. In section 4.3 we explore the characteristics of successful forecasters and the contributing role of overconfidence. In the penultimate section, we document that filtering out weaker forecasters can lead to meaningful out-of-sample predictability. Finally, in section 4.5, we discuss our findings and sum up.

4.2 ZEW survey

The *ZEW Finanzmarkttest* is a monthly survey of over 300 private sector forecasters in Germany. From 1991 to the present it has solicited predicted directional changes (rise/fall/unchanged) in a series of key macroeconomic and financial market variables for the key industrialized economies as of six months in the future.[34] Starting in February 2003, ZEW survey respondents were also asked to provide quantitative forecasts and confidence intervals for the DAX. Specifically, point estimates for the DAX six months in the future, as well as lower and upper bounds forming 90% confidence intervals began to be solicited.

[34] Most of these individuals work for a commercial bank, investment bank, insurance company or investment department of a large German company. For example, participants are asked to predict the inflation rate, long-term and short-term interest rates, economic activity, and stock market levels for these countries.

These are the forecasts that we investigate here.[35] The cleaned dataset has over 20,000 forecaster-survey observations, with a survey minimum/mean/maximum of 135/228/269.

To avoid the overlapping data problem inherent in the fact that forecasts are made monthly for six-month-ahead DAX levels, we here follow the methodology of Deaves, Lüders and Schröder (2010), where one-month point forecasts and 90% confidence intervals are imputed from six-month. It is assumed that forecasters believe that the growth rate in the DAX will be constant over the next six months. More specifically, letting L6, F6 and U6 be the six-month interval lower bound, forecast point estimate and interval upper bound respectively, the one-month forecast point estimate (F1) is calculated as*:*

$$F1 = \left(\frac{F6}{DAX0}\right)^{1/6} * DAX0 \qquad (4.1)$$

where *DAX0* is the (respondent-specific) current level of the DAX. On the assumption of *i.i.d.* DAX one-month returns, the standard deviation of one-month returns is 1/√6 times the six-month standard deviation. Confidence intervals are chosen to reflect what is believed to be the correct number of standard deviations on each side of the point estimate, as follows:

$$U1 = F1 * \left(\frac{U6}{F6}\right)^{\frac{1}{\sqrt{6}}} \qquad (4.2)$$

$$L1 = F1 * \left(\frac{L6}{F6}\right)^{\frac{1}{\sqrt{6}}} \qquad (4.3)$$

Respondents typically are given several weeks to make their forecasts, with first solicitation occurring usually near the end of the preceding month. For example, for the September 2004

[35] The final survey in our dataset is May 2010.

survey the first received response was on August 28, and the last on September 14. For these reasons, equations (4.1)-(4.3) require adjustment. Since they are not told to do otherwise, logically respondents would be making their forecasts for *exactly* six months in the future. If we use these equations without adjustment, respondents' imputed one-month forecasts (and intervals) would be for different DAX dates and thus would not be comparable. The way to obviate this problem is to use a respondent-specific imputation that doesn't generate a one-month ahead forecast (and interval) but rather yields a one-month-ahead-of-the-end-of-forecast-month forecast (and interval), as follows:

$$F1a = (\frac{F6}{DAX0})^{(30+d)/180} * DAX0 \qquad (4.1a)$$

$$U1a = F1a * \left(\frac{U6}{F6}\right)^{\sqrt{\frac{30+d}{180}}} \qquad (4.2a)$$

$$L1a = F1a * \left(\frac{L6}{F6}\right)^{\sqrt{\frac{30+d}{180}}} \qquad (4.3a)$$

where *d* is the number of days from forecast receipt to the end of the forecast month. Averaging subsets of *these* imputed forecasts provides the ZEW consensus forecasts that are investigated here.

4.3 Characteristics of successful forecasters

In this section we explore the characteristics of successful forecasters, where forecast success is calculated using *MSPE*. Certain of the variables considered are logical *ex ante* markers of superior performance, while others are potentially linked to overconfidence. Table 4.1 summarizes our expectations.

Beginning with logical *ex ante* markers of superior performance, as described in section 4.2, forecasts are made at different times. Those made later, when more information is likely to be available, would be expected to be better forecasts. Cross-sectionally, individuals tend to have different survey response habits, with some tending to forecast early and others doing so towards the end of the survey month. *STALENESS_MEAN*, which is defined as the average number of days prior to the end of the survey month the forecaster in question submits her forecast, captures this. The expectation is that those contributing early and thus having higher *STALENESS_MEAN* will tend to have higher *MSPE*.

Second, forecasters submit not only point forecasts (which are used to assess *MSPE*) but also 90% confidence intervals surrounding their point forecasts. Logically those who feel they have a better sense of where the DAX is going should submit narrower confidence intervals. Thus average (scaled) confidence interval width (*CONF_INT_MEAN*), defined as *(U6-L6)/DAX0*, provides information on confidence. Importantly, this is not the same as overconfidence, which requires a comparison of perceived and revealed ability. The expectation is that those with lower *CONF_INT_MEAN* will tend to have lower *MSPE*. Of course it is possible that their confidence is entirely unfounded, in which case there will be no impact.

Third, the tendency to produce extreme forecasts thereby relying to a great extent on one's own intuition points in the direction of overconfidence. Consistent with Denrell and Fang (2010), the expectation is that those whose forecasts tend to be more variable (i.e., have a higher standard deviation (*SD*)) will be weaker forecasters. Such a relationship is far from obvious, since, given the volatility that exists in stock indexes, a "perfect foresight" forecaster will have extremely variable forecasts. It is expected that *SD* and *MSPE* are positively related.

Finally, frequent submission is likely to be a signal of attention. On the other hand, consistent with the inattention model of Peng and Xiong (2006), those participating sporadically are signaling inattention and perhaps a reduced ability to see where markets are moving. We define *EXPERIENCE* as the overall number of forecasts submitted during the sample, with the expectation that higher *EXPERIENCE* is associated with lower *MSPE*. Diminishing returns seem likely: logically going from 10 forecasts to 20 is a stronger incremental signal of interest than going from 50 to 60, since everyone responding 50 times or more is exhibiting commitment. For these reasons we perform not only regressions with *EXPERIENCE* but also those including a squared term (*EXPERIENCE_2*), with the expectation that the coefficient on the latter should be positive to reflect convexity vs. *MSPE*.

[Table 4.1 about here]

Table 4.2 reveals whether the data conform to expectations.[36] Its four panels differ in the minimum number of forecasts that a forecaster must submit in order to remain in the sample, with minima ranging from n=5 to n=30. While each panel displays three regressions, initially we focus on the first two, with the first positing a linear relationship for *EXPERIENCE*, and the second by including a squared term allowing for diminishing returns. Turning to regression (2) in Panel B (where forecasters are only included if they have made at least 10 forecasts over the full sample and non-linearity in *EXPERIENCE* is allowed for), we see the coefficients line up exactly as anticipated, with all variables being of the

[36] In unreported results, a version of Table 4.2 that excludes 2007-08, a tumultuous period in financial markets, is broadly similar to what is reported here.

anticipated sign and statistically significant at 1% or very close to it. Regression (1) from the same panel is comparable, with a reduced significance level for *EXPERIENCE* because linearity is imposed.

The other panels can be thought of as robustness checks. *STALENESS_MEAN*, *CONF_INT_MEAN*, and the overconfidence marker *SD* are extremely robust, with all other coefficients indicating significance in the anticipated direction at 10% or better. As for *EXPERIENCE*, both the unsquared and squared terms become insignificant for n=30, which should perhaps not be surprising because given non-linearity most of the meaningful impact of *EXPERIENCE* comes for more moderate *EXPERIENCE* levels.

As a further robustness check, we re-estimate regression (2) by replacing *CONF_INT_MEAN* with average relative imputed individual volatility, or *RELATIVE_IMPUTED_IND_VOL_MEAN*. The latter variable begins with *IMPUTED_IND_VOL*, namely the conversion of respondents' confidence intervals into individual volatility estimates by using the Davidson and Cooper (1976) method to recover respondent-specific probability distributions under normality:[37]

$$IMPUTED_{IND_{VOL}} = \frac{(U1a - L1a)}{3.2 * DAX0} \qquad (4.4)$$

This variable is calculated for each forecaster in every survey month. We then standardize relative to all forecasters participating in the same survey month. Finally, we calculate for

[37] See Pearson and Tukey (1965), Moder and Rodgers (1968), and Ben-David, Graham, and Harvey (2013). Equation (4.4) is based on the fact that respondents' confident intervals are 90%.

all forecasters the average across all months for which there was participation. Regression (3) appears in the third column. Consistent with regression (2), survey respondents with higher average relative imputed individual volatilities have higher *MSPE*s.

[Table 4.2 about here]

The miscalibration-based variant of overconfidence, which exists when *x%* confidence intervals (subject to sampling error) contain fewer than *x%* correct answers, can be directly calculated from the data. Using the first two years of the ZEW forecasts, Deaves, Lüders and Schröder (2010) found that the average forecaster in this dataset was egregiously overconfident in this sense, but, consistent with learning, they adjusted their confidence interval widths depending on past success. Here we take a different perspective. If overconfidence gets in the way of judicious forecasting, then we would expect more overconfident forecasters to have higher *MSPE*s. Letting *HIT_PERCENTAGE* be defined as the percentage of the time one's (imputed) one-month confidence interval contains the eventual value of the DAX, with lower values indicating higher overconfidence, according to this argument *HIT_PERCENTAGE* should be negatively related to *MSPE*.

While on the surface it might appear viable to introduce *HIT_PERCENTAGE* as an additional explanatory variable in the *MSPE* regressions, there is a problem in doing so. Once we control for the average confidence width (*CONF_INT_MEAN*), *HIT_PERCENTAGE* will *by construction* be negatively related to *MSPE*. This is because holding constant interval width a successful forecaster will almost certainly have more "hits" than an unsuccessful one. Matters are quite different however if we relate *HIT_PERCENTAGE* to *MSPE without* controlling for *CONF_INT_MEAN*. It is helpful to roughly partition overconfidence as follows:

$$OVERCONFIDENCE = KNOWLEDGE\ PERCEPTION - ACTUAL\ KNOWLEDGE \quad (4.5).$$

Overconfidence exists when one's perception of knowledge (i.e., one's confidence) exceeds one's actual knowledge. More precisely, an increase in *KNOWLEDGE PERCEPTION* (in the present context, confidence interval shrinkage) reflects *ceteris paribus* higher overconfidence, while an increase in *ACTUAL KNOWLEDGE* (in the present context, lower *MSPE*) reflects *ceteris paribus* lower overconfidence. Since the regression results show that confidence interval width and *MSPE* are positively related (i.e., low-*MSPE* forecasters not only have high perceptions of their knowledge but also high levels of actual knowledge), the relationship between overconfidence (i.e., lower *HIT_PERCENTAGE*) and revealed *MSPE* is an open question. We conjecture a negative relationship between overconfidence and forecast performance (revealed *MSPE*), which is logical if the tendency to be overly certain of one's view induces one to economize on effort.

To test this conjecture, terciles based on *MSPE*s are formed. These terciles are designated as 'High,' 'Medium,' and 'Low' based on *MSPE*s, with the High group containing the highest-*MSPE* forecasters and the Low group containing the lowest-*MSPE* forecasters. For each tercile, in Table 4.3 *HIT_PERCENTAGE*s are calculated for the same four cross-sectional samples as in Table 4.2. Further, the last column shows a *t*-test for the difference in means between the extreme groups. If overconfident forecasters tend to make weak forecasts, then this would imply that High forecasters will have a lower *HIT_PERCENTAGE* than Low forecasters. There is evidence to this effect. In all four cases, Low has a higher average *HIT_PERCENTAGE* than does High. When there are at least 5-20 survey responses, the difference is statistically significant at 10% or better.

[Table 4.3 about here]

4.4 Filtering the ZEW survey

There are compelling reasons to pool forecasts (Timmermann (2009)). For example, if different forecasts use non-matching sources of information, efficient information aggregation may result. And diverse forecasting techniques may be affected differently by structural breaks. While in theory weighting individual forecasts is appealing, a simple equal-weighted approach often dominates because of parameter estimation error. Moreover, more subtle techniques such as least squares estimation of weights are difficult to operationalize with an unbalanced panel such as the one studied here (Capistran and Timmermann (2009b)). Trimming or filtering out poor forecasters (or models) who mostly contribute noise has been shown to improve forecast combinations (e.g., Aiolfi and Favero (2005)).[38]

Here we consider the mean ZEW DAX forecast either with or without filtering based on prior performance.[39] The purpose is to investigate whether elimination of some of the weaker forecasters improves forecast combination accuracy. While we later document that one factor driving inferiority is overconfidence, for now the focus is merely on unconditional performance. In order to generate out-of-sample forecasts it is important that filtering be based on known information. Specifically we eliminate the *z%* of forecasters whose prior *MSPE*s fall in the bottom *z%* of all forecasters participating in a given month. We consider

[38] Though unexplored here, further improvement may also arise by combining survey data with time series models (Pesaran and Weale (2006)).
[39] All results presented here are little affected by using the median instead of the mean.

increments of 10% (10-90%) along with 95%, 99% and "All but best." The latter means that only the forecaster with the lowest prior *MSPE* is kept.[40]

When utilizing past information, the two choices are a recursive or rolling window.[41] In the former case, all previous data are conditioned on while in the latter a constant-length window is maintained. The advantage of the former is that all information is used, but the disadvantage is some of this information might be so stale that it is best ignored. For example, suppose there are two ways to forecast the DAX, one primarily technical and the other primarily fundamental, with some forecasters employing the first approach and others the second.[42] Further suppose that the return generating function for the DAX is regime-dependent. Under the first regime, a technical approach would generate better forecasts, while under the second regime a fundamental approach would outperform. The problem with using a recursive approach is that it is less sensitive to the current regime since it could well be the case that a forecaster looks good because her technique performed well early in the sample when one regime was in place but her recent performance has been weaker now that a second regime is in effect. By varying the length of the rolling window one can get a sense of the optimal amount of past data to condition on. In truth, however, such a comparison is going to have an in-sample flavor, as there is no guarantee that this optimal window length will continue to be optimal going forward.

To evaluate the out-of-sample performance of the ZEW mean equity premium forecast, we calculate OS-R^2, after Campbell and Thompson (2008). This calculation requires a

[40] For the 99% filter, typically two forecasters remain, though with ties the number can reach seven.
[41] Note that we say "window" we mean the number of monthly forecasts that we look back at to assess performance *prior* to the forecast in question. Thus this forecast is *not* included in the window.
[42] Dick and Menkhoff (2013) use this categorization in investigating ZEW exchange rate forecasts.

forecast methodology against which the ZEW forecast is compared. The simplest benchmark is the mean realized equity premium. Against such a benchmark, OS-R^2 is calculated as follows:

$$R_{OS}^2 = 1 - \frac{\sum_{k=q_0+1}^{q}\left(r_{m+k} - \hat{r}_{m+k}^{ZEW_{Mean}}\right)^2}{\sum_{k=q_0+1}^{q}\left(r_{m+k} - \bar{r}_{m+k}^{Hist_{Mean}}\right)^2} \qquad (4.6)$$

where m is the number of in-sample observations; q is number of out-of-sample observations; q_0 is the initial out-of-sample forecast of the equity premium; r_{m+k} is the realized equity premium at $m+k$ in the out-of-sample period; $\hat{r}_{m+k}^{ZEW\_Mean}$ is the ZEW mean out-of-sample equity premium forecast at $m+k$; and $\bar{r}_{m+k}^{Hist\_Mean}$ is the historical mean equity premium calculated using data up to $m+k$. Note that R_{OS}^2 gauges the proportional reduction in *MSPE* for the ZEW mean forecast relative to the benchmark.[43]

When $R_{OS}^2 > 0$, the ZEW forecast on average outperforms the historical mean forecast according to the *MSPE* metric.[44] Based on Clark and West (2007), the null hypothesis that $R_{OS}^2 \leq 0$ is tested against the alternative hypothesis that $R_{OS}^2 > 0$ in two steps. First, define the *MSPE*-adjusted statistic as follows:

$$f_{t+1} = \left(r_{t+1} - \bar{r}_{t+1}^{Hist\_Mean}\right)^2 - \left[\left(r_{t+1} - \hat{r}_{t+1}^{ZEW_{Mean}}\right)^2 - \left(\bar{r}_{t+1}^{Hist_{Mean}} - \hat{r}_{t+1}^{ZEW_{Mean}}\right)^2\right] \quad (4.7).$$

[43] The benchmark forecast is the historical average of monthly excess returns. It is the historical mean taken over all available excess returns at each point of time for recursive windows. For rolling windows, the historical mean benchmark is computed over a corresponding fixed window size.

[44] Throughout this paper, monthly rate of 3-month Frankfurt Interbank Offered Rate (FIBOR3M) is used as the risk-free rate to calculate the mean one-month-ahead forecast of the excess market return.

Second, regress $\{f_{s+1}\}_{s=m+q_0}^{T-1}$ on a constant. And, finally, calculate the *t*-statistic of this constant. A *p*-value for a one-sided (upper-tail) test is then obtained with the standard normal distribution.

Figure 4.1 displays both OS-R^2s and corresponding *p*-values for one-, two- and three-year recursive windows. Specifically, in the (say) two-year case, for possible inclusion in the consensus respondents are ranked based on *MSPE* over the first 24 surveys and if they are in the lowest *z%* they remain in the sample for the 25th survey. Moving forward one period, to form the 26th survey consensus, the holdout sample is based on the first 25 forecasts, and so on. Note that to be considered for inclusion we impose the screen that at least 10 forecasts must have been made by a forecaster during the holdout window (i.e., prior to the forecast to be evaluated). It can be observed in Figure 4.1 that while filtering improves matters somewhat the OS-R^2 is never significant even at 10%.[45] Evidently, there is little obvious value added in using a recursive approach.[46]

[Figure 4.1 about here]

In Figure 4.2 the same one-, two- and three-year windows as in Figure 4.1 are utilized, this time though using a rolling methodology. Again, we employ the screen that at least 10 forecasts over the rolling window must have been made. The first evaluated forecast is done in an identical fashion to the recursive approach, but moving forward the window size is kept constant, implying that early observations are ignored in forecast evaluation. Again, in all cases at least 10 observations over the preceding one, two or three years are required in order

[45] As it were, there are two filters. The first, which to avoid confusion we call a screen, requires a sufficiently long track record so that past performance can be assessed, and the second drops people based on poor past performance.
[46] Note that even the 0% filter is based on the "minimum of 10" restriction.

to be considered for inclusion. A rolling one-year approach reveals some improvement vs. no filtering with OS-R^2s for 30-50% filters ranging from 2.66-3.38% with *p*-values at 10% or better. The superiority of a one-year vs. two- and three-year windows suggests that it is best to limit the window length so that forecasting success in the more distant past is ignored.

[Figure 4.2 about here]

Figure 4.3 investigates how narrow the window should be in order to maximize combination forecast improvement. Four approaches are displayed. The first (Min_10_for_12) repeats the rolling one-year window used in Figure 4.2 as a point of departure. The other three filters employ rolling windows of six months (Min_5_for_6), three months (Min_*2*_for_3) and one month (Min_1_for_1). It is also necessary to specify a minimum number of prior forecasts in the rolling window (again noting that the window does not include the forecast under consideration). For six months/three months/one month, the minimum is five/two/one. To interpret the Min_1_for_1 case, included forecasters must participate in two consecutive surveys, the one whose success is being examined as well as the one immediately preceding (where past success is based on how close the latter forecast was to the eventual DAX).

Beginning with Min_1_for_1, the highest OS-R^2 observed in Figure 4.3 (6.75%, *p*-value=0.063) is *without* filtering. Thus, exclusion of forecasters is not helpful: in fact it worsens matters, and for filters of 70% or more it is very much counterproductive. This should not be surprising since a track record of a single previous forecast (beyond the one under examination) is naturally rife with noise, and is clearly subject to the Denrell and Fang (2010) extreme-forecast success critique. Nevertheless it should be noted that there is a marginal gain from attention due to the fact that only those forecasters participating twice in a row are considered. The reference point in this regard is an OS-R^2 of 6.19% (p-value = 0.073), which applies to the case when we only assess the mean forecast without any past history requirement.

As for the other two (new) cases in Figure 4.3, filtering improves matters for both the rather short 6-month and 3-month rolling windows. For example, for the very narrow three-month window (where we insist that a forecaster was active for the majority (i.e., 2 of 3) of prior forecasts), the OS-R^2s range from 3.35-4.18% for 10-50% filters. These values are statistically significant at the 5% level when compared to the historical mean.

[Figure 4.3 about here]

Related to Figure 4.3 is Figure 4.4. Figure 4.4 ascertains the success of filtering, utilizing the same four approaches, but now the unfiltered mean forecast (rather than the historical mean) is the benchmark against which we compare filtered mean forecasts (which is why we begin at 10%). Broadly speaking, filtering out inferior forecasters is somewhat helpful, with a moderate amount of filtering producing the best results. Again, for the Min_*2*_for_3 case, the OS-R^2 (vs. no filtering) at a 10% filter is 1.45% with a p-value of 0.090.[47]

[Figure 4.4 about here]

Next we investigate whether those weaker forecasters who are filtered out are dropped in part because of their overconfidence. Turning to Table 4.4, which employs the screen that

[47] For the Min_5_for_6 case, the OS-R^2 (vs. no filtering) at a 20% filter is 2.11% with a p-value of 0.087. For the Min_10_for_12 case, the OS-R^2 (vs. no filtering) at a 10% filter is 1.50% with a p-value of 0.078. For brevity, we do not provide the "vs. 0% filter" analogous (to Figures 4.1 and 4.2) charts. In a nutshell 10% filtering is effective (at 10% or close to it) for the three recursive approaches. On the other hand, filtering does not pay off for the 24-month and 36-month rolling windows.

a forecaster for potential inclusion must have made at least five forecasts over the previous six months, we provide the average levels (both mean and median) of relevant variables for three groups of forecasters, designated as ‘Most,’ ‘Between’ and ‘Least,’ based on the percentage of the time that a forecaster is filtered out over the sample period (where the Most group contains individuals who are filtered out the most and the Least group contains individuals who are filtered out the least). Focusing on variables from Table 4.2, it is salient that forecasters with narrow forecast intervals – recall such forecasters are signaling *confidence* – are less likely to be filtered out. Further, one indicator of *overconfidence,* the standard deviation of point estimates, is also positively associated with a reduced likelihood to be included in the survey. While Table 4.2 suggests that overconfident forecasters (in the sense that they release extreme forecasts) are weak forecasters (i.e., they have higher *MSPE*s), Table 4.4 suggests that those forecasters who are often filtered out based on prior *MSPE*s also turn out to be overconfident forecasters (in the sense that their forecasts are too extreme).

[Table 4.4 about here]

Apart from academic interest, what if were considering hiring various individuals in a forecasting capacity, but while we had no track record of their forecasting performance we did possess proxies (perhaps obtained through the administration of a questionnaire) for various manifestations of overconfidence. The results presented here impel us to think twice before retaining applicant forecasters who reveal themselves to be overconfident.

Corroboration of this view exists in Figure 4.5, where forecasters are filtered out not because of previous forecasting performance but because of prior point forecast standard deviation. It is apparent that there is a payoff to filtering out forecasters who display overconfidence through their past tendency to make extreme forecasts. In Figure 4.5, six-month to three-year rolling windows are used. Take the one-year rolling window: while the OS-R^2 is close to zero, using 60-90% filters generates OS-R^2s of 3.92-4.43% which are statistically significant at less than 5%.

[Figure 4.5 about here]

4.5 Discussion and concluding remarks

The ability to forecast market returns is critical for many decision-makers. It matters for market timing, asset allocation, pension fund deficit calculation and corporate planning. While it is recognized that returns have at best a modest predictable component, any improvements that can be garnered over such naïve models as the short rate plus the average realized equity premium are without doubt worth pursuing. Panels of expert forecasters are a ready source of informed opinion, but it is not clear how to make the best use of panel data.

We have considered how overconfidence impacts forecast performance. Overconfidence as proxied by the tendency to make extreme forecasts leads to poor performance. Further, controlling for the fact that good forecasters have some knowledge of their skill which causes them to generate more narrow confidence intervals, it is still true that overconfidence as proxied by the hit ratio (i.e., percentage of the time that an interval contains the eventual realization) is associated with poor performance. It is beneficial to have information on the sources of forecast weakness because if one has such information but the forecaster under the microscope has an insufficient track record one can still make educated guesses about future performance.

Given forecaster heterogeneity it is logical to explore whether filtering out weak forecasters is a viable strategy. Filtering can be done directly by conditioning on past performance. Particularly useful when performance information is sparse is the fact that conditioning can also be done *indirectly* by taking into account overconfidence markers. Fairly short rolling windows, which delicately balance ignoring relevant information and noise reduction, work best.

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Table 4.1
Sign Expectations of Determinants of MSPE

This table presents sign expectations of determinants of mean squared prediction errors (*MSPE*s). *STALENESS_MEAN* is the average number of days prior to the end of the survey month the forecaster in question submits his or her forecast. *CONF_INT_MEAN* is defined as *(U6-L6)/DAX0*, or the difference between the six-month interval upper bound and lower bound deflated by the current level of the DAX. *SD* is the standard deviation of point forecasts. *EXPERIENCE* is the overall number of forecasts submitted during the sample. *EXPERIENCE_2* is *EXPERIENCE* squared.

Dependent variable: MSPE	Expected sign
STALENESS_MEAN	+
CONF_INT_MEAN	+
SD	+
EXPERIENCE	-
EXPERIENCE_2	+

Table 4.2

Cross-sectional *MSPE* regressions

This table reports the estimated coefficients from the cross-sectional regressions of *MSPE* on various potential determinants. The dependent variable is scaled by 10^4. *STALENESS_MEAN* is the average number of days prior to the end of the survey month the forecaster in question submits his or her forecast. *CONF_INT_MEAN* is defined as the average of *(U6-L6)/DAX0*, the difference between the six-month interval upper bound and lower bound deflated by the current level of the DAX for each forecaster. *SD* is the standard deviation of point forecasts over the sample. *EXPERIENCE* is the overall number of forecasts submitted during the sample. *EXPERIENCE_2* is *EXPERIENCE* squared. *RELATIVE_IMPUTED_IND_VOL_MEAN* is calculated in two steps (as in Ben-David, Graham, and Harvey (2013)). First, for each forecaster in every survey month, we convert respondents' confidence intervals into individual volatility estimates by using the Davidson and Cooper (1976) method to recover respondent-specific probability distributions under normality. Second, we standardize them relative to all forecasters participating in the same survey month and then average across all months for which there was participation. Panels A through D differ in the minimum number of forecasts that a forecaster must submit in order to remain in the sample, with minima of n=5, 10, 20, and 30, respectively. The *t*-statistics are reported below the coefficients and corrected for heteroscedasticity using the White (1980) correction. Note that ***, **, and * indicate significance at 1%, 5%, and 10%, respectively.

Panel A: At least 5 survey responses

Dependent variable: MSPE	(1)	(2)	(3)
STALENESS_MEAN	0.740***	0.817***	0.751***
	(4.27)	(4.62)	(4.47)
CONF_INT_MEAN	30.769***	28.518***	
	(2.98)	(2.92)	
SD	0.012***	0.013***	0.013***
	(2.83)	(3.25)	(3.25)
EXPERIENCE	-0.108***	-0.701***	-0.731***
	(-2.75)	(-3.84)	(-3.96)
EXPERIENCE_2		0.006***	0.006***
		(3.64)	(3.77)
RELATIVE_IMPUTED_IND_VOL_MEAN			2.766**
			(2.41)
Constant	7.585	16.659***	23.776***
	(1.53)	(3.01)	(4.37)
Observations	381	381	381
Adj. *R*-squared	0.09	0.12	0.12

Panel B: At least 10 survey responses

Dependent variable: MSPE	(1)	(2)	(3)
STALENESS_MEAN	0.619***	0.685***	0.634***
	(4.20)	(4.69)	(4.41)
CONF_INT_MEAN	24.189***	22.262**	
	(2.67)	(2.57)	
SD	0.013***	0.015***	0.015***
	(3.68)	(3.99)	(3.97)

EXPERIENCE	-0.094**	-0.661***	-0.689***
	(-2.24)	(-3.59)	(-3.72)
EXPERIENCE_2		0.005***	0.006***
		(3.55)	(3.69)
RELATIVE_IMPUTED_IND_VOL_MEAN			2.043**
			(2.26)
Constant	8.227	17.373***	23.142***
	(1.64)	(3.28)	(4.85)
Observations	347	347	347
Adj. *R*-squared	0.09	0.12	0.12

Panel C: At least 20 survey responses

Dependent variable: MSPE	(1)	(2)	(3)
STALENESS_MEAN	0.621***	0.724***	0.687***
	(4.15)	(4.74)	(4.55)
CONF_INT_MEAN	17.781**	16.699**	
	(2.05)	(1.97)	
SD	0.013***	0.015***	0.015***
	(3.43)	(3.67)	(3.68)
EXPERIENCE	-0.080*	-0.944***	-0.960***
	(-1.69)	(-3.18)	(-3.22)
EXPERIENCE_2		0.008***	0.008***
		(3.25)	(3.29)
RELATIVE_IMPUTED_IND_VOL_MEAN			1.518*
			(1.85)
Constant	8.018	25.912***	29.883***
	(1.46)	(3.27)	(3.87)
Observations	296	296	296
Adj. *R*-squared	0.09	0.13	0.13

Panel D: At least 30 survey responses

Dependent variable: MSPE	(1)	(2)	(3)
STALENESS_MEAN	0.613***	0.647***	0.610***
	(4.24)	(4.35)	(4.18)
CONF_INT_MEAN	17.028**	16.188*	
	(1.97)	(1.92)	
SD	0.014***	0.014***	0.014***
	(3.61)	(3.67)	(3.71)
EXPERIENCE	0.014	-0.380	-0.383
	(0.31)	(-0.95)	(-0.96)
EXPERIENCE_2		0.003	0.003
		(1.06)	(1.08)
RELATIVE_IMPUTED_IND_VOL_MEAN			1.610**
			(1.98)
Constant	1.455	10.997	14.407
	(0.27)	(0.98)	(1.29)
Observations	264	264	264
Adj. *R*-squared	0.12	0.13	0.13

Table 4.3
Hit percentages for *MSPE* groups

This table investigates whether more overconfident forecasters have higher *MSPE*s. *HIT_PERCENTAGE* is defined as the percentage of the time one's (imputed) one-month confidence interval contains the eventual value of the DAX, with lower values indicating higher overconfidence. High, Medium, and Low groups based on *MSPE* are formed, with the High group containing the highest-*MSPE* forecasters and the Low group the lowest-*MSPE* forecasters. The last column reports the difference in means between High and Low with a *t*-test for equality. Note that ***, **, and * indicate significance at 1%, 5%, and 10%, respectively.

Group based on *MSPE*	Low	Medium	High	Difference (High-Low)
Panel A: At least 5 survey responses				
HIT_PERCENTAGE (%)	51.88	51.70	47.38	-4.50**
Panel B: At least 10 survey responses				
HIT_PERCENTAGE (%)	52.54	50.78	48.49	-4.05*
Panel C: At least 20 survey responses				
HIT_PERCENTAGE (%)	51.54	50.51	46.54	-5.00**
Panel D: At least 30 survey responses				
HIT_PERCENTAGE (%)	51.96	49.49	48.79	-3.17

Table 4.4
Characteristics of filtered out forecasters

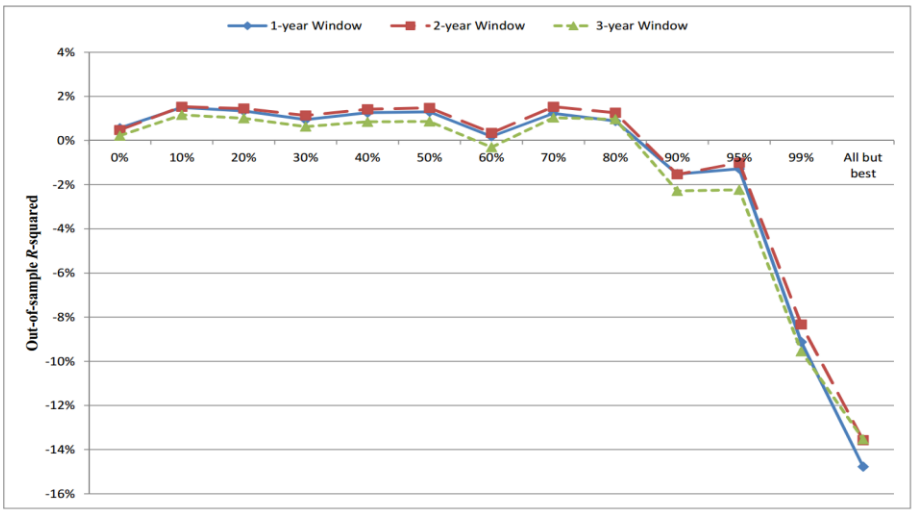
This table investigates the characteristics of filtered out (*ex post* weaker) forecasters based on historical *MSPE*. We employ the screen that at least five forecasts over the rolling window of six months must have been made. We form Most, Between, and Least groups based on the percentage of the time that each forecaster is filtered out over the sample period, with the High group containing those filtered out most often. The sample sizes for Least, Between, and Most are 126, 123, and 130, respectively. The last column reports the difference in means and medians of the characteristics of filtered out forecasters between Most and Least with both a *t*-test and a Wilcoxon *Z*-test for equality. Note that ***, **, and * indicate significance at 1%, 5%, and 10%, respectively.

Group based on percentage of time forecasters are filtered out		Least	Between	Most	Difference (Most-Least)
STALENESS_MEAN	Mean	20.957	21.711	21.760	0.803**
	Median	20.146	21.226	20.988	0.841**
CONF_INT_MEAN	Mean	0.166	0.162	0.193	0.027**
	Median	0.153	0.154	0.170	0.017***
SD	Mean	1,194	1,302	1,293	99***
	Median	1,312	1,349	1,329	16**
RELATIVE_IMPUTED_IND_VOL_MEAN	Mean	-0.107	-0.104	0.258	0.365***
	Median	-0.204	-0.191	0.059	0.262***

Figure 4.1
OS-R²s and *p*-values for one-year to three-year recursive screens

This figure investigates whether filtering out weaker forecasters based on prior performance (*MSPE*) improves forecast combination accuracy. This figure displays both OS-R^2s and corresponding *p*-values for one-, two- and three-year recursive windows. For forecast evaluation, OS-R^2 is calculated based on Campbell and Thompson (2008). This statistic gauges the proportional reduction in *MSPE* for a competing model relative to the historical average benchmark. *P*-values are computed based on the *MSPE*-adjusted statistic of Clark and West (2007). We employ the screen that at least 10 forecasts over the rolling window must have been made.

Panel A: OS-R²s



Panel B: *P*-values

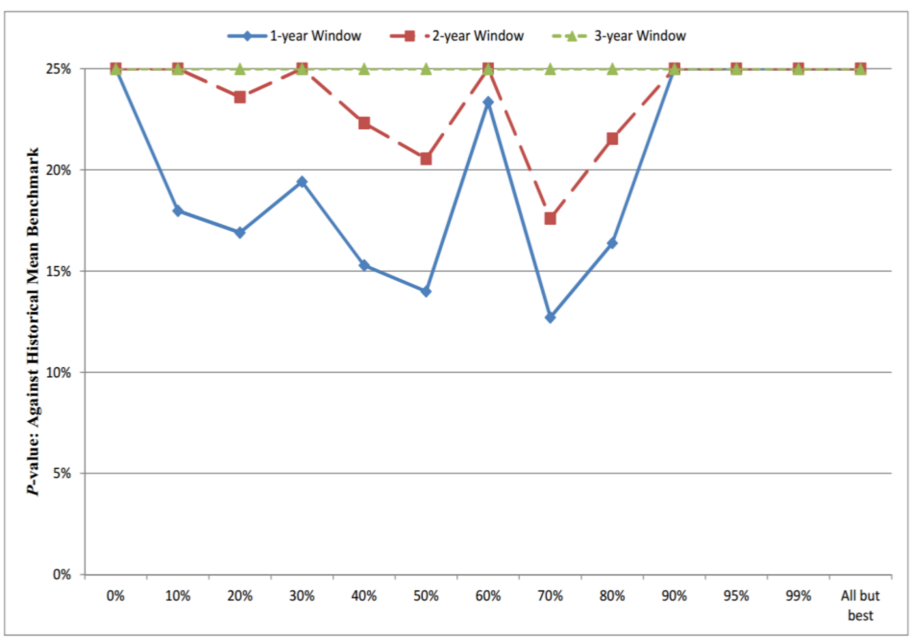
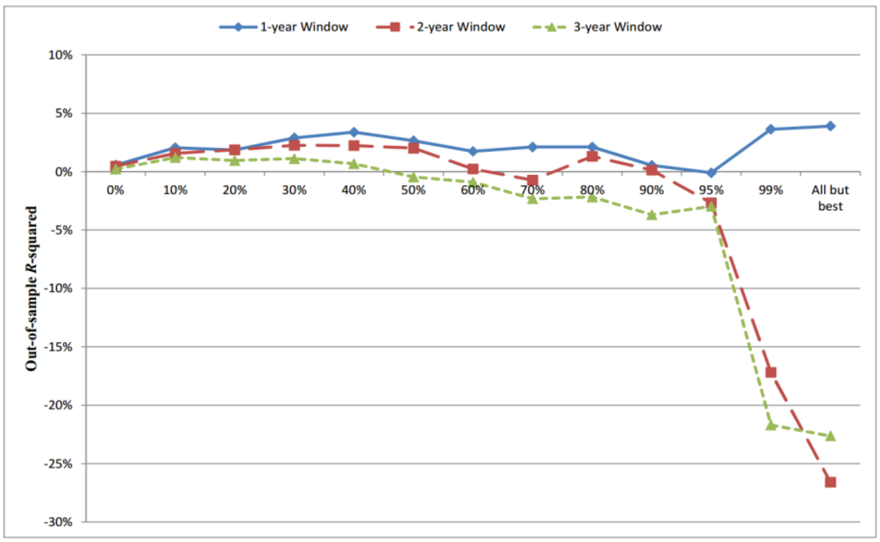


Figure 4.2
OS-R^{2}s and *p*-values for one-year to three-year rolling screens

This figure investigates whether filtering out weaker forecasters based on prior performance (*MSPE*) improves forecast combination accuracy. This figure displays both OS-R^{2}s and corresponding *p*-values for one-, two- and three-year rolling windows. For forecast evaluation, OS-R^2 is calculated based on Campbell and Thompson (2008). This statistic gauges the proportional reduction in *MSPE* for a competing model relative to the historical average benchmark. *P*-values are computed based on the *MSPE*-adjusted statistic of Clark and West (2007). We employ the screen that at least 10 forecasts over the rolling window must have been made.

Panel A: OS-R^{2}s



Panel B: *P*-values

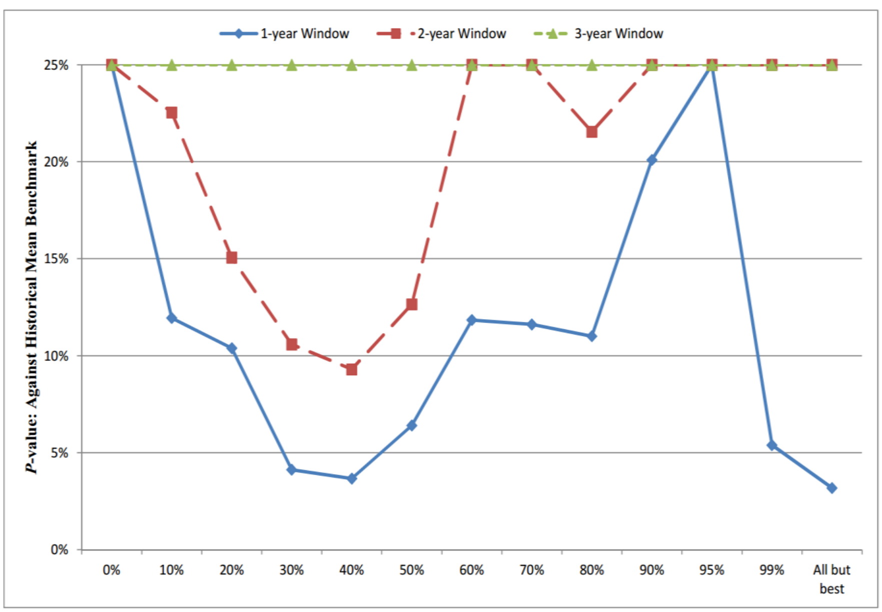
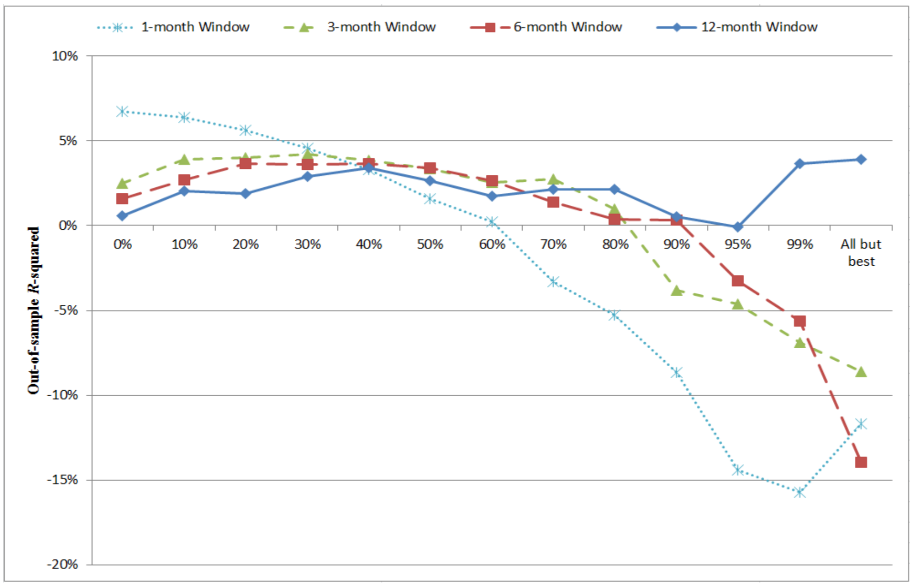


Figure 4.3
OS-R2s and *p*-values for short rolling screens

This figure investigates how narrow the window should be in order to maximize combination forecast improvement. Four approaches are displayed. The first (Min_10_for_12) repeats the rolling one-year window used in Figure 4.2 as a point of departure. The other three filters employ rolling windows of six months (Min_5_for_6), three months (Min_2_for_3) and one month (Min_1_for_1). OS-R^2 is calculated based on Campbell and Thompson (2008). *P*-values are computed based on the *MSPE*-adjusted statistic of Clark and West (2007).

Panel A: OS-R^2s



Panel B: *P*-values

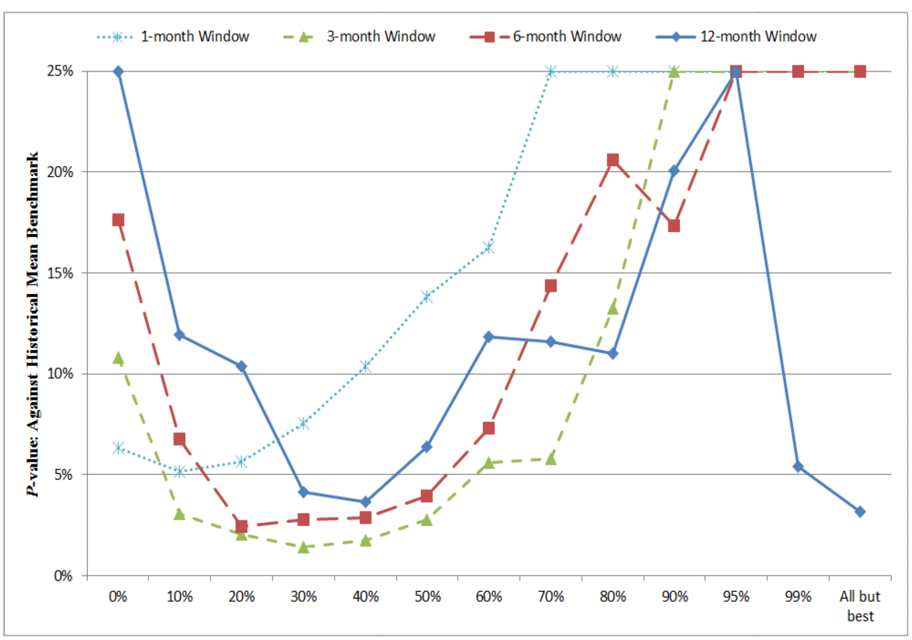
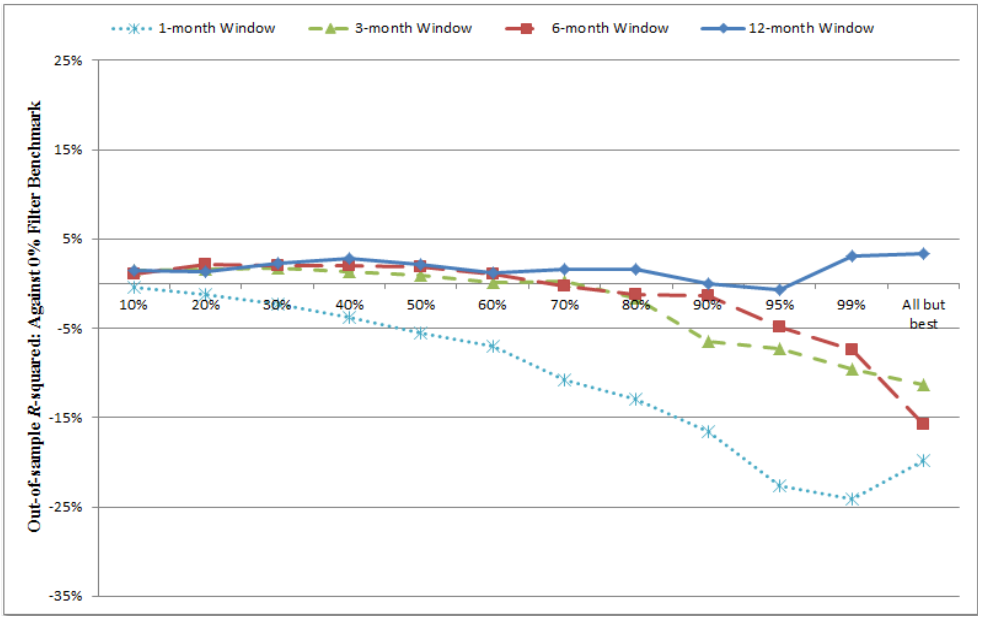


Figure 4.4
OS-R2s and *p*-values for short rolling screens (against 0% filter benchmark)

This figure investigates the economic significance of the forecast improvement by filtering out weaker forecasters based on prior performance (*MSPE*). The same four windows as in Figure 4.3 are used, but now the unfiltered mean forecast is the benchmark against which we compare filtered mean forecasts.

Panel A: OS-R^2s



Panel B: *P*-values

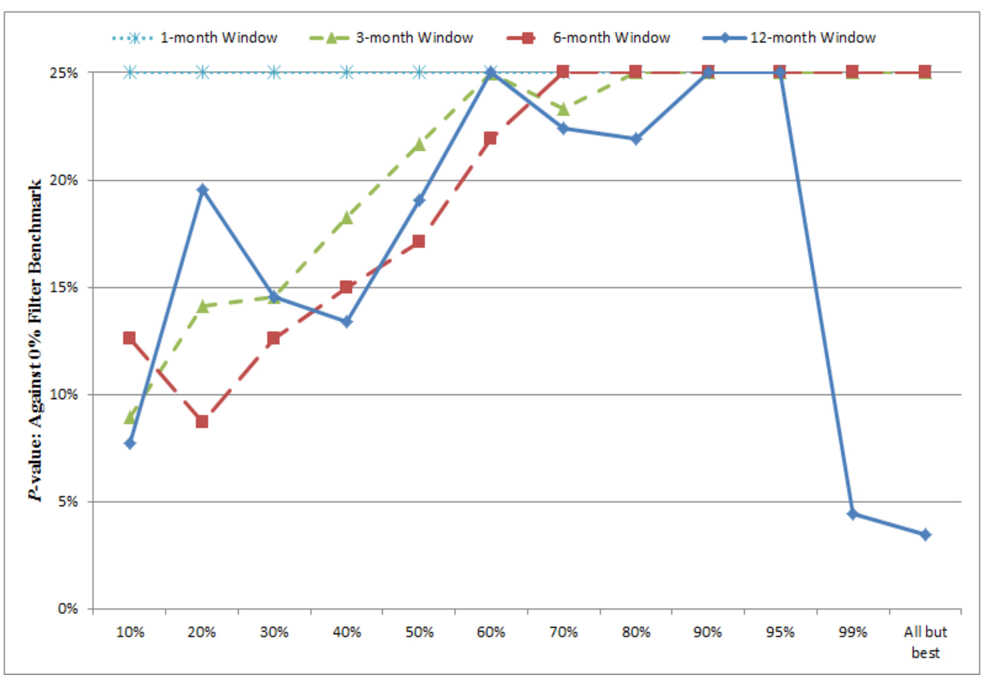
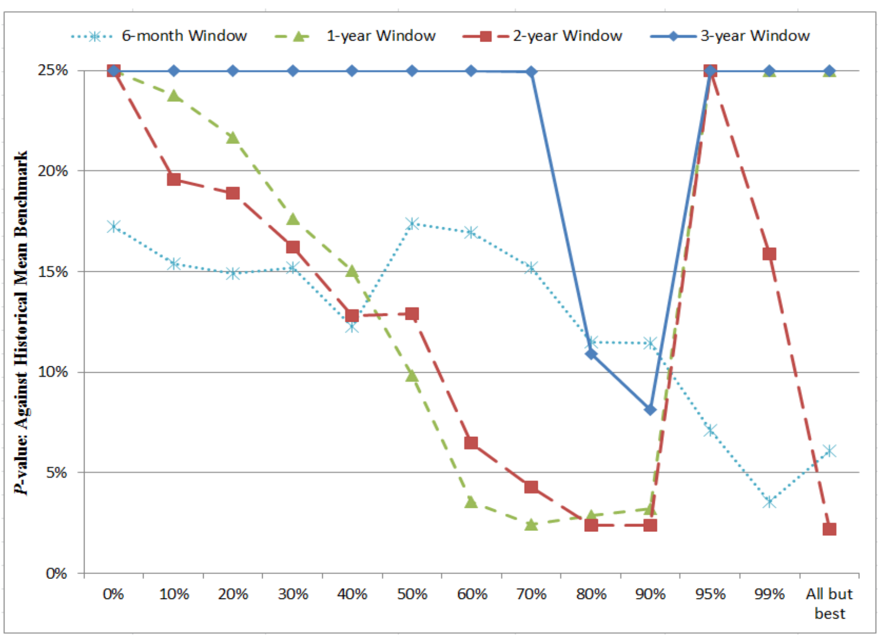


Figure 4.5
Filtering out forecasters based on *SD*s

This figure investigates whether filtering out forecasters based on *SD* improves forecast combination accuracy. This figure displays both OS-R^2s and corresponding *p*-values for six-month, one-, two- and three-year rolling windows. Each forecaster's *SD* is calculated over the rolling window. We eliminate the *z%* of forecasters whose prior *SD* falls in the top *z%* of all forecasters who make a forecast in a given month. We consider increments of 10% (10-90%) along with 95%, 99% and "All but best." OS-R^2 is calculated based on Campbell and Thompson (2008). *P*-values are computed based on the *MSPE*-adjusted statistic of Clark and West (2007).

Panel A: OS-R^2s

Panel B: *P*-values



Chapter Five: Conclusions

This thesis answered the following three questions:

i) Does the financial distress of a firm's industry peers affect the firm's cash holding policy?

ii) What is the role of financial development in shaping corporate cash holding policy through the cash-tangibility sensitivity and what is its implication on economic growth?

iii) Does overconfidence weaken forecast accuracy? If so, is there a way to improve the survey accuracy (consensus survey forecasts) using "limited" historical survey data?

The three answers provided in this thesis are:

i) The financial distress of a firm's industry peers exerts both a negative contagion effect (if they are "buddies" with/or share similar characterises such as cash flows, management practices, or clienteles) and a positive competition effect (if they are industry rivals). The former dominates the latter, on average. As a result, consistent with the precautionary saving motive, high-contagion risk firms tend to hold more cash because creditors are reluctant to extend credits to them or creditors would charge higher rates or impose more stringent loan terms. This study highlights the role of firm interdependence in influencing an individual firm's financial decisions.

ii) First, firms hold less cash if they have abundant tangible assets as collateral. But what if they don't, then financial development could make this negative link between cash and tangible assets weaker. We show that financial development decreases the collateral role of tangible capital. By contrast, financial development reflected through better institutions may increase the collateral role of intangibles such as patents or even allow softer collateral requirements such as the use of financial covenants, or borrowers' goodwill and reputation as collateral. In this case, creditors are well protected and loan contracts are well enforced. Moreover, the information asymmetry between creditors and borrowers is reduced through better financial disclosures. As a result, firms with high intangible assets would have easier access to external funds and become less financially constrained due to their increased debt capacity under better financial development. This would promote corporate investments and hence boost economic growth.

iii) Overconfidence does weaken forecast accuracy because overconfident forecasters tend to make extreme forecasts, which very often lie outside the boundary of their knowledge. One way to improve consensus survey forecasts, of course, is to moderately filter out those weaker forecasters based on past performance measured by their historical mean squared prediction errors (MSPEs). But we show that when performance information is sparse, one could still improve forecast accuracy by removing overconfident forecasters whose prior forecast volatility is relatively high and whose hit ratio (i.e., percentage of the time that an interval supplied by the forecaster contains the eventual realization) is relatively low.