Three Essays on Frictions in Financial Markets

by

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ABSTRACT

In the first chapter, I develop and estimate a novel dynamic model of the secondary market trading of intangible assets in an environment where financial market frictions interfere with firm investment. Intangible asset trading (IAT) not only serves as an alternative means of financing but also reallocates investment opportunities to firms in better positions to exploit them. Estimation of the model uncovers high trading frictions, but the option to trade still leads to significant efficiency gains. These gains stem both from IAT's direct effect on relaxing firms' financial constraints and especially from ex ante changes in firms' expectations, which influence their investment choices. I also show that the impact of financial frictions depends largely on the ease with which firms can trade intangibles. Finally, I present corroborating reduced-form evidence that firms sell a particular type of intangible asset, patents, during times of financial distress and their financial conditions appear to improve after these sales.

The second chapter is motivated by the phenomenon that sophisticated financial market participants frequently choose to disclose private information to the public, which is inconsistent with most theories of speculative trading. In this paper, we propose and test a model to bridge this gap. We show that when a speculator cares about both the short-term value of her portfolio and her long-term profit, information disclosure is optimal: Public disclosure in the form of a mixture of fundamental information and the speculator's position induces competitive dealership to revise prices in the direction of the speculator's position. Using mutual fund disclosure through newspaper articles, we find that when fund managers have stronger estimated short-term incentives, the frequency of strategic non-anonymous disclosures about stocks in their portfolios increases and those stocks' liquidity improves, consistent with our model.

In the third chapter, we quantify the impact of bank market power on the pass-through of monetary policy to borrowers. To this end, we estimate a dynamic banking model in which monetary tightening increases banks' funding costs. Given their market power, banks optimally choose how much of a rate increase to pass on to borrowers. In the model, banks are subject to capital and reserve regulations, which also influence the degree of pass-through. Compared with the conventional regulation-based channels, we find that in the two most

recent decades, bank market power explains a significant portion of monetary transmission. The quantitative effect is comparable in magnitude to the bank capital channel. In addition, the market power channel interacts with the bank capital channel, and this interaction can reverse the effect of monetary policy when the Federal Funds rate is low.

CHAPTER I

Intangible Asset Reallocation and Financial Frictions

I.1 Introduction

It has long been recognized that financial frictions constrain firms' ability to make profitable investments (e.g., Fazzari et al., 1988). Such constraints are particularly restrictive for firms that primarily hold intangible assets (Williamson, 1988; Hall, 2002). A less-studied aspect of the financing of intangibles, however, is the trading of these assets in a secondary market. For instance, Serrano (2010) shows that 13.5% of all granted patents are traded at least once over their life cycle. How much does such trading affect economic efficiency in the presence of financial frictions? This question is intriguing given the prominent role of intangible capital in modern-day production (Nakamura, 2001; Belo et al., 2018). In this study, I investigate this question by building and estimating a dynamic model on the financing, use, and trading of intangible assets.

Several findings stand out. First, I find that intangible asset trading (IAT) by firms leads to sizable efficiency gains. For instance, a 1% reduction in the trading cost of intangibles increases the average firm value by 1.19%. Such efficiency improvement comes about via two channels: IAT provides an alternative means to raise cash and also reallocates investment options to firms in better financial positions to exercise them. In equilibrium, both channels are further amplified through ex ante changes in firms' expectations, which influence their investment decisions.

Second, I find that the ease with which firms can trade their intangibles influences the impact of financial frictions. For example, the financing cost elasticity of the value of the average firm is 0.59% when the trading costs are 50% above their estimates, versus only 0.16% when the trading costs are 50% below their estimates. This result adds to the literature quantifying the effects of financial frictions, as previous studies typically do not explicitly account for IAT. I show that financial frictions are costly only to the extent that firms cannot circumvent inefficient cash reallocation by reallocating investment opportunities.

Trading in intangible assets differs from tangible asset trading in fundamental ways. Tangibles can be easily pledged to raise outright financing, but physically relocating them across firms may be costly. Intangible assets, on the other hand, are easy to transfer, but the high uncertainty regarding their valuation renders their outright financing difficult (Leland and Pyle, 1977). Thus, to the extent that a potential buyer may be better able to evaluate an intangible asset than a financial institution, transferring the asset to a cash-rich firm may be a more viable means of financing. Additionally, intangible assets often offer rich investment opportunities (Lach and Schankerman, 1989), and hence their allocation is crucial for economic growth.

In this paper, I model intangible assets as one-time options for the firm to make investments to improve future productivity. Investments require early-stage cash inputs, but the financial market is imperfect. When short of cash, firms may abandon their intangibles, which is inefficient given that there exist other firms thirsty for more investment opportunities. Alternatively, cash-constrained firms may sell some of their intangibles. In the model, IAT enhances economic efficiency in two ways. First, it injects cash into the selling firm, alleviating its financial constraints. Second, it reallocates investment options to firms with more financial slack to undertake them. IAT, however, is also costly, reflecting real frictions, such as adverse selection in the market for knowledge capital or search costs to find counter-parties.

I estimate the model by matching a set of model-generated moments to their data counterparts. Empirically, I examine one specific form of intangible asset, patents. Patents are a natural laboratory because they are frequently traded (e.g., Serrano, 2010), and, unlike most other intangible assets, their universal use across industries, as well as their established metrics for evaluation (Hall et al., 2001; Kogan et al., 2017) facilitate a systematic study. Accordingly, I construct a comprehensive sample of patent trading by U.S. public firms from 1980 to 2010. Estimation using this sample reveals that non-trivial costs are associated with IAT. For instance, the fixed component of these costs amounts to 11.1% of the average firm's capital stock. Such estimates are consistent with evidence on the lack of depth in patent markets (Hagiu and Yoffie, 2013).

I conduct several counterfactual experiments with my model. First, I find IAT is associated with considerable efficiency improvements. When cutting the trading costs by 1% from their estimates, firms exercise 0.73% more investment options, and the losses due to costly external financing decrease by 0.43%. Overall, the option to trade intangible assets obviates 19.4% of the need for costly financing and increases investment option utilization by 45.6%. Interestingly, I find the direct effects of IAT are rather small; efficiency improvements accrue because these direct effects are significantly amplified in equilibrium through ex ante changes in firms' expectations, as well as their investment choices. Two features of intangibles are behind this result: investment in these assets is sensitive to cash availability but enhances the productivity of extant capital stock. The amplification of efficiency improvements begins with IAT allowing firms to undertake more investment projects and become more productive. Higher productivity puts firms in a better position to buffer expected future cash shortfalls, which in turn incentivizes them to launch even more projects. This cycle leads to an economically meaningful overall effect on firm value.

In another counterfactual experiment, I examine how financial frictions affect the value of the average firm and the allocation efficiency of cash and investment options at different levels of IAT costs. I find that the effects of financial frictions are largely dampened when firms can trade their intangible assets with ease. This result is qualitatively intuitive, but it is also quantitatively important.

These findings contribute to the recent debate on the effect of the patent market (US

Federal Trade Commission, 2011; Hochberg et al., 2018), where a key concern is that patent sales may lead to excessive rent-seeking by means of litigation and holdup. My model points to a beneficial aspect of patent trading and implies that policies aimed at facilitating intangible asset reallocation, such as mandating IAT price transparency, may stimulate innovating activities by alleviating firms' financial constraints.

Finally, I use the patent trading data to show corroborating, reduced-form evidence that provides support for the model. In the cross-section, I find that patents tend to flow out of financially unhealthy firms and into healthy ones: small (large) and low (high) cash holding firms are on average net patent sellers (buyers). Patents also on average flow to firms with smaller patent portfolios. In the time series, higher patent sales coincide with periods of low cash holdings for small firms and firms without bond ratings. Large and rated firms, however, do not exhibit such timing patterns. Additionally, patent sales are associated with signs of improved financial conditions: R&D spending spikes following patent sales, but again only in small and unrated firms.

To rule out the possibility that firms are simply looking to shed their unneeded patents, I compare the sales of "core" and "peripheral" patents, based on their technological distances to the firm's patent portfolio. Consistent with the model, I find that core patent sales are higher during periods of low cash holdings and are followed by stronger increases in R&D spending compared to peripheral patent sales. Lastly, I show that the evidence above is not the result of firms that specialize in patent development selling patents to firms that specialize in patent commercialization.

This paper fits in the vast literature on financial frictions. For instance, evidence suggests that firm investments depend on their cost of fundings (e.g., Fazzari et al., 1988; Whited, 1992). Financial frictions have been shown to hurt economic efficiency both empirically (Midrigan and Xu, 2014) and theoretically (Jensen and Meckling, 1976; Myers, 1977; Myers and Majluf, 1984). I examine a less investigated aspect of the financing of intangibles, that is, their trading. I highlight that both the reallocation of intangible assets and cash can affect the efficiency with which investment opportunities are funded and show that IAT is quantitatively important.

Several studies examine the reallocation of *physical* capital. For instance, Eisfeldt and Rampini (2006) find that the cost of reallocating capital is countercyclical while Eisfeldt (2004) and Li et al. (2015) rationalize this cost on the basis of adverse selection in the used capital market. In this paper, I examine the reallocation of *intangible* capital, which is more susceptible to financial constraints but offers richer growth opportunities. IAT also affects the cross-sectional allocation of firm productivity to a greater extent compared to the trading of tangible assets. For instance, Eisfeldt and Rampini (2006, p. 370) assume that "the productivity of a unit of [physical] capital is not embedded in the capital itself, but is determined by who deploys it."

Another strand of the literature looks into the trading of patents or intangible assets in general. For instance, Serrano (2010) shows that patent trading depends on a number of factors, such as their ages and citations. Akcigit et al. (2016) show that patent trading narrows the technological distance between patents and the firms making use of them. Levine (2017), in particular, studies the role of mergers and acquisitions as a means to reallocate investment opportunities. The author develops a model where firms with more efficient management, or stronger marketing, sales, or distribution channels acquire other firms for their investment projects and show the model is able to reconcile many empirical patterns of mergers and acquisitions. I, on the other hand, examine the interaction between IAT and financial frictions, with a specific focus on the efficiency gains that stem from IAT improving the allocation of investment opportunities and cash.

This paper also adds to the literature on the role of real frictions in shaping firms' financial decisions. Tserlukevich (2008) shows that irreversibility and fixed costs of investment may lead to lumpy leverage adjustment. Bazdresch (2013) argues that non-convex financing costs are quantitatively important to explain financing and investment via a model featuring both financial and capital adjustment costs. In contrast to these models, the equilibrium framework in this paper allows me to track the endogenous flow of intangible assets among a cross-section of firms.

A further related strand of the literature considers how asset trading frictions affect firms' access to outright financing. Benmelech (2008) shows that, in the nineteenth-century railroad industry, asset salability was a significant determinant of debt maturity and the amount of debt issued by firms. Hochberg et al. (2018) finds that thicker trading in the secondary market for patents increases the likelihood that a start-up will receive a loan. In this paper, I focus on a different aspect of asset trading, that is, the sales of intangibles as a substitute for outright financing.

The rest of the paper proceeds as follows. In Section I.2, I describe the model and derive the equilibrium properties of IAT and its implications for economic efficiency. I estimate the model in a broad sample of patents in Section I.3. In Section I.4, I present several counterfactual experiments designed to gauge the quantitative importance of IAT. In Section I.5, I report several novel stylized facts regarding patent trading, which are consistent with the model predictions. Concluding remarks are given in Section I.6.

I.2 The Model

In the model, intangible assets take the form of seeds, which are options to invest and increase future productivity. A firm that is short of cash for an investment may turn to external financing, which is more costly than internal cash given the presence of financial frictions. As firms face different funding costs, an investment project may have positive net present value (NPV) to one firm while having negative NPV to another. In this model, seed trading improves efficiency in two ways: it injects cash into the financially constrained seller, and it reallocates investment opportunities to firms in better financial positions to undertake them.

I start by describing a typical firm's production technology and investment. I then introduce the firm's financing sources and the market for seeds. I solve for the equilibrium and then show key properties of the firm's value and policy functions. I also provide some remarks on the model's micro-foundations.

I.2.1 Production and Project Development

In this model, I assume that time is discrete, and the horizon is infinite. The economy consists of a unit mass of long-lived firms. Each period, a firm generates a before-tax output (y) according to the production function:

$$y = f(\epsilon, z), \tag{1}$$

where z denotes the firm's current productivity and ϵ is an idiosyncratic cash flow shock. For notational convenience, I suppress the time subscript in the variables. Note that the production function does not depend on the firm's physical capital K. Throughout the paper, I assume $K = 1$ is fixed for all firms and interpret variables as fractions of the firm's fixed physical capital stock if not noted otherwise. Abstracting away from physical capital accumulation choices allows me to study the endogenous intangible asset reallocation while keeping the model parsimonious.[1] I also assume that $f(\cdot)$ is strictly increasing in both ϵ and z and weakly concave in z.

One central component of this model is the productivity z, which firms can affect endogenously by developing innovative projects. I define a project as a series of investments that improve a firm's ability to generate cash flows in the future. A project may start with a crude business idea. Over time, as the firm devotes further managerial time, capital input, research, or marketing efforts, the project becomes more mature and eventually turns into productive capacity. I capture the life cycle pattern of a project with the following set of assumptions.

[1]Adding physical capital accumulation to the model will likely increase the tension between project development and financial frictions, as the firm with good investment opportunities must also direct resources towards adjusting physical capital stock. Thus with costly physical capital adjustment, the benefits to IAT will likely be more substantial.

First, the fruition of a project is random. Each period, a project matures with probability η (in other words, it takes on average $\frac{1}{\eta}$ periods to develop a project). Second, projects form a continuum. Hence, assuming fruitions are independent, a known fraction η of a firm's project portfolio will mature each period. Third, each unit measure of maturing projects increases the firm's productivity by $\psi > 0$. Lastly, in each period throughout the lifetime of a project, the firm will incur a cost (R&D expense), which I normalize to one per unit measure. Note a project is "ageless"; regardless of how long it has been around, it incurs the same cost, has the same maturing probability, and will increase productivity by the same amount.[2]

In the absence of new innovative projects, however, a firm's productivity gradually declines. This decline reflects the long-established notion of creative destruction (see, e.g., Aghion and Howitt, 1992; Klette and Kortum, 2004). For instance, a firm may suffer a loss of market share when its competitors upgrade to newer and possibly superior production techniques. Accordingly, I assume that every period, with a probability π, a firm loses a fraction δ of its current productivity. From a technical perspective, this downward drift in z makes the model stationary, as otherwise z would grow without bound.

Taken together, a firm's productivity z follows a process as summarized below:

$$z' = (1 - \delta \times I_\delta)z + \psi\eta q, \tag{2}$$

where q is the number of projects the firm chooses to develop, and I_δ is an indicator variable that equals one with probability π and otherwise equals zero. In equation (2) as well as the rest of this paper, I use variables with primes to denote values one period ahead.

[2]Project homogeneity and stochastic maturing allow me to economize on the model's state space. Real-world projects may differ in their prospects. For instance, projects that are further along in their development may be more revolutionary. Such heterogeneity may lead to interesting dynamics, but I leave their exploration to future works.

I.2.2 Projects and Seeds

A firm must have an investment opportunity before starting a project. The Coca-Cola Company can add a new flavor only if it has the recipe, and Pfizer develops and markets drugs based on successful research protocols. In the model, I assume that to develop a project, a firm must have what I call a "seed" (e.g., Jovanovic, 2009). A seed is a one-time option to develop a project for one period. Accordingly, the number of projects a firm can invest in is limited by the number of seeds it has, or, in other words,

$$q \leq s, \tag{3}$$

where s denotes the firm's current seed stock.

Seeds are scarce. Each period, a firm's seeds come from two sources. The first source is old projects from the previous period. Since only a fraction of these projects mature, those that survive can be further developed and are one part of the firm's seed pool. The other source is new seed inflows. Specifically, new seeds arrive at the beginning of each period, the quantity of which is given by a random variable $i \in [0, \infty)$. i is distributed independently across both firms and time. Formulating new seed arrival as exogenous captures the fortuitous nature of business idea generation and R&D fruition. Note that because projects are ageless, the option to continue an old project is no different from the option to start a new one. Thus, I do not distinguish between the two sources and only track the total size of a firm's seed pool, which evolves according to:

$$s' = (1 - \eta)q + i'. \tag{4}$$

Implicit in equation (4) is the assumption that all seeds are fleeting, one-time opportunities. The only way to carry over a seed to the next period is to plant it today. Delaying investment is not an option, as unplanted seeds (i.e., $s - q$) cannot be stored. This assumption, on the one hand, reflects the reality that a business idea can be preempted if a firm does not make a move promptly. On the other hand, it sharpens the tension between project development and access to finance—when a firm falls short of funding, it does not have the luxury to wait until it builds up a cash stock.[3]

I.2.3 Financing

A firm finances its expenditures in three ways: debt, equity, and retained earnings. Debt takes the form of a short-term, riskless bond. Creditors charge the risk-free rate r_f, and there is no default. However, the firm's borrowing capacities are bounded. The use of limited, riskless debt is a stylized way to capture credit market frictions (e.g., DeAngelo et al., 2011). For instance, in an environment where managers' expertise is inalienable to the firm's operation and the firm cannot commit not to withdraw their human capital, then lenders may demand collateral for secured lending (e.g., Hart and Moore, 1994). The firm's borrowing capacity is thus determined by the amount of physical capital it can pledge.

I model equity issuance as a rights offer to existing shareholders. As studying endogenous equity frictions demands a far more complex model than necessary for my analysis, I assume for simplicity that, for every dollar a firm raises, shareholders must pay $1 + \lambda$ dollars out of their pockets. I interpret the parameter $\lambda > 0$ as transaction costs, such as the fees paid to an investment banker, as well as other equity market frictions, such as the adverse selection discount (Myers and Majluf, 1984). It is immediate that firms will never find it optimal to issue equity and pay dividends at the same time. Hence the net payout, which I denote by d, captures both dividends and equity issuances. That is, if $d < 0$, the firm collects cash (in the amount $|d|$) from shareholders; otherwise the firm makes a distribution. From the

[3] Allowing seeds to be partially storable will not materially affect my analysis. One can interpret the seeds in this model as the perishable part of a firm's investment opportunities. The other, persistent part blends into the firm's daily operations and any ensuing cash flows will net out part of the firm's fixed operating costs.

shareholders' perspective, their cash flow e is given by:

$$e = \big(1 + \mathbb{1}\{d < 0\} \times \lambda\big) \times d, \tag{5}$$

where $\mathbb{1}\{\cdot\}$ is an indicator function that equals one if the term in curly brackets is true and zero otherwise.

A firm can also retain earnings in the form of excess cash. I assume the firm invests all its cash holdings in liquid, riskless securities, which earn return r_f.

Note that in the model, creditors charge the same interest rate, r_f, as firms earn on their liquidity holdings. This construct implies that debt is equivalent to the negative of cash. Accordingly, instead of tracking outstanding debt and liquidity holdings separately, I collapse the two into one variable, the net cash holdings, defined as cash minus outstanding debt. I denote by a_{beg} and a_{end} a firm's net cash at the beginning and end of a period, respectively. The firm's borrowing constraint is expressed as:

$$a_{end} \geq \underline{a}, \tag{6}$$

where $-\underline{a} \in [0, 1]$ reflects the firm's debt capacity.

I.2.4 Seed Trading

Seed (intangible asset) trading takes place in a centralized market where all firms are price takers. I denote by p the price of a unit measure of seeds. This market opens every period after the firm observes its shocks (ϵ, i, and I_δ), but before it starts developing projects or making financing decisions. I summarize the sequence of events for a typical firm in Figure 1.

The centralized market assumption is no doubt a simplification of actual IAT. Real-world intangible assets are vastly heterogeneous, and no single form of dominant market arrangement exists.[4] I abstract from these complications but use the centralized market construct to build in two features of seed trading key to my analysis. First, seeds flow out of firms that attach lower values to them and into firms that attach higher values to them. In this model, the value differentials arise primarily from variations in the firms' financial conditions. A financially constrained firm faces high funding costs and tends to become a seed seller. Second, real frictions of various sorts may deter IAT, thereby interfering with the efficient flow of seeds. My setting captures such inefficiency parsimoniously.

A number of frictions are known to underlie IAT. First, intellectual properties are difficult to trade by their very nature. In his seminal paper, Arrow (1962) points out that the seller must reveal information about the intellectual property in sufficient detail so the potential buyer can assess its value. Yet once the buyer has acquired that knowledge, the seller has in effect transferred the intellectual property to the buyer without any compensation.[5] Second, adjusting to new or unfamiliar technologies can be costly. For instance, Åstebro (2002) studies technology adoption in the metalworking industry and finds there are non-trivial fixed capital replacement costs and information acquisition costs. In another study, using a small sample of 26 technology transfers within multinational firms, Teece (1977) shows that the cost of transmitting and absorbing relevant knowledge is substantial, averaging 19% of total project costs. Third, the vast diversity of intangible assets means that the market for each specific one is thin. Finding a counterparty may, therefore, will likely require

[4]Taking patent trading as an example, historically, patent agents and lawyers performed the role of intermediaries in facilitating transactions (Lamoreaux and Sokoloff, 1999); inventors seeking to sell could also market their patents in the scientific and mechanical journals of the time. Nowadays, firms and inventors trade patents via auctions, exchanges, and brokers (Serrano, 2018), online platforms (Akcigit et al., 2016), as well as so-called "patent aggregators" (Hagiu and Yoffie, 2013). Some examples of patent brokers and intermediaries are Inflexion Point, IPotential, Ocean Tomo, ICAP, and Intellectual Ventures (Serrano, 2018; Hagiu and Yoffie, 2013).

[5]Legally imposed property rights can only partially mitigate the risk of expropriation. As Arrow (1962) puts it, "there are obviously enormous difficulties in defining in any sharp way an item of information and differentiating it from other similar sounding items." Apart from legal protection, several other remedies have been proposed to facilitate intellectual property trading. For instance, the seller may disclose partial information to the potential buyer before negotiating a payment (Anton and Yao, 2002). Alternatively, the seller may make a full disclosure, but if the buyer fails to pay "properly," the seller may threaten to reveal the intellectual property to the buyer's competitor (Anton and Yao, 1994). These solutions, however, are also partial and will unlikely fully eliminate the expropriation risk.

effort (Hagiu and Yoffie, 2013; Hochberg et al., 2018). Fourth, as most intangible assets are unique and complex, their owners may have insider information about their value, instigating adverse selection risk in the intangible asset market. Lastly, complexity of the knowledge system may add to patent trading costs. As a product is likely covered by a large number of interdependent patents, potential buyers may not place much value on a given patent unless it complements a portfolio they already own (Hagiu and Yoffie, 2013).

I model these frictions in a stylized fashion. I denote $|\Delta s|$ as a firm's trading volume. The firm must incur a cost from participating seed trading that is given by:

$$\chi(\Delta s) = \begin{cases} \chi^{+}(|\Delta s|) & \text{if } |\Delta s| > 0, \\ 0 & \text{otherwise.} \end{cases} \tag{7}$$

I assume $\chi^{+}(\cdot)$ is non-negative, increasing, and weakly convex. Naturally, there is no cost if the firm does not trade ($|\Delta s| = 0$). The function $\chi(\cdot)$ is potentially discontinuous at zero to accommodate any fixed trading cost. When taking the model to the data where multiple trading venues may coexist, I interpret $\chi(\cdot)$ as the cost of using the cheapest (combination) of such venues.

Equation (7) implies that buying and selling seeds at the same time is never optimal. Therefore, it is convenient to think of Δs as net seed purchase, i.e., $\Delta s > 0$ if the firm buys and $\Delta s < 0$ if the firm sells. Finally, with the option to trade, I modify the feasibility constraint for the firm's project development q as:

$$0 \leq q \leq s + \Delta s, \tag{8}$$

that is, a firm may plant its own seeds, as well as those acquired in the market.

I.2.5 Tax

I assume a firm's operating and interest income is subject to taxation. Denoting by τ the corporate tax rate, in each period t, the tax the firm pays is;

$$\tau \times \Big[y_t + a_{end,t\text{-}1} \times r_f \Big]. \tag{9}$$

The terms in the brackets are operating profit/loss and interest income/expense, respectively. Note that the tax rate τ applies to both positive and negative income. Implicit in this equation is the assumption that the firm enjoys the full extent of tax carry-forwards and carry-backs so that when income is negative, the firm receives a tax rebate.

Two remarks regarding interest taxation are in order. First, the fact that firms get rebates on negative interest income is better known as the interest tax shield of debt. Absent the borrowing constraint (equation (6)), firms would prefer to be entirely debt financed so as to capture the tax rebates fully. Second, interest taxation also drives a wedge between the firm's discount rate and the rate it earns on free cash holdings. This wedge is essential as it makes building buffer cash stocks costly. Otherwise, firms can easily shield themselves from any funding shortfall by keeping a large savings account, in which case no firm will ever need to tap external equity, and the financing cost λ becomes irrelevant.

I.2.6 Firm's Problem and Equilibrium

I now describe the firm's optimization problem in full. There are no aggregate shocks and each firm bases its decisions on three idiosyncratic state variables: beginning-of-period net cash holdings a_{beg}, productivity z, and stock of seeds s. Each firm maximizes the discounted future cash flow to its shareholders, taking as given the seed price p. I solve for a steady state where p is constant over time. Denoting by v a firm's beginning-of-period value function, the firm's optimization problem can be formulated recursively as follows:

$$v(a_{beg}, z, s) = \max_{d,q,\Delta s,a_{end}} e + \frac{1}{1+r_f}\mathbb{E}v(a'_{beg}, z', s'), \tag{10}$$

subject to the budget constraint:

$$a_{beg} - a_{end} = d + q + \chi(\Delta s) + p\Delta s, \tag{11}$$

the flow of funds condition (equation (5)), the transitions of net cash holdings:

$$a'_{beg} = (1-\tau)\Big[f(\epsilon', z') + a_{end}r_f\Big] + a_{end}, \tag{12}$$

productivity (equation (2)), and seed stock (equation (4)), the feasibility constraint (equation (8)), and the borrowing constraint (equation (6)). In Proposition 1, I establish the key properties of the value function $v(\cdot)$. Proofs of all propositions are in the Internet Appendix.

Proposition 1 *Given the seed price $p > 0$, let $\Omega \subset \Re^3$ be the space of a firm's state variables. The following holds:* (1) *I can restrict attention to a compact state space Ω without loss of generality,* (2) *there exists a unique solution $v : \Omega \mapsto \Re$ to the firm's problem, and* (3) $v(\cdot)$ *is continuous and weakly increasing in all its arguments.*

I define a stationary (industry) with two conditions. First, taking the seed price p as given, all firms optimize. Second, let Γ be the invariant distribution of firm states (a_{beg}, z, s) under the transition probabilities induced by the firm's endogenous policies (d, a_{end}, q, and Δs) and the exogenous shocks (i, ϵ, and I_δ). Then the market for seeds clears under Γ, that is,

$$\int \Delta s^*(a_{beg}, z, s)d\Gamma = 0, \tag{13}$$

where $\Delta s^*(\cdot)$ is the optimal net seed purchase of a firm in the state (a_{beg}, z, s).

I.2.7 Firm Policies and Efficiency Implications of Seed Trading

I start with a proposition showing how optimal seed trading depends on a firm's financial condition.

Proposition 2 *Denote by $\Delta s^*(a_{beg}, z, s)$ and $q^*(a_{beg}, z, s)$ the optimal net seed trading and project development policies when a firm is in the state (a_{beg}, z, s), respectively. The following holds: (1) without equity issuance cost $(\lambda = 0)$, $\Delta s^*(a_{beg}, z, s)$ and $q^*(a_{beg}, z, s)$ are independent of a_{beg}; and (2) with positive equity issuance cost $(\lambda > 0)$, $\Delta s^*(a_{beg}, z, s)$ and $q^*(a_{beg}, z, s)$ increase monotonically in a_{beg} when the borrowing constraint (equation (6)) binds.*

Part (1) is straightforward. In the absence of equity issuance cost, cash may costlessly flow into or out of firms (via dividends or issuances). Each firm is effectively its real operations, plus a separate bank account. The firm makes its real decisions without regard to the balance in that account.

Part (2) addresses the more interesting case where equity issuance is costly. Behind this result is a simple intuition. When cash holdings (a_{beg}) fall, funding real operations becomes increasingly expensive. The firm responds by cutting its overall expenses. As seed purchase and project development are complementary, both are reduced at the same time. Therefore, both Δs^* and q^* decrease in a_{beg}. Accordingly, in this model, seeds on average flow from low cash holding firms to high cash holding firms.

Figure 3 presents the numerically derived policy functions using estimated parameter values. The solid lines are the policies of an individual firm, and the dashed lines are the averages of the corresponding policies in the equilibrium. In Panels A and B, I plot the two real policies—net seed purchase (Δs) and project development (q)—against the beginning-of-period cash holdings (a_{beg}). Confirming Proposition 2, both policies increase monotonically with a_{beg}.

Panels C and D in Figure 3 show the dependences of the two financial policies—net payout (d) and end-of-period net cash savings (a_{end})—on a_{beg}. The firm has a "target level" for a_{end}, as shown by the flat part of the solid line in the right of Panel D. When cash is plentiful (i.e., when a_{beg} is sufficiently high), the firm pays out until a_{end} is at the target. Notice that at this a_{end}, the borrowing constraint, equation (6), is slack: the firm does not borrow more to reap tax benefits because it precautionarily preserves some debt capacity to buffer against potential cash shortfalls.

As a_{beg} drops, however, the firm no longer finds it optimal to maintain the target a_{end}. In the intermediate range in Panel D, a_{end} decreases with a lower a_{beg}, showing that the firm taps into its preserved debt capacity to support operating expenses. Meanwhile, d remains at zero, that is, the firm refrains from equity issuance. Intuitively, the firm resorts to debt before equity as the latter is more costly.

When a_{beg} continues to decrease, the firm eventually exhausts all debt capacity and begins issuing equity. Equity issuance, however, does not always increase with lowering a_{beg}: at some point, the firm starts to substitute seed sales for equity (see Panel A) to save on the issuance cost. This substitution does not happen earlier due to the fixed trading cost. Selling seeds is only worthwhile when the issuance cost would otherwise be high enough.

Panels E and F present the dependences of net seed trading on the firm's other two state variables: productivity (z) and seed stock (s). Intuitively, more productive firms buy fewer seeds as the return from project development is lower. Firms with more internal seeds also acquire fewer from the market.

Proposition 3 below is intuitive and shows how seed trading affects economic efficiency.

Proposition 3 *The value function $v(\cdot)$ decreases with seed trading costs. Specifically, let $\chi_1(\Delta s)$ and $\chi_2(\Delta s)$ be two cost specifications, such that $\chi_1(\Delta s) \leq \chi_2(\Delta s)$. Then:*

$$v^{\chi_1}(a_{beg}, z, s) \geq v^{\chi_2}(a_{beg}, z, s), \;\; \forall (a_{beg}, z, s) \in \Omega, \tag{14}$$

where $v^{\chi}(\cdot)$ denotes the firm's value function under the trading cost specification $\chi(\cdot)$.

Note that Proposition 3 is derived in a partial equilibrium, that is, in varying trading costs, I fix the price of seeds and consider how a single firm's value function changes. To see the effect of seed trading in a "general" equilibrium where seed price endogenously arises from market clearing, I consider two specifications. In the first specification, all parameters are estimated from the data and the seed price is solved endogenously. In the second specification, I keep the seed price the same but set trading costs to infinity. As the second specification is essentially one where trading is not allowed, seed price is irrelevant. Moving from the second to the first specification hence captures the "general" equilibrium changes induced by allowing firms to trade. Proposition 3 shows that, intuitively, efficiency improves.

The efficiency improvement comes about in a number of ways. First, selling seeds is an alternative means to raise cash, which may alleviate the seller's financial constraint. Second, trading reallocates seeds to firms in better positions to invest. Consequently, some seeds that otherwise would be abandoned are planted instead. Note that one primary reason why firms differ in their willingness to exercise investment options is the variation in their funding costs. Thus the conventional wisdom that financial frictions force firms to forgo their investment options is less consequential when the option to trade exists.

I.2.8 Remarks on Model Micro-Foundations

In this subsection, I discuss several micro-foundations of the model and address potential concerns about related model assumptions.

A. Financial Frictions and Trading Frictions

IAT alleviates financial constraints because, for some firms, selling intangibles (seeds) for cash is less costly than raising external equity or debt. One might be concerned that firms have difficulties selling their seeds for the same reasons they are financially constrained in the first place. For instance, uncertainty regarding asset value prevents the pledging of such assets as collateral, and at the same time depresses their selling prices. Similarly, if an intangible asset has low redeployability, lenders may be reluctant to extend credit to the firm (Shleifer and Vishny, 1992), and for the same reason, the firm may have a hard time finding a buyer.

I address this concern by providing several micro-founded reasons for why selling an intangible asset can be less costly than financing with it. It is worth pointing out, though, that my model works as long as a wedge exists between the financing and trading costs for some firms. Hence it is the magnitude of the frictions, rather than the specific micro-foundations, that matters for my quantitative analysis.

First, a firm may suffer from debt overhang (Myers, 1977). Such a firm may not be able to raise external finance against their intangible assets as investors are concerned that any ensuing proceeds will be used to pay back existing debt. The firm, however, can still sell the asset at a "fair" price.

Second, to raise external financing is to sell a claim backed by all the firm's assets, whereas to sell an intangible asset is to sell a claim on the asset alone. Hence these two exercises may be subject to different degrees of information discount. For instance, if a firm owns other assets that are more uncertain in value than the focal one, selling the entire asset pool (equity) would be more costly than selling the focal asset alone (Myers and Majluf, 1984; Edmans and Mann, 2018).

Third, certain agency problems may prevent external financing, but would not affect the sales of assets. For instance, if the manager of a firm has a tendency for empire building, investors are unwilling to fund the firm's investment for fear that the manager may waste their cash. Selling an intangible asset is not subject to such concern because, unlike investors, the buyer does not have a stake in the manager's actions.

Fourth, a firm may also prefer selling an intangible asset to borrowing with it if the firm cannot maintain stable cash flows to service the coupon repayment.

B. Physical Asset Sales and Intangible Asset Sales

In addition to selling intangibles, a firm can also sell physical assets to raise cash. Moreover, because physical assets are typically more liquid, it is likely they are sold before intangibles. Although I do not explicitly model physical assets, such concern should not affect my analysis for the following reason. Compared to intangible assets, physical assets are less uncertain in value and much easier to adjust and trade. Thus, one can interpret the cash flows and liquidity buffers in the model as those that the firm obtains after having optimally taken into account all physical capital considerations. In other words, physical capital, like other flexible factors of production, are "maxed out" of the firm's optimization problems, given that the trade-offs underlying these choices are much smaller in magnitude compared to the decisions regarding intangibles.

I.3 Estimation

In this section, I describe the sample construction and estimation procedures, discuss the identification of model parameters, as well as present the estimation results.

I.3.1 Data and Sample Construction

Empirically, I examine patent trading. Patent trading is an ideal laboratory for my analysis both conceptually and from a practical perspective. On the one hand, patents have limited borrowing capacity (e.g., Hall, 2002) and provide firms with rich investment opportunities (see Lach and Schankerman, 1989 and the references therein).[6] On the other hand, patents are frequently traded (e.g., Serrano, 2010), and, unlike most other intangible assets, they are universally used across industries with established metrics for evaluation (Hall et al., 2001; Kogan et al., 2017).

I obtain patent trading data from the United States Patent and Trademark Office (USPTO). I then map the data to Compustat firms via a set of string matching algorithms. In the In-

[6]There is evidence that intangibles can sometimes be used as collaterals, but only to a limited extent. For instance, Loumioti (2012) studies a sample of syndicated loans and finds that the probability a firm will collateralize intangibles depends on borrower reputation and the redeployability of the pledged assets. Moreover, it is difficult for lenders to diversify the associated credit risk and most lenders are reluctant to invest in assets backed by intangibles. Mann (2018) shows that patents can be pledged as collaterals, and, after shocks to creditor rights, patenting companies raise more debt and spend more on R&D. The fact that R&D is responsive to patent collateralizability shows that, on the margin, firms are constrained by their borrowing limits. In other words, the amount of debt issued against patents is insufficient for the desired R&D expenses.

ternet Appendix, I describe this mapping procedure in detail. My sample spans from 1980 to 2010, during which time patent transaction data are both available from USPTO and can be reliably mapped to GVKEYs. I also restrict the sample to firms that own at least one patent. My final sample consists of 95,410 buy transactions and 49,148 sell transactions, involving 7,612 firms and 450,838 utility patents.

To quantify patent trading, I compute the citation-weighted patent count. More specifically, I define *Patent Purchase* as:

$$\text{Patent Purchase} = \sum_{j \in \mathbb{P}_{i,t}^{\text{buy}}} \frac{C_j}{\hat{\mathbb{E}}\left[C_k \middle| Y_k = Y_j, T_k = T_j\right]}, \tag{15}$$

where $\mathbb{P}_{i,t}^{\text{buy}}$ is the set of patents bought by firm i in quarter t. C_j is the number of times patent j is cited, and Y_j and T_j denote the patent's grant year and technology class, respectively.[7] The denominator, therefore, is the average number of citations received by all patents granted in the same year and technology class as the focal patent j. This scaling scheme adjusts for variations in citing intensities across both time and technology fields. By construction, the scaled citation number has a mean of unity. I construct *Patent Sales* analogously and define *Net Patent Buy* as:

$$\text{Net Patent Buy} = \text{Patent Purchase} - \text{Patent Sales}. \tag{16}$$

To measure a firm's *Patent Stock*, I accumulate all patents granted to or bought by the firm, minus the patents sold or expired, with each term weighted by the adjusted citation numbers as discussed above. All variable definitions are in Table 1.

I obtain equity issuance data from SDC Platinum and financial statement data from Compustat. I define the data variables to be conceptually as close as possible to their model counterparts. Capital stock is measured by total book assets (AT). Before-tax profit is defined as *OIBDP*. I define dividends as the sum of dividends ($CDVC$ plus $PDVC$) and

[7] I define technology classes using the one-digit technology classification established by Hall et al. (2001).

equity repurchase ($PRSTKPC$) less stock sales ($SSTK$), and define equity issuance as the proceeds from SDC. Net cash holdings is measured as cash and short-term investment (CHE) less debt (DLC plus $DLTT$). Project development expenditures are defined as R&D expenses (XRD).

Panel A in Table 2 reports summary statistics of the sample. Patent trading is quite common: the average firm owns 109 (citation-adjusted) patents and trades half a patent per quarter. Patent trading is also lumpy—firms on average trade patents only once in three years. Panel A also presents the same set of statistics for the Compustat universe. As a result of my sample restriction to patent owners, the firms in my sample are larger, more profitable, and more R&D intensive relative to the rest of Compustat firms. Panel B reports the industry composition of my sample and the Compustat universe. It shows that my sample is slightly more concentrated in high-tech industries, such as pharmaceutical, computer and information technology, and precision instruments.

I.3.2 Model Parametrization

To estimate the model, I further parametrize the production function, trading costs, and shock processes. First, let:

$$f(\epsilon, z) \equiv (1+\epsilon)z^{\alpha} - c_f, \tag{17}$$

where $\alpha \in (0,1)$ denotes the returns to scale of production capacities (z) and c_f is the fixed cost of operation. I assume the cash flow shock ϵ is uniformly distributed over the range $[-1,1]$. Second, I assume seed trading costs $\chi^+(\cdot)$ take the following form:

$$\chi^+(|\Delta s|) = \chi_0 + \chi_1|\Delta s| + \chi_2|\Delta s|^2,\ \chi_j > 0,\ j = 0,1,2. \tag{18}$$

This quadratic formulation captures, in a stylized fashion, the myriad frictions underlying IAT, e.g., the costs of technology adoption, difficulties with finding a trading counterparty, as well as adverse selection discounts due to uncertain asset qualities. Finally, I parametrize the new seed shock (i) as an exponential distribution, independent across both firms and time. This assumption allows me to capture the seed generation process with a single parameter $\mu_i \equiv \mathbb{E}(i)$. In the Internet Appendix, I motivate this assumption with the empirical patent grant processes, which fit well with exponential distributions for the full sample and subsamples sorted by firm sizes.

I.3.3 Estimation Procedure

The estimation proceeds in two steps. In the first step, to simplify computation, I choose a subset of parameters outside the main model estimation. Table 3 reports these parameter choices. I set the risk-free rate r_f to 2.5%, the average Treasury bill rate during my sample period. I also set the average technological depreciation rate, $\delta \times \pi$, to be 8% per annum, which is consistent with the estimated depreciation rate of R&D capital and organization capital in Grabowski and Mueller (1978) and McGrattan and Prescott (2010). I estimate the equity issuance cost λ to be 5.24%, the average issuance fee paid per dollar raised through outside equity in my sample. Next, note that because the only effect of the debt capacity parameter $\underline{a}$ is to shift the firm's cash holding levels, any choice of this parameter is innocuous to the estimation as long as I do not directly match cash holdings (see the second step below). Following the collateralizability estimate in DeAngelo et al. (2011), I set $\underline{a}$ to be -0.72. Finally, I set the returns to scale parameter α to 0.5, as is commonly used in the macro literature. For robustness, I also estimate the model with $\alpha = 0.75$.

In the second step, I estimate the rest of the parameters—η, μ_i, π, χ_0, χ_1, χ_2, ψ, and c_f—using the simulated method of moments (SMM). Specifically, this algorithm searches for parameter values to "fit" an array of model-generated moments to their data counterparts. The level of fit is determined by the following objective function:

$$\Pi(\Theta) = -\Big[g(\Theta) - \hat{g}\Big]' \hat{\Xi} \Big[g(\Theta) - \hat{g}\Big], \tag{19}$$

where Θ is the set of parameters, $g(\cdot)$ is a vector of simulated moments derived from solving the model at Θ, $\hat{g}$ denotes the corresponding moments in the data, and $\hat{\Xi}$ is a positive semi-definite matrix that assigns weights to the moments. In general, the closer $g(\Theta)$ is to $\hat{g}$, the greater is $\Pi(\Theta)$, and the better the model fits the data. An optimal weighting scheme is given by:

$$\hat{\Xi} = \frac{1}{N}\left[v\hat{a}r(\hat{g})\right]^{-1}. \tag{20}$$

Intuitively, $\hat{\Xi}$ places greater weights on more precisely estimated moments.

Identifying the model by maximizing equation (20) requires choosing a set of informative moments. Intuitively, the function $g(\Theta)$ should exhibit enough variation that it can be used to back out a unique parameter combination $\hat{\Theta}$ that matches the data moments most closely. I hence choose moments regarding firm R&D, profitability, and patent trading as the model has clear and strong implications on these policies. In particular, I include in $\hat{g}$ the mean and variance of R&D expenses, the mean and variance of profit, patent trading frequency, mean patent trading volume, the variance of net patent trading, the correlation between patent trading and leverage, the correlation between patent trading and patent stock, and the correlation between R&D and leverage. I scale R&D expenses and profit by firm sizes and scale patent trading by the mean patent stock.

Figure 4 shows several key moment-parameter relations. In general, every moment to some extent affects all parameter estimates, but some parameter-moment dependences are stronger and more informative. In Panel A, I show that with a higher maturing rate η, the returns from investing in projects improve; thus both average R&D and profit increase. η also affects trading, as shown in Panel B. On the one hand, a faster project maturing rate induces more frequent trading—with greater η, a firm needs to replace a larger proportion of its seed stock each period, which creates a stronger demand should there be a low inflow of new seeds. On the other hand, the mean seed-stock-weighted trading volume is non-monotonic, resulting from the simultaneous increases in trading and seed stocks. Panel C illustrates the effects of varying μ_i, the average per-period inflow of new seeds. Not surprisingly, with stronger inflows, firms develop more projects, and R&D goes up. Trading frequency, however, is hump-shaped in μ_i. Intuitively, when μ_i is low, a larger seed inflow increases the number available for trading, while when μ_i is high, most firms already have more seeds than they can plant, reducing the need for trading. Panel D illustrates changes in π, the probability of productivity depreciation. Because I fix the average depreciation rate, $\pi \times \delta$, a smaller π implies that depreciations are of greater magnitudes, which increases the variation of marginal seed value and hence the volatility of trading. At the same time, with greater depreciation magnitudes, R&D comoves more strongly with leverage. Following large productivity losses, firms seek to develop more projects and end up taking on more debt. Panels E, F, and G show how seed trading depends on its costs. As expected, trading frequency, volume, and volatility decrease in the fixed, linear, and quadratic components of the trading costs, respectively. All three components also tend to suppress the correlation between patent trading and firm leverages. Panel H shows, when maturing projects boost firm productivity by more (i.e., larger ψ), both average R&D and profitability increase. Finally, as shown in Panel I, a larger fixed cost of operation c_f pushes the firm closer to its borrowing constraints, suppressing project development and shrinking the correlation between R&D expenses and leverage. Not surprisingly, a higher fixed cost also hurts the firm's profit.

I.3.4 Estimation Results

Table 4 reports the estimation results with the return-to-scale parameter α set at 0.50. Overall, the model exhibits good fit. All the first moments—mean R&D expenses, profits, and patent trading frequency and volume—match their data counterparts closely. However, the model generates higher (absolute) correlations and lower variances compared to the data. In the model, because all the firm's policies are driven by three shocks, ϵ, I_δ, and i, these policies are more correlated but less volatile compared to when firms base their decisions on a variety of complex contingencies, as is the case in the data.

Table 4 reveals that non-trivial costs are associated with IAT. Recall that the trading costs have fixed, linear, and quadratic components. To explain the lumpiness of patent trading in the data, the estimate of the fixed cost χ_0 is as high as 11% of capital. The firm also incurs a marginal cost for each additional patent they trade, as captured by the parameter χ_1. Given the simulated seed stock $\mathbb{E}(s) = 0.0644$, the estimate of χ_1 translates into a marginal cost equivalent to 0.135% of capital if the firm were to trade an additional 1% of its patents. On top of the linear part χ_1, the estimate of χ_2 shows that this marginal cost is also slightly increasing in the trading volume. For instance, if the firm were to sell all its patents, then the last (unit measure of) patent sold costs more than the first one by an amount equivalent to 0.69% of capital.

Table 5 reports the estimation results when setting $\alpha = 0.75$. Compared with Table 4, both the estimated fixed operating cost c_f and the probability of technological depreciation π change significantly, but the trading cost parameters are mostly unaffected; the χ_2 estimate differs from the $\alpha = 0.5$ case, but under either specification, its economic magnitude is small.

I.4 Counterfactual Experiments

In this section, I conduct a number of counterfactual experiments to gauge the quantitative importance of IAT. In Subsection I.4.1, I examine how the firm, both in its normal state and when its financial condition is poor, optimally responds to emerging investment opportunities. In Subsection I.4.2, I quantify the direct and indirect efficiency gains due to IAT. The direct gain results from the ex post option to trade seeds, and the indirect gain accrues as IAT affects the firm's ex ante decisions in equilibrium. Finally, in Subsection I.4.3, I examine how IAT influences the impact of financial frictions.

I.4.1 Firm Impulse Responses to Seed Shocks

I next examine how a firm responds to seed shocks that make new investment opportunities available to the firm. Two cases are considered: shocks during normal times and shocks during periods of financial difficulties.

Figure 5 shows the firm's impulse response functions. I start with a firm in its "steady state," that is, the firm has been receiving median-level seed and cash shocks, i and ϵ, respectively, and its productivity depreciation has been constant at the mean rate, $\pi \times \delta$, for a long time. At time zero, however, the firm is hit with a large and positive seed shock. In Panel A, this seed shock arrives alone, whereas, in Panel B, it arrives with a simultaneous negative cash shock. All shocks are one-time occurrences. I track the firm's cash holdings, net payout, seed trading, project development, as well as productivity afterward.

Panel A shows that, when investment opportunities present themselves during normal times, the firm is able to exploit it by investing in more projects. Debt (or internal cash) is used to fund these investments since it is the least expensive form of financing. Accordingly, net cash holdings decline while equity issuance remains zero. The firm refrains from trading seeds as doing so is costly. Lastly, productivity increases due to the newly developed projects.

If at the same time as the seed shock there is a large operating loss, then the firm's preserved debt capacity is insufficient to both roll over its old debt and invest in new projects. As shown in Panel B, the firm resorts to external equity financing after hitting the borrowing constraint, which raises its marginal financing cost. Developing more projects is no longer worthwhile at this point. Instead, the firm responds to the seed shock by selling these seeds. The sale of these seeds is appealing despite the high trading costs because the proceeds allow the firm to cut back on its otherwise costly equity issuance. Note that even though the firm is not able to exercise the new investment opportunities, the sale of the seeds provides other firms with opportunities to improve their productivities.

Figure 5 shows during normal times, the firm will behave as if the option to trade seeds does not exist; the high costs of trading deter the firm from exercising this option. However, this option is valuable when the firm is financially constrained as it reduces the otherwise high financing costs. In the simulated equilibrium distribution, I find that 93.7% of the sellers have binding borrowing constraints or would have binding constraints were they not to sell. These firms account for 97.6% of the traded seeds.

I.4.2 The Direct and Indirect Effects of Seed Trading

I quantify the efficiency gains of IAT in this subsection. These gains may stem directly from the ex post options to substitute seed sales for outright financing or to acquire seeds from the market. IAT may also improve economic efficiency indirectly through ex ante changes in the firm's expectations and hence its investment choices as the direct effects ripple through the equilibrium.

I decompose the direct and indirect effects of seed trading as follows. First, I compute their combined effects by comparing two model specifications: a with-trade specification and a ceteris paribus without-trade specification, where seed trading is not allowed. Second, to isolate the direct effects, I need to turn off any equilibrium feedback and ex ante changes in firm behaviors. To that end, I consider an interim specification, in which I force the firm's project development and borrowing policies, q and a_{end}, to be the same as those in the without-trade specification. As q and a_{end} are the only two policies that affect a firm's future states, in this interim specification, both the equilibrium distribution and firm expectations are anchored to the without-trade specification. However, I allow the firm residual discretion over how to obtain the seeds and finance their project development.[8, 9] Therefore, differences between the without-trade and interim specifications reflect the direct effects of seed trading; the indirect effects are the differences between the combined and direct effects.

I compute the direct and indirect effects of IAT for a range of trading costs and present the results in Figure 6. The x-axis is the number of multiples of the trading cost estimates. In other words, $x = 1$ is the benchmark case where all parameters are set to their estimates in Table 4, and, when moving along the x-axis, I vary the trading cost parameters, χ_0, χ_1, and χ_2, while fixing other parameters. The y-axis is constructed as the percentage changes

[8] In solving the interim specification, I set the seed price to be the same as in the with-trade specification.

[9] Another efficiency improvement comes from the decreasing returns to scale of z, which lead to differential marginal seed values across firms. This improvement is likely small given that the trading volume is small relative to the average seed stock.

in efficiency measures due to either the direct, indirect, or combined effects as fractions of their without-trade-specification levels. I consider three such measures: the average number of planted seeds, the average losses due to costly external financing, and the average firm value.

I highlight two aspects of Figure 6. First, IAT has sizable efficiency implications. Starting from the benchmark case, a 1% local reduction in trading costs obviates 0.43% of the need for costly external financing and increases the number of planted seeds by 0.73%. Overall, the option to trade reduces external financing losses by 19.4%, induces firms to plant 45.6% more seeds, and more than doubles the average firm value compared to the without-trade specification. Second, while the direct effects are rather small, the indirect effects account for almost all of the economic efficiency improvements. The intuition of this result is as follows. In my sample as well as in the model, the average trading volume amounts to about only 2% of the average seed stock; hence, the direct effects of such trading are limited. In equilibrium, however, these effects are amplified through a chain of changes. When the firm knows it has the option to sell seeds when it is financially constrained, it is willing to take on more investments ex ante. Also, since projects are long-term, increases in planted seeds today yield more investment options in the future. As the firm becomes more productive, it is in a better position to buffer adverse cash shocks, which provides an incentive to plant even more seeds. This cycle then repeats itself. Note that behind this chain reaction are two distinguishing features of intangibles assets: investments in these assets are sensitive to cash availability and they future firm productivity.

In light of the substantial gains from IAT, it is worthwhile to consider policies that facilitate intangible asset reallocation. One potential policy is to enforce information disclosures regarding intangibles, which should alleviate adverse selection risk in the market. Similarly, mandating the price transparency of IAT may stimulate future trading, as prices provide benchmarks to evaluate analogous assets. Alternatively, creating or subsidizing transaction venues (such as online patent trading platforms) may help reduce the search frictions. The findings in this subsection also contribute to the recent debate on the effect of patent trading on innovative activities. As illustrated in Hagiu and Yoffie (2013) and Hochberg et al. (2018), patent sales may stifle innovation if these intellectual properties are reallocated to nonpracticing entities, commonly known as patent trolls, that extract rents through litigation and holdup. Such aspect of patent trading has been a major concern for policy makers. My results, on ther hand, point to another, beneficial aspect of patent trading, which provides important information for relevant policy designs.

I.4.3 IAT and the Efficiency Losses from Financial Frictions

In this subsection, I examine how IAT impacts the effects of financial frictions on economic efficiency. To measure the effects of financial frictions, I compute the financing cost elasticity of several efficiency measures, namely, the average firm value, $\mathbb{E}[v - a_{beg}]$, the average marginal value of net cash holdings, $\mathbb{E}[\frac{\partial v}{\partial a_{beg}}]$, which captures how restrictive the borrowing constraint, equation (6), is, and the percentage value loss to seed misallocation, L^s. While the first term reflects the overall effect of financial frictions on firm value, the last two terms measure the efficiencies with which cash and seeds are allocated in the economy, respectively. I define the value loss to seed misallocation as:

$$L^s = 1 - \frac{\int \left[v(a_{beg}, z, s) - a_{beg}\right] d\Gamma}{\int \left[v(a_{beg}, z, s^*) - a_{beg}\right] d\Gamma}, \tag{21}$$

where Γ is the equilibrium distribution of firm states (a_{beg}, z, s). $s^* = s^*(a_{beg}, z)$ is the socially optimal seed stock, defined as:

$$s^*(a_{beg}, z) = \underset{\tilde{s} \text{ s.t. } \int \tilde{s} d\Gamma = \int s d\Gamma}{\arg\max} \int \left[v(a_{beg}, z, \tilde{s}) - a_{beg}\right] d\Gamma. \tag{22}$$

L^s captures the loss in value relative to the benchmark where, given the distribution of (a_{beg}, z), seeds are redistributed optimally across firms.

I next examine how the financing cost elasticities of the efficiency measures vary with the trading costs, $\chi_j,\ j = 0, 1, 2$. The results of this counterfactual experiment are plotted as solid lines in Figure 7. The x-axis corresponds to the number of multiples of the trading costs' estimates. For example, if $x = 1$, χ_0, χ_1, and χ_2 are equal to their estimated values, whereas if $x = 1.5$, they are 50% above these values.

Figure 7 reflects the intuition that both external financing and seed trading enhance the match between investment opportunities and the funding needed to implement them. Lower trading costs dampen the effects of financial frictions on all three measures of economic efficiency, i.e., $\mathbb{E}[v - a_{beg}]$, $\mathbb{E}[\frac{\partial v}{\partial a_{beg}}]$, and L^s. This dampening result is also quantitatively large. For instance, a 1% increase in the equity issuance cost decreases the average firm value by 0.59% when the trading costs are 50% above their estimates, versus by only 0.16% when the trading costs are 50% below their estimates.

These results have important implications for studying financial frictions, which, as my findings show, affect economic efficiency in tandem with IAT frictions. Therefore, to evaluate the impact of financial frictions, it is essential to account for the possibility that firms may reallocate their investment options. Since this aspect is not considered in many studies on financial frictions, my results call for caution when interpreting their conclusions.

Finally, lower financial frictions should also dampen the effects of trading frictions in a symmetric way. Accordingly, the dashed lines in Figure 7, which are analogous to the solid lines, show how the trading cost elasticity of economic efficiency varies with the degree of financial frictions. Consistent with intuition, trading costs are less consequential when external financing is more viable.

I.5 Stylized Patterns of Patent Trading

In this section, I provide corroborating evidence for my model by examining the trading patterns of patents. Many features of my patent trading sample are consistent with firms utilizing patent trading to get around financial difficulties.

I.5.1 Patent Trading in the Cross-section

I examine patent flows in the cross-section. Specifically, I examine how patent trading depends on a firm's financial state. I report the results in Table 6. To construct the table, in each year, I sort the cross-section of firms into five quintiles using lagged capital stock and then sort firms in each quintile into another five quintiles using lagged (capital-scaled) net cash holdings. Panel A reports the average (assets-scaled) net patent purchases in each of the resulting 25 subsamples. A clear pattern emerges when moving along each row of the panel: after controlling for firm sizes, net patent purchases increase with net cash holdings. I further decompose net patent purchases into average trading frequency and the net quantity per trade, which I report in Panels B and C, respectively. This decomposition shows that, in each size quintile, firms with higher cash holdings trade more often and purchase more patents per trade. Taken together, patents appear to flow from cash-poor to cash-rich firms in the cross-section. Notice also that larger firms and firms with more abundant cash holdings trade more frequently, consistent with the existence of fixed trading costs.

To construct Table 7, I sort the sample first by size and then by patent stock. This table shows that, for any given size, firms that have a larger patent portfolio spend more on R&D and trade their patents more often. These firms are also net patent sellers, consistent with the existence of decreasing returns to scale in owning patents.

I.5.2 Patent Trading in Time Series

This subsection presents patent trading patterns in the time series. I first sort each firm's time series into five bins by lagged cash holdings. I then pool firm-quarters in each bin and compute the average *Net Patent Sales*, defined as the negative of *Net Patent Buy* (equation (16)). I consider four subsamples: large, small, rated, and unrated firms. Large (small) firms are firms with capital stocks above (below) the sample median. Rated firms are those that ever receive bond ratings from Standard & Poor's during the sample period; I group the rest as unrated. For each panel of Figure 8, I plot the average *Net Patent Sales* by cash holding bins in one subsample. I find that large and rated firms exhibit no discernible changes in net patent trading with a reduction in cash holdings, while the net sales of small and unrated firms exhibit economically and statistically significant increases. The panels show that patent sales concentrate at times of low liquidity holdings and in firms with limited access to external finance, which is consistent with such firms seeking alternative funding to mitigate their financial difficulties.

In the Internet Appendix, I compare the timings of patent sales and equity issuances and find a strong similarity. Both concentrate when the cash holdings of firms are low and in small and unrated firms.

I.5.3 Patent Trading and R&D

I further examine whether patent sales mitigate firms' financial difficulties, that is, whether by selling some patents, the firm is able to implement other or future R&D projects. I first open a four-year event window bracketing each patent-sale quarter. I then track the average (assets scaled) R&D expenses during the four-year period for small, large, unrated, and rated firms. Figure 9 shows that, for small and unrated firms, patent sales are clear turning points. Before them, R&D decreases over time, but this trend reverses immediately after the event quarter. The post-event increase in R&D is also steady during the following two-year period. In contrast, large and rated firms see no such pattern; R&D changes only mildly throughout the event window.

In the model, seed trading opens the possibility that some firms can acquire and utilize otherwise-abandoned seeds. Consistent with this model mechanism, in unreported tests, I find that R&D also increases following patent purchases. Additionally, in the Internet Appendix, I compare R&D trends around patent sales and equity issuances. I again find strong similarities between them. In both cases, R&D increases significantly after the event quarter for small and unrated firms, but not for large and rated firms.

I.5.4 What Patents Do Firms Sell

Firms may trade patents for technological reasons. For instance, Akcigit et al. (2016) show that firms tend to buy patents that are closely related to their primary field of operation (core patents, for short) and sell the less related ones (peripheral patents). I examine if patent trading in my sample is driven by this technological motive. I define core and peripheral patent sales using the "technological distance" between the patents sold and the firm's patent portfolio; core (peripheral) patent sales are those whose technological distance is below (above) the sample median.[10]

Panels A and B of Figure 12 show R&D expenses around patent-sale quarters for core- and peripheral-patent sales, respectively. These two panels show that the increases in R&D are stronger after the sales of core patents. I next sort each firm's time series into five bins by its lagged (assets scaled) cash holdings and plot the average net sales of core and peripheral patents in each cash-holding bin in Panels C and D, respectively. As can be seen, compared to peripheral patents, firms have a stronger tendency to sell core patents during periods of financial difficulties.

Taken together, contrary to the technology-driven motive, when firms are in poor financial conditions, it is the core patents that they will sell; additionally, R&D also improves more after the sales of core patents.

[10] I measure the technological distance between two sets of patents: the patents being sold and the portfolio of all patents owned by the seller. To construct this distance measure, I use a two-step procedure. First, I measure the technological distance between two patent classes T^X and T^Y as $d^T(T^X, T^Y) = 1 - \frac{\#(T^X \cap T^Y)}{\#(T^X \cup T^Y)}$ (see Akcigit et al., 2016), where the numerator is the number of patents that cite both classes T^X and T^Y, and the denominator is the number of patents citing at least one of the two classes. Second, I compute the technological distance between two arbitrary sets of patents as $\nu_1' \Omega^T \nu_2$. The vector ν_j denotes the technology-class composition of patent set j, i.e., the Xth element of ν_j is the fraction of patents in the set j that belongs to the class T^X. Accordingly, ν_j's number of elements equals the total number of technology classes, and its elements sum to unity. Ω^T is a square matrix with the numbers of elements in both dimensions equal to the number of technology classes. Element (X, Y) of Ω^T is the pairwise distance $d^T(T^X, T^Y)$.

I.5.5 An Alternative Explanation

I have shown that firms in poor financial conditions more often sell patents and that their financial conditions subsequently improve. I also show these patterns to be more pronounced for small and unrated firms. These findings suggest that firms utilize seed trading to mitigate financial difficulties, yet they may also be consistent with an alternative explanation where some firms specialize in early-stage R&D and patent development. Under this alternative explanation, what appears to be financially-driven patent sales may actually reflect such firms' operation cycles. For instance, after an extensive R&D process, such a firm is granted a patent and is in the position to sell it. Cash holdings are depleted before the sale due to past expenditures. At the same time, the sale proceeds would allow the firm to initiate another round of patent development, giving rise to R&D patterns consistent with those in Figure 9. Moreover, given their specialization, these firms are likely small and unrated.

I examine the alternative explanation using a set of tests. For ease of exposition, I refer to this specialization-based hypothesis as H0 and my primary, finance-based hypothesis as H1.

A. Patent Sales and Past Shocks

I first explore a key difference between H0 and H1. Under H1, patent sales are unintended outcomes. The firm is "forced" to sell its patents after experiencing a sequence of bad shocks that expose it to potential financial difficulties. In contrast, H0 implies that the firm always plans to sell the patents. Hence, unlike H1, patent sales do not follow bad shocks. If anything, they should follow positive shocks, which indicate good research progress. To distinguish H1 from H0, I test the dependence of the patent sale frequency on past shocks, which I measure using a firm's past stock returns:

$$\mathbb{1}\{\Delta s_{i,t} < 0\} = \beta_0 + \beta_1 \sum_{h=1}^{12} r_{i,t-h} + \beta_2 a_{i,t-1} + \beta_3 a_{i,t-1} \times \sum_{h=1}^{12} r_{i,t-h} + \nu_{i,t}, \tag{23}$$

where $\mathbb{1}\{\Delta s_{i,t} < 0\}$ is an indicator variable that equals one if firm i sells patents in month t, $r_{i,t}$ is the firm's stock return in month t, and $a_{i,t-1}$ is the firm's net cash holdings as of the end of the latest quarter.

Table 8 reports the regression results. Column (1) reveals that a greater tendency to sell patents follows sequences of bad shocks ($\hat{\beta}_1 < 0$). Column (2) shows that this tendency is especially strong when cash holdings are low ($\hat{\beta}_3 < 0$). Column (3) shows that the first order effect of past shocks on patent sales remains negative and significant when a firm fixed effect is included. These results suggest that patent sales are unplanned choices made only in response to adverse realizations, favoring H1. When I measure past shocks using risk-adjusted returns based on CAPM (Columns (4)–(6)) and Fama-French three-factor models (Columns (7)–(9)), I find that adjusting for risk does not qualitatively affect the regression results.

B. Timing of Patent Sales After Patent Grants

H0 confounds H1 because, for firms specializing in developing patents, patent grants follow research expenditures but precede patent sales. Thus, it appears that patent sales come after periods of decreasing cash holdings. To test H1 against H0, I examine the timing of patent sales after the patents are granted. H0 provides no prediction on such timing—a patent sale takes place at a random point at which the firm finds a buyer. In contrast, H1 implies patent sales coincide with poor financial conditions regardless of whether the patents have been granted. Hence I track the patent owners' net cash holdings between patent grants and their eventual sales (See Figure 13). It is evident that conditioning on patent grants, sales still take place when cash holdings are low, consistent with H1.

In summary, the evidence suggests that it is unlikely that firms specializing in patent development drive my empirical findings.

I.6 Conclusion

In this paper, I study and quantify the efficiency implications of intangible asset trading in the presence of financial frictions. As is well understood, financial frictions interfere with the market's ability to direct cash to firms with good investment options. Much less studied is the reallocation of the investment options themselves, which takes place through intangible asset trading. An efficient market for investment options obviates the need for external financing and therefore dampens the effects of financing frictions. Since existing studies of financial frictions typically do not allow for the explicit IAT, it is important to know whether such an omission would affect the interpretations of their findings.

I show that the answer to this question is yes. By building and estimating a dynamic model on the use, finance, and trading of intangible assets, I find that, despite high trading costs, the option to trade leads to sizable reductions in the financing costs and improvements in firms' ability to utilize investment options. Interestingly, the direct effects of IAT are rather small; the efficiency improvements accrue because these direct effects are significantly amplified in equilibrium through ex ante changes in firms' expectations and investment choices. Additionally, I show that the implications of high financial frictions are materially different in environments featuring high and low trading costs. Therefore, not accounting for IAT may substantially affect the conclusions about financial frictions. Finally, I provide corroborating evidence of patent trading that is consistent with my model predictions. For instance, patents flow from firms with poor financial conditions to financially healthy firms, and R&D spending increases after patent sales.

This paper implies that policies that facilitate IAT, such as enforcing information disclosures regarding intangibles or mandating price transparency of IAT, may improve firm productivity and economic efficiency. My findings also contribute to the recent debate on the effect of patent trading on innovative activities.

CHAPTER II

Speculation with Information Disclosure

II.1 Introduction

Private information is valuable. Much research in financial economics over the last three decades illustrates both its benefits to speculators and its impact on financial market quality through their trading activity. For instance, Kyle (1985) shows that speculators trade cautiously (and anonymously) with private information to minimize its disclosure to less informed market participants. Importantly, in this model and many others, since speculators' trading profits monotonically depend on their informational advantage, protecting information leakage ensures maximal extraction of the rent of being informed.

Yet in reality, we also observe speculators strategically and publicly giving away their supposedly valuable information. These disclosures may take a variety of forms. Portfolio managers share perspectives on their covered firms through media interviews or public commentaries; activist investors have their opinions posted through Twitter feeds or blogs; etc. In a recent paper, Ljungqvist and Qian (2016) document an interesting phenomenon whereby some boutique hedge fund managers reveal evidence of questionable business activities by possibly overvalued firm—which they have gone through considerable trouble (and incurred great costs) to discover. Barring irrationality, this suggests that (cautious) non-anonymous disclosure of private information may indeed be optimal. For instance, Ljungqvist and Qian (2016) suggest that these hedge funds' voluntary disclosures may minimize the noise trader risk they face when taking short positions in those troubled firms (e.g., De Long et al. 1990; Kovbasyuk and Pagano 2015). Intuitively, for fear that market prices may further deviate from (poor) fundamentals, therefore forcing them to liquidate prematurely, fund managers disclose some private information to expedite convergence of prices to fundamentals.

The goal of this paper is to shed further light on the strategic disclosure of information in financial markets. Using a model of speculative trading based on Kyle (1985), we show that if an informed speculator's objective function includes not only long-term profit but also the short-term value of her portfolio, public (i.e., non-anonymous) disclosure of private information may naturally arise. This short-term objective captures parsimoniously a variety of forms of short-termism among sophisticated market participants: a hedge fund manager with a short position may be concerned about forced liquidation because of a sharp drop in portfolio value (as in Ljungqvist and Qian 2016); a mutual fund manager may care about her fund's NAV, upon which her compensation is often contingent; financial derivatives holders have their gains or losses hinge on the price movements of the underlying asset before the expiration date; liquidity constraint or risk-aversion in general can also lead to concerns over short-term values. A recent literature on "portfolio pumping" examines the impact of similar incentives for speculators on their trading activity and resulting market outcomes. For instance, Bhattacharyya and Nanda (2013) argue that fund managers may "pump" the short-term value of their portfolios by trading "excessively" in the direction of their initial holdings—i.e., away from what is warranted by long-term profit maximization. Consequently, equilibrium prices are distorted in the short term, the more so the larger weight the fund manager places on her short-term NAV or when she has a larger initial position. We refer to this pumping strategy as "pumping by trading" (PBT).

In our model, we show that public disclosure of private information is an additional tool to achieve portfolio pumping. A sophisticated speculator may optimally reveal private information about her holdings and asset fundamentals at the same time, but in a mixed fashion. Unable to distinguish between the two, uninformed market participants (market-makers) may revise their priors about asset fundamentals in response to such disclosures when clearing the market. Accordingly, short-term equilibrium prices are pumped in the direction of the speculator's holdings. We refer to this pumping strategy as "pumping by disclosing" (PBD).

PBT hurts the speculator's long-term profit as she deviates from her long-term profit-maximizing strategy. When available, PBD reduces the adverse effects of PBT by limiting the equilibrium extent of "excessive" trading. Disclosure, however, is also costly, as it compromises the speculator's informational advantage, which in turn deteriorates the speculator's long-term profits. Nonetheless, we show that, in equilibrium, the benefits from alleviating PBT and boosting the speculator's short-term value always outweigh the costs of compromising her informational advantage. Strategic disclosure, therefore, optimally arises in our model.

PBD has important, original implications for our understanding of the determinants of financial market quality. Disclosure has two opposite effects on market liquidity. On the one hand, as more private information is revealed, market-makers face less adverse selection risk and so lower the price impact of order flow, increasing market depth. On the other hand, as speculators refrain from PBT, a larger fraction of the aggregate order flow is driven by information-based trading, decreasing market depth. We show that when disclosure is optimal, the former effect dominates the latter such that PBD improves market liquidity. We further show that with optimal disclosure, equilibrium prices are more informative (and at the same time more volatile) in the sense that they reflect a larger proportion of speculators' private information, even though speculators trade more cautiously with their private information and aggregate order flow carries less fundamental information.

Our empirical analysis provides support for the model's implications. Our model suggests that strategic disclosure may be commonplace: Given a reasonably low cost, any partly-short-term-oriented speculator should find it optimal to disclose. Anecdotal evidence broadly supports this implication. For instance, portfolio managers "talk their book", i.e., discuss their positions in order to create or reduce interest and therefore promote buyers or sellers of the securities.[11] Yet, with the noteworthy exception of Ljungqvist and Qian (2016), empirical evidence on this issue remains scarce. To that end, we focus on strategic non-anonymous disclosures made by mutual fund families through three major newspapers: the Wall Street Journal, the Financial Times and the New York Times. We then show that likely stronger short-term incentives of mutual fund managers are associated with increased occurrence of strategic disclosures and greater liquidity improvement for the disclosure targets, especially when more suitable to such strategic disclosures by virtue of their greater fundamental uncertainty, consistent with our model.

Overall, our novel insights on the determinants and non-trivial externalities of strategic disclosure contribute to a recent theoretical literature on the disclosure activity of sophisticated market participants.

Kovbasyuk and Pagano (2015) argue that when uninformed investors have limited attention, *price-taking* arbitrageurs in several undervalued assets may optimally choose to overweight and advertise their private payoff information about only one such asset to expedite convergence to fundamentals. When studying bilateral transactions with imperfect competition, Glode et al. (2017) also show that a privately informed agent facing a counterparty endowed with market power may find it optimal to voluntarily disclose his *ex post* verifiable information in order to mitigate the counterparty's inefficient screening, leading to socially efficient trade. However, Han and Yang (2013) postulate that social communication may hinder information production and worsen market efficiency by enabling traders to free-ride on better informed friends or prices, while Liu (2017) finds that optimal disclosure of private long-lived information by a reputable short-horizon investor to uninformed long-horizon followers (but not to market makers) may lower prior informed trading intensity and equilibrium price informativeness. Relatedly, in a model of "cheap talk" (Crawford and

[11] This phenomenon has received ample coverage in the media. See, for instance, *"Everybody Talks Their Book, Everybody"* on Abnormal Returns, available at http://abnormalreturns.com/2010/02/18/everybody-talks-their-book-everybody/, or *"New Investing Strategy: Talk Your Book"* on BloombergView, available at https://www.bloomberg.com/view/articles/2014-03-07/new-investing-strategy-talk-your-book.

Sobel 1982), Schmidt (2018) argues that *anonymous price-taking* "rumormongers" may find truthful information sharing attractive when short-term oriented, while choosing to lie when long-term oriented. Others investigate the notion that firm managers have discretion to disclose information that investors do not observe (e.g., Shin 2003; Goto et al. 2009; Hertzberg 2017) or whether they should be required to do so when selling risky assets (e.g., Kurlat and Veldkamp 2015).

Relative to these studies, the focus of our theory is on the interaction between speculators' *strategic* trading and strategic *public* disclosure of private information about asset payoffs and endowments to competitive dealership, and its novel implications for the process of price formation in the affected markets. Our accompanying empirical evidence is both suggestively supportive of these implications and (to our knowledge) novel to the literature on mutual fund management (e.g., surveyed in Elton and Gruber 2013).

The rest of the paper proceeds as follows. Section II.2 introduces our model and derives its implications. Section II.3 describes our data sources, while Section II.4 presents the empirical results. We conclude in Section II.5.

II.2 The Theory

In this section, we show how strategic disclosure may naturally arise in a standard Kyle (1985) setting, in contrast with the conventional wisdom in market micro-structure that information leakage hurts speculation. As we show, the key ingredient leading up to this result is that speculators face a trade-off between maximization of long-term profit and short-term portfolio value. As we discuss next, this stylized trade-off captures parsimoniously a variety of real-life conflicting incentives for sophisticated financial market participants.

We begin by describing a baseline model of speculative trading based on Kyle (1985) and Bhattacharyya and Nanda (2013), which gives rise to PBT. Next, we enrich this model by allowing for informative disclosure and derive novel implications of PBD for the equilibrium quality of the affected market. All proofs are in the Appendix.

II.2.1 The Baseline Model

Our basic setting is a batched-order market as in Kyle (1985), with three dates, $t = 0, 1$ and 2, and one risky asset. At date $t = 2$, the payoff of the risky asset—a normally distributed random variable v with mean P_0 and variance σ_v^2—is realized. Three types of risk neutral market participants populate the economy: An informed trader (the speculator or "speculative sector"), competitive market makers (or "market making sector", MM), and liquidity traders. The structure of the economy and the decision processes leading up to order flow and prices are common knowledge among all market participants.

At date $t = 0$, the speculator privately observes the liquidation value of the risky asset (v), as well as receives an initial endowment (e) of the risky asset, also unobservable to all others. Throughout this paper, we use the terms "initial position", "initial endowment" and "initial holding" interchangeably, all referring to the speculator's position in the risky asset before the model's single round of trading. Individual allocations are endogenous in a number of models (see, e.g., Back and Zender 1993, among others). This paper takes as given the level of information asymmetry (regarding both endowments and fundamentals) to study the speculator's strategic behavior thereafter. Hence, as in Bhattacharyya and Nanda (2013), we parsimoniously assume that e is normally distributed with $\mathrm{E}[e] = \bar{e}$ and $\mathrm{Var}\left(e\right) = \sigma_e^2$, as well as independent of v ($\mathrm{Cov}\left(v, e\right) = 0$). Relaxing these assumptions such that the speculator's private fundamental information is noisy and/or correlated with her endowment ($\mathrm{Cov}\left(v, e\right) \neq 0$) would complicate the analysis without affecting its main insights (see also Pasquariello 2003, Chapter 1; Pasquariello and Vega 2009).

At date $t = 1$, both the speculator and liquidity traders submit market orders, x and z, respectively, to the MM, where $z \sim N(0, \sigma_z^2)$ is independent of all other random variables. The MM observes the aggregate order flow $\omega = x + z$ and sets the equilibrium price $P_1 = P_1(\omega)$ that clears the market.

The departure we take from Kyle (1985) lies in the speculator's objective function. In

Kyle (1985) as well as many other theoretical studies of price formation, long-term profit maximization is the sole objective of the speculator. In reality, however, many sophisticated market participants are found to be short-term oriented, or at least partly so. For instance, mutual fund managers are compensated on the basis of the funds' current net asset value (NAV; see, e.g., Warner and Wu 2011). A fund's recent performance is crucial to its competition for fund flows (e.g., see Ippolito 1992; Sirri and Tufano 1998; Brown et al. 1996) as well as the success of its fund managers in the job market (see, e.g., Chevalier and Ellison 1999). Short-term performance also concerns activist investors as many of them choose to exit from their block holdings after carrying out interventions in a firm (e.g., Becht et al. 2017 find activist hedge funds' holding period spans an average of 1.7 years; likewise, Brav et al. 2008 estimate the median holding period to be above 1 year); the firm's valuation at the time of the exit would therefore largely affect the return to the activist investors.[12] More broadly, any speculator plagued by liquidity constraints (see Ljungqvist and Qian 2016, and references therein), professional money manager facing relatively short expected tenure due to mobility and turnover (as in Dow and Gorton 1994; Goldman and Slezak 2003), or investor preferring early resolution of uncertainty (e.g., under Epstein and Zin 1989 preferences) may wish all or part of her investment to pay off early. Lastly, the short-term performance of an asset may be relevant to investors holding both the asset and options on it. Following Pasquariello and Vega (2009) and Bhattacharyya and Nanda (2013), we capture these short-term incentives parsimoniously by assuming that the speculator's value function is separable in her short-term (i.e., date $t = 1$) value $W_1 = e(P_1 - P_0)$, and long-term (i.e., date $t = 2$) profit $W_2 = x(v - P_1)$, such that:

$$W = \gamma W_1 + (1 - \gamma) W_2, \tag{24}$$

where $\gamma \in [0, 1]$ can be interpreted as the speculator's rate of substitution between short-

[12] Accordingly, Greenwood and Schor (2009) associate abnormal returns surrounding hedge funds' announcements of activist intentions about a target to their ability to induce a takeover for that target.

and long-term objectives.[13] Finally, at date $t = 2$, the risky asset is liquidated at price v.

Consistent with Kyle (1985), we define a Bayesian Nash Equilibrium of this economy as a trading strategy $x(v, e)$ and a pricing rule $P_1(\omega)$, such that the following conditions are satisfied:

1. Utility Maximization: $x(v, e) = \arg\max \mathrm{E}\left[W|v, e\right]$;

2. Semi-strong form market efficiency: $P_1 = \mathrm{E}\left[v|\omega\right]$.

The following proposition characterizes the unique linear equilibrium of this economy.

Proposition 4 (Baseline, Bhattacharyya and Nanda 2013) *The unique equilibrium in linear strategies of this economy is characterized by the speculator's demand strategy*

$$x^*(v, e) = \beta\bar{e} + \frac{v - P_0}{2\lambda^*} + \frac{\beta}{2}(e - \bar{e}), \tag{25}$$

and the MM's pricing rule

$$P_1 = P_0 + \lambda^*(\omega - \beta\bar{e}), \tag{26}$$

where

$$\lambda^* = \frac{\sigma_v}{2(\beta^2\frac{\sigma_e^2}{4} + \sigma_z^2)^{\frac{1}{2}}}, \tag{27}$$

and

$$\beta = \frac{\gamma}{1 - \gamma}. \tag{28}$$

In this model, β captures the relative importance the speculator attaches to her short-term objective (W_1). When $\beta = 0$, the speculator reduces to a long-term profit maximizer and the ensuing equilibrium to the one in Kyle (1985): $x^k = \frac{v - P_0}{2\lambda^k}$ and $\lambda^k = \frac{\sigma_v}{2\sigma_z}$. As β increases,

[13] Specifically, Pasquariello and Vega (2009) and Bhattacharyya and Nanda (2013) assume the speculator's objective function to be separable in her portfolio's short-term ($t = 1$) and long-term ($t = 2$) net asset value (NAV, or wealth), i.e., $U = \gamma \times \mathrm{NAV}^{t=1} + (1 - \gamma) \times \mathrm{NAV}^{t=2}$, where $\mathrm{NAV}^{t=1} = \mathrm{NAV}^{t=0} + e(P_1 - P_0)$, $\mathrm{NAV}^{t=2} = \mathrm{NAV}^{t=0} + e(v - P_0) + x(v - P_1)$, and $\mathrm{NAV}^{t=0}$ is her initial ($t = 0$) NAV. The reduced-form objective function of Eq. (24) is then derived by removing from U those terms in $\mathrm{NAV}^{t=1}$ and $\mathrm{NAV}^{t=2}$ that are not affected by (hence do not affect) the speculator's decision process, i.e., $W = U - \mathrm{NAV}^{t=0} - (1 - \gamma)e(v - P_0)$. This simplification is only for economy of notation and has no bearing on our analysis.

the speculator's trading strategy deviates from long-term profit maximization ($x^* \neq x^k$) to pump up/down the equilibrium price in the direction of her initial position in the risky asset ($\text{Cov}\left(P_1, e\right) = \frac{1}{2}\lambda^* \beta \sigma_e^2 > 0$), a behavior that we call portfolio pumping by trading (PBT). In particular, PBT improves market liquidity ($\lambda^* < \lambda^k$) by alleviating market makers' adverse selection risk. Further insights on PBT can be found in Pasquariello and Vega (2009) and Bhattacharyya and Nanda (2013).[14]

II.2.2 Equilibrium with Disclosure

We now extend the baseline model of Section II.2.1 by allowing the speculator to publicly disclose information before trading and clearing.

Sophisticated market participants often make public announcements on asset fundamentals in a variety of forms. For instance, Ljungqvist and Qian (2016) document that some small hedge funds, after spending considerable resources to discover that a target firm is overpriced, not only take short positions in that firm but also publicly disclose that information in detailed reports (e.g. alluding the target firm of fabricating accounting figures or inflating productive capacity). Other disclosures are less aggressive. For instance, portfolio managers and financial analysts often make media appearances (on such outlets as CNBC, WSJ, etc.) discussing recent corporate events or market outlook. These talks may allow the involved speculator to reveal her private knowledge of asset fundamentals.

Importantly, however, these disclosures may reveal information not only about asset fundamentals, but also the speculator's own stake in that asset. To begin with, U.S. law mandates that the speculator be explicit about the conflict of interest in her disclosures such that the reader or audience should realize that the speculator stands to gain once her

[14] Pasquariello and Vega (2009) and Bhattacharyya and Nanda (2013) also find these insights to be unaffected by allowing for a discrete number of either heterogeneously informed (hence, less aggressively competing) or homogeneously informed (hence, more aggressively competing) speculators, respectively, yet at the cost of greater analytical complexity relative to the baseline model. Accordingly, in this study we concentrate on the trading and disclosure activity of a single speculator (or speculative sector, as in our accompanying empirical analysis of the mutual fund industry), and leave the investigation of competition in disclosure for future research.

suggestions are followed.[15]

Even without conflict of interest, investors may rationally perceive public disclosures by speculators as tainted. After all, a speculator may be inclined, if she holds a long (short) position in an asset, to use her disclosures about that asset to induce investors to buy (sell) it. Current regulations, albeit stringent, may leave the information provider sufficient wiggling room for toning her message. The speculator may, for instance, disclose evidence with selective emphasis, but without crossing the line between truthful revealing and misrepresentation. Consequently, upon seeing a strongly negatively-toned disclosure about an asset by a speculator, a reader has every reason to suspect that the speculator is intentionally tilting her tone and that she is likely to hold a short position in that asset.[16]

Lastly, information on asset fundamentals and speculator's holdings are likely indistinguishable to an uninformed investor. On the one hand, any bias in a speculator's disclosure about asset fundamentals will likely depend on the speculator's stake in that asset. On the other hand, speculators are often not entirely transparent about their holdings. Many studies find that institutional investors attempt to disguise their portfolio holdings, e.g., by window dressing, to reduce the leakage of potentially valuable proprietary information (e.g., Lakonishok et al. 1991; Musto 1999; Agarwal et al. 2013; Shi 2017).[17] How much the spec-

[15]The Securities Exchange Commission (SEC) imposes fiduciary duty on financial advisors, which is made enforceable by Section 206 of the U.S Investment Advisers Act of 1940. Under the Act, an adviser has an affirmative obligation of utmost good faith and full and fair disclosure of all facts material to the client's engagement of the adviser to its clients. This is particularly pertinent whenever the adviser is faced with a conflict—or potential conflict—of interest with a client. The SEC has stated that the adviser must disclose all material facts regarding the conflict such that the client can make an informed decision whether to enter into or continue an advisory relationship with the adviser. Additionally, the Act also applies to prospective clients. The SEC has adopted rule 206(4)–1, prohibiting any registered adviser from using any advertisement (that includes notice through radio or television) that contains any untrue statement of material facts or is otherwise misleading. Accordingly, Ljungqvist and Qian (2016, p. 1989) note that each of the stock reports prepared by boutique hedge funds in their sample "prominently discloses that the arb[itrageur] has a short position in the target stock."

[16]Relatedly, Banerjee et al. (2016) show that in an investment game in which two players endowed with noisy private fundamental information have an incentive to coordinate, both the sender and the receiver may prefer strategic communication—in the form of only partially informative cheap-talk—to the sender's commitment to perfect disclosure.

[17]For instance, Shi (2017) shows that the mandatory disclosure of hedge funds' positions via Form 13F filings may reveal valuable private information by leading both to a subsequent drop in their performance and to an increase in its correlation with their competitors.

ulators hide their positions may in turn depend on the fundamental information they want to keep private.

In short, speculators' disclosures are likely to reflect both their private fundamental information and their unobservable holdings; accordingly, uninformed market participants are likely to view any public disclosure by speculators as a function of both their private fundamental information and their unobservable holdings. We capture parsimoniously this observation in the model by assuming that the speculator has the option to publicly disclose a signal s that is a convex combination of e and v:

$$s(v, e) = \delta e + (1 - \delta)v, \tag{29}$$

where the publicly known coefficient $\delta \in [0, 1]$ represents the extent to which the signal is informative about speculators' holdings (e) versus asset fundamentals (v). The speculator may freely choose which δ to use, but she must commit to disclosing the resulting signal (s) at the chosen δ *before* observing e and v. Eq. (29) is a parsimonious characterization of the speculator's reporting strategy. More detailed discussions about the plausibility of this assumption is in Section II.2.5.

Specifically, we model the strategic disclosure of the signal s of Eq. (29) in our setting by introducing a date $t = -1$, in which the speculator can choose either (1) to do nothing and proceed to date $t = 0$ (yielding the baseline equilibrium of Proposition 4), or (2) to commit to the following reporting strategy: She first chooses and commits to a particular δ at $t = -1$; then, at $t = 0$ (or at any subsequent time *before* the market clearing price P_1 is set), after observing v and e, she discloses the resulting signal $s(v, e)$ to the public. Each reporting strategy thus corresponds to a choice of the weight δ. When the speculator commits to disclose, the ensuing model has a unique equilibrium in linear strategies, in which the price schedule is a linear function of the signal and the order flow and the speculator's trading strategy is linear in the asset's liquidation value, initial position, and the signal.

Proposition 5 (Equilibrium with Disclosure) *If the speculator chooses to send a signal s of Eq.* (29) *with publicly known weight δ (PBD), the ensuing linear equilibrium of the economy is characterized by the speculator's demand strategy*

$$x^*(v,e) = \frac{\beta}{2}(e+\bar{e}) + \frac{v-P_0}{2\lambda_1} - \frac{\lambda_2}{2\lambda_1}(s-\bar{s}) = \beta\bar{e} + \frac{\beta\lambda_1 - \delta\lambda_2}{2\lambda_1}(e-\bar{e}) + \frac{1-(1-\delta)\lambda_2}{2\lambda_1}(v-P_0), \quad (30)$$

and the MM's pricing rule

$$P_1 = P_0 + \lambda_1(\omega - \bar{\omega}) + \lambda_2(s - \bar{s}), \quad (31)$$

where

$$\lambda_1 = \frac{1}{\sqrt{\alpha^2\beta^2 + 4\frac{\sigma_z^2}{\sigma_v^2} + 4\alpha^2\frac{\sigma_z^2}{\sigma_e^2}}} > 0, \quad (32)$$

$$\lambda_2 = -\frac{\lambda_1}{\delta}\left(\beta - \frac{4\lambda_1\sigma_z^2}{(\frac{1}{\alpha} - \beta\lambda_1)\sigma_e^2}\right), \quad (33)$$

and

$$\alpha = \frac{1-\delta}{\delta}. \quad (34)$$

The coefficients λ_1 and λ_2 represent the equilibrium price impact of the order flow and public signal, respectively. In particular, it can be shown that for any δ such that disclosure is *ex ante* optimal (as discussed next), $\lambda_2 > 0$.[18] Accordingly, relative to the baseline equilibrium and for any given level of market liquidity λ', the speculator trades "less" both on private fundamental information ($\frac{1-(1-\delta)\lambda_2}{2\lambda'} < \frac{1}{2\lambda'}$) and her endowment ($\frac{\beta\lambda'-\delta\lambda_2}{2\lambda'} < \frac{\beta}{2}$). Intuitively, because the signal partly resolves fundamental uncertainty, information-based trading is less profitable; this captures the "cost" of PBD. However, PBD both alleviates the need for PBT and makes it less effective (by improving market depth, i.e., lowering λ_1). As we show shortly, the former effect of PBD translates into a reduction in long-term profit,

[18] *Ceteris paribus* for other model parameters, there exist some *ex ante* suboptimally "high" δ coefficients such that $\lambda_2 < 0$, as in those circumstances the MM uses the resulting disclosed signal s of Eq. (29) to learn mostly about e and so offset any effect of PBT on P_1 via the aggregate order flow.

whereas the latter yields an increase in long-term profit because of the reduced scale of PBT.

The MM incorporates the signal's information content about fundamentals in the market clearing price of Eq. (31). However, since the MM is unable to disentangle the signal's fundamental-related component and endowment-related component, both components have a positive impact on the equilibrium price. The fact that the signal moves prices in the direction of the endowment is especially desirable to a speculator who is at least partly short-term-oriented. The equilibrium price is high/low exactly when a high/low price is desirable—i.e., when her initial holdings of the asset are large ($e > \bar{e}$)/small ($e < \bar{e}$).

As we noted earlier, the equilibrium in Proposition 5 is conditional on the speculator committing to disclose a signal s. We now discuss when such a commitment is optimal. As we show in the following proposition, there always exist suitable choices of signal weight δ, at which committing to disclosure is *ex ante* optimal.

Proposition 6 (Optimality of Disclosure) *Let D be the indicator variable for disclosure: $D = 1$ if the speculator commits to sending signal $s(v, e)$ and $D = 0$ otherwise. The following results hold:*

1. *The ex ante ($t = -1$) expected value function to the speculator of committing to sending a signal with weight δ is given by*

$$\mathrm{E}\left[W \middle| D = 1, \delta\right] = (1-\gamma)\lambda_1 \sigma_z^2 \frac{1 + \alpha\beta\lambda_1}{1 - \alpha\beta\lambda_1}, \tag{35}$$

   where λ_1 is defined in Eq. (32)*.*

2. *The ex ante ($t = -1$) expected value function to the speculator of not disclosing a signal is given by*

$$\mathrm{E}\left[W \middle| D = 0\right] = \frac{1-\gamma}{4\lambda^*}(\sigma_v^2 + \beta^2 \lambda^{*2} \sigma_e^2), \tag{36}$$

   where λ^* is defined in Eq. (27)*.*

3. Disclosing is incentive compatible. Let δ^* be the optimal signal weight with disclosure:

$$\delta^* = \arg\max_{\delta} \mathrm{E}\left[W \middle| D = 1, \delta\right], \tag{37}$$

then $\delta^* \in (0, 1)$ and

$$\mathrm{E}\left[W \middle| D = 1, \delta^*\right] > \mathrm{E}\left[W \middle| D = 0\right], \quad \forall \sigma_v^2 > 0, \sigma_e^2 > 0, \sigma_z^2 > 0, \gamma > 0. \tag{38}$$

The intuition for this result is that even with disclosure, the speculator can still replicate the equilibrium outcome in the baseline model by carefully choosing the signal weight δ. If the speculator sends a signal with no information content above and beyond that of the aggregate order flow, then such a signal is redundant and the equilibrium reduces to the baseline equilibrium. It can be shown that such a redundant signal is one with the weight $\hat{\delta} = \frac{1}{1+\lambda^* \beta \frac{\sigma_e^2}{\sigma_v^2}} \in (0, 1)$ for any $\beta > 0$, where λ^* is given by Eq. (27).[19] Thus the action set of the speculator in the signaling equilibrium of Proposition 5 is $\delta \in [0, 1]$ versus $\delta \in \{\hat{\delta}\}$, which is effectively her action set in the baseline equilibrium of Proposition 4. With a strictly larger action set, optimality of disclosure follows.

It might be counterintuitive that it is suboptimal for the speculator not to disclose. It is an established notion that (more) private information yields (more) trading profit. For instance, in Kyle (1985), the greater her informational advantage, the more profit the speculator could reap from trading. Releasing a signal of her private information is thus tantamount to (at least partly) giving away expected trading profits. Accordingly, most

[19] Specifically, under $\hat{\delta}$, the MM's two sources of information are: (a) The order flow $\omega - \bar{\omega} = \frac{1}{2\lambda^*}(v - P_0) + \epsilon_\omega$, where $\epsilon_\omega = \frac{\beta}{2}(e - \bar{e}) + z$, is the noise about fundamentals; and (b) the (scaled) signal $\frac{s - \bar{s}}{2\hat{\delta}\lambda^{*2}\beta\frac{\sigma_e^2}{\sigma_v^2}} = \frac{1}{2\lambda^*}(v - P_0) + \epsilon_s$, where $\epsilon_s = \epsilon_\omega + \eta$ with $\eta = \frac{2\sigma_z^2}{\beta\sigma_e^2}(e - \bar{e}) - z$. Since ϵ_ω, η and $v - P_0$ are mutually independent, the signal is just the order flow plus uninformative noise. This implies that $v \perp s|\omega$, i.e., that given the order flow, a signal with weight $\hat{\delta}$ is redundant in learning about asset fundamentals. Thus, $\lambda_1 = \lambda^*$, $\lambda_2 = 0$, and the equilibrium reduces to the baseline equilibrium of Proposition 4. Accordingly, when $\beta = \gamma = 0$, the above economy reduces to Kyle (1985) such that the long-term profit maximizing speculator is indifferent to her endowment shock e and both the optimal and redundant signals fully reveal it to the MM ($\delta^* = \hat{\delta} = 1$).

existing models in the micro-structure literature do not leave room for voluntary disclosure. In our model, however, the speculator is not a pure long-term profit maximizer. The loss of long-term profit caused by information revelation is compensated by gains in the short-term value of her portfolio; and the gains outweigh the losses—as shown in Proposition 6. By incorporating short-termism in the speculator's objective function, our model has the potential to explain the frequently observed voluntary disclosures in financial markets.

The following example may shed further light on the intuition behind Proposition 6. Assume that a speculator has the intention to "pump" price by disclosing a signal. In order for that signal to have any price impact, it must contain at least some fundamental information. Intuitively, any signal containing only information about the endowment e and possibly some noise ϵ would not affect the MM's fundamental priors while also reducing *ex post* uncertainty about e and so making any PBT by the speculator less effective (see also Bhattacharyya and Nanda 2013). Thus, in general, the signal should be a function of v and possibly some noise ϵ. If the speculator follows a "naïve" strategy by setting ϵ to be purely random noise, such a disclosure would move prices in the desired direction only when the speculator's endowment shock happens to be in the same direction as the fundamental shock; otherwise the signal may backfire. The net effect of such a signal is that the speculator obtains no short-term gain on average but only lower long-term profits due to a compromised informational advantage.[20]

Consider now a disclosure strategy that sets $\epsilon \propto e$. Since from a Bayesian perspective, how the noise is constructed is irrelevant to the inference of v, a signal with $\epsilon \propto e$ has the same impact on the MM's fundamental priors as a signal with purely random noise (given the same noise variance). But now the signal has an added benefit of leading the MM to interpret, e.g., a "large" endowment shock as a high fundamental shock, potentially leading to a "large" price change. Note that when $\epsilon = \frac{1}{\alpha}e$, this is effectively the signal in Eq. (29).

[20] Accordingly, the disclosure of two *separate* such signals for e and v, respectively, would cost the speculator both short-term gains and long-term profits. A formal proof of these arguments in our setting for the class of linear signals $s = e + \epsilon$ and/or $s = v + \epsilon$ is available in Section 1 of the Internet Appendix.

Hence, pumping by disclosing is most effective exactly when the speculator cares most about it—when her endowment is "large."

II.2.3 Pumping by Trading and Pumping by Disclosing

In order to achieve her short-term objective, the speculator may either trade "excessively" in the direction of her initial endowment (PBT) or disclose a mixed signal (PBD). Our earlier discussion suggests that the speculator optimally uses both tools in equilibrium. In this section, we isolate the two tools and examine separately their effect on the speculator's short-term and long-term objectives (W_1 and W_2, respectively).

To that end, it is useful to take a closer look at the process by which information is used by the MM and the speculator. In the signaling equilibrium of Proposition 5, the MM receives the signal and the order flow simultaneously (Eq. (31)). Alternatively, one could think of the MM as separately absorbing the information in two steps. First, the MM observes the signal and updates his priors about v and e. Second, the MM observes the order flow, and, together with his updated priors, sets the price. One could also think of the speculator as acting in two steps. First, she observes v and e, discloses the signal according to Eq. (29), and forms belief about the MM's updated priors. Second, she trades in the updated information environment.

While both approaches yield the same equilibrium outcomes, the two-step approach allows for a more intuitive interpretation: The first step involves no trading and the second step represents a baseline equilibrium without disclosure. This helps isolate the effects of PBT and PBD.

II.2.3.1 A Two-step Formulation of the Signaling Equilibrium

We begin by formally describing an alternative approach to construct the signaling equilibrium of Proposition 5. Consider a two-stage game. In the first stage, the speculator privately observes v and e and then announces her signal s of Eq. (29) at a predetermined weight

δ. In the second stage, trading takes place at the realized market clearing price P_1 (as the baseline equilibrium).

We consider the Perfect Bayesian Equilibrium of this two-stage game. Note that with the *ex ante* commitment to disclose and a predetermined signal weight, no optional action occurs in the first step: Nature draws v and e, publicly reports s, the speculator observes v and e directly and the MM updates her priors about v and e according to s. Thus we only need to study the equilibrium in the second step. We start with the information environment in the continuation game after Nature's draw - the common prior in the second step. Since the speculator is fully informed, the updated common prior is the MM's perceived distribution of (v, e) conditional on s:

$$\begin{pmatrix} v \\ e \end{pmatrix} | s \sim N\left[\begin{pmatrix} \tilde{v} \\ \tilde{e} \end{pmatrix}, \begin{pmatrix} \tilde{\sigma}_v^2 & -\tilde{\sigma}_v\tilde{\sigma}_e \\ -\tilde{\sigma}_v\tilde{\sigma}_e & \tilde{\sigma}_e^2 \end{pmatrix}\right] \tag{39}$$

where

$$\tilde{v}(v,e) = P_0 + \frac{(1-\delta)\sigma_v^2}{\delta^2\sigma_e^2 + (1-\delta)^2\sigma_v^2}(s - \bar{s}) \tag{40}$$

$$\tilde{e}(v,e) = \bar{e} + \frac{\delta\sigma_e^2}{\delta^2\sigma_e^2 + (1-\delta)^2\sigma_v^2}\left(s - \bar{s}\right) \tag{41}$$

$$\tilde{\sigma}_v^2(v,e) = \frac{\delta^2\sigma_v^2\sigma_e^2}{\delta^2\sigma_e^2 + (1-\delta)^2\sigma_v^2} \tag{42}$$

and

$$\tilde{\sigma}_e^2(v,e) = \frac{(1-\delta)^2\sigma_v^2\sigma_e^2}{\delta^2\sigma_e^2 + (1-\delta)^2\sigma_v^2} \tag{43}$$

Proposition 4 can be applied to fully characterize the second stage equilibrium by replacing the prior distribution with the updated posteriors of Eqs. (39) to (43). The entire game is therefore a set of baseline equilibriums, one for each realization of (v, e). Our next result shows that this two-stage approach yields the same equilibrium outcome as the single-stage signaling equilibrium.

Proposition 7 (Equivalence) *The Perfect Bayesian Equilibrium of the two-step game is* *identical to the single-step signaling equilibrium: For any realization of v, e, and z, the speculator submits the same market order, and the MM sets the same price.*

This two-step approach emphasizes the role of disclosure as reshaping the information environment before trading and clearing. Effectively, price is formed in two steps: First, information in the signal is incorporated in the form of the MM's updated posteriors about v and e; second, information in the order flow is incorporated through trading. This is a convenient result as it allows to separate the effects of PBT and PBD on the equilibrium.

II.2.3.2 Decomposing the Effects of PBD

Following the two-step approach, we decompose the speculator's *ex ante* expected value function in equilibrium as:

$$\mathrm{E}\left[W|D=1,\delta\right] = \underbrace{\mathrm{E}\left[\overbrace{\gamma e(\tilde{v}-P_0)}^{\text{Short-term}}|D=1,\delta\right]}_{\text{Signaling (first stage)}} + \underbrace{\mathrm{E}\left[\overbrace{\gamma e(P_1-\tilde{v})}^{\text{Short-term}} + \overbrace{(1-\gamma)x(v-P_1)}^{\text{Long-term}}\big|s,D=1,\delta\right]}_{\text{Trading (second stage)}} \tag{44}$$

(see also Eq. (138)).[21] Only trading can generate long-term profit, whereas both disclosure and trading serve to the speculator's short-term objective. The signal firstly shifts the price via updating the MM's inference of v; then this inference (and the market clearing price) is further affected by the speculator's trading in the aggregate order flow. The effect of the signal persists through the trading stage, as it shifts the prior mean of the MM's valuation. By construction, the signal positively depends on both v and e. The first dependence means that the MM adjusts his inference ($\tilde{v}$) of v upward on seeing a positive signal, whereas the

[21] In particular, the speculator's *ex ante* expectation of W, i.e., given her date $t=-1$ information set, is given by

$$\begin{aligned}
&\mathrm{E}\left[W|D=1,\delta\right]\\
=&\,\mathrm{E}\left\{\mathrm{E}\left[W|s,D=1,\delta\right]\big|D=1,\delta\right\}\\
=&\,\mathrm{E}\left\{\mathrm{E}\left[\gamma e(\tilde{v}-P_0)|s,D=1,\delta\right]\big|D=1,\delta\right\}+\mathrm{E}\left\{\mathrm{E}\left[\gamma e(P_1-\tilde{v})+(1-\gamma)x(v-P_1)\big|s,D=1,\delta\right]\big|D=1,\delta\right\},
\end{aligned}$$

where, in the last line, the inner expectation in the first term drops because of the law of iterated expectations while the outer expectation in the second term drops because the expected value function conditional on the information set $(s,D=1,\delta)$ is independent of s.

second dependence means that a positive endowment shock e leads to a positive signal. This feature serves to the speculator's short-term objective as it implies a positive correlation between e and $\tilde{v}$ ($\text{Cov}\left(e, \tilde{v}\right) = \frac{(1-\delta)\delta\sigma_v^2\sigma_e^2}{\delta^2\sigma_e^2+(1-\delta)^2\sigma_v^2}$).

Table 9 decomposes the speculator's *ex ante* expected value function by PBT and PBD and their contributions to her long-term and short-term objectives. Comparing each component of the value function under disclosure ($D = 1$) versus no disclosure ($D = 0$) reveals that: (1) The direct effect (first step) of PBD is a boost to the speculator's short-term objective ($\frac{1}{2}\gamma\tilde{\sigma}_v\tilde{\sigma}_e$) but there is no direct effect on the long-term objective; (2) PBD allows the speculator to optimally cut back on her PBT such that the effect of PBT on her short-term objective is reduced ($\frac{\gamma\beta}{2}\lambda^*\sigma_e^2 > \frac{\gamma\beta}{2}\lambda_1\tilde{\sigma_e}^2$);[22] (3) PBD has two opposing effects on the speculator's long-term objective: First, the signal gives away part of the speculator's private information about v; second, less PBT means less information leakage about v by the order flow; the net effect is a loss in long-term profit, as reflected by the improved price impact ($(1-\gamma)\lambda_1\sigma_z^2 < (1-\gamma)\lambda^*\sigma_z^2$).[23]

Proposition 6 shows that, after aggregating these effects, the speculator's value function is improved by PBD.

II.2.4 Equilibrium Properties and Comparative Statics

A. Comparative Statics

[22]We show in Corollary 1 next that $\lambda_1 < \lambda^*$ in equilibrium.

[23]Note that since the equilibrium price is semi-strong form efficient, the speculator's expected long-term profit is just noise traders' loss, and therefore depends solely on the price impact λ. Using Eqs. (39) to (43), the expression for price impact with disclosure (λ_1 in Eq. (32)) can be rewritten as:

$$\lambda_1 = \frac{\tilde{\sigma}_v}{2\sqrt{(\frac{\beta}{2})^2\tilde{\sigma}_e^2 + \sigma_z^2}}.$$

Intuitively, the numerators and denominators of both the above expression and the one for price impact without disclosure (λ^* of Eq. (27)) reflect the amount of information and non-information-based trading, respectively. With PBD, there is less information-based trading as the signal compromises the speculator's informational advantage, improving the price impact and reducing the speculator's profit. However, with PBD, non-information-based trading (PBT) is also reduced; this leads to the opposite effects on price impact and long-term profit. The net effect is that the speculator loses long-term profit.

The optimal signal weight (δ^*) depends on the model's primitives. There is, unfortunately, no analytically tractable solution for δ^*. Therefore, we derive its comparative statics (and some of the properties of the ensuing equilibrium) numerically. We begin with Figure 15, where we plot δ^* as a function of γ—the relative importance of the speculator's short-term objective—for different combinations of such primitives as σ_v^2, σ_e^2 and σ_z^2. For all combinations, optimal signal weight decreases monotonically in γ. Intuitively, when δ is smaller, the signal becomes more informative about v, leading to a larger loss of the speculator's informational advantage and long-term profit. Of course, if the speculator only cared about the long run ($\gamma = 0$), she would choose never to disclose valuable private information (i.e., $\delta = 1$). On the other hand, when the speculator values the short run ($\gamma > 0$), she wants the signal to have a large price impact; thus she needs the signal to be informative about both v and e. It can be shown that a $\delta = \frac{\sigma_v}{\sigma_e+\sigma_v}$ induces the largest price impact of the signal in the direction of the speculator's endowment; in other words, this is the signal weight the speculator would choose if she cared only about the short-run.[24] Correspondingly, as γ increases, the optimal choice of δ decreases from 1 to $\frac{\sigma_v}{\sigma_e+\sigma_v}$.

Figures 16 and 17 plot δ^* against σ_v^2 and σ_e^2, for different choices of γ while holding all other parameters fixed. These plots show that the optimal choice of δ increases in σ_v^2 but decreases in σ_e^2. There are two forces driving this result. First, as noted earlier, the direct effect of PBD is maximized at $\delta = \frac{\sigma_v}{\sigma_e+\sigma_v}$, which is increasing in σ_v^2 and decreasing in σ_e^2, since in those circumstances so is the *ex ante* effectiveness of PBD at updating the MM's priors about v toward e. For example, as σ_e^2 decreases, so do the MM's *ex ante* uncertainty about the speculator's endowment and its comovement with his fundamental posteriors ($\operatorname{Cov}\left(\tilde{v}, e\right)$); hence, the speculator has to disclose more of e in the signal s to sway those posteriors in the direction of her short-term objective (see, e.g., Eq. (44) and Table 9). Second, since the indirect effect of disclosure involves reduction in long-term profit, a larger

[24]Note that $\operatorname{Cov}\left(\tilde{v}, e\right) = \frac{\delta(1-\delta)\sigma_v^2\sigma_e^2}{\delta^2\sigma_e^2+(1-\delta)^2\sigma_v^2}$, which is maximized at $\delta = \frac{\sigma_v}{\sigma_v+\sigma_e}$. Note also that when the speculator cares only about the short-run, order flow would have zero price impact as the speculator's trades would have no information content. Thus only the signal can move the price and her short-run value would be given by $\operatorname{E}\left[\gamma e(\tilde{v} - P_0)\right] = \gamma \operatorname{Cov}\left(\tilde{v}, e\right)$, implying that optimal δ is $\frac{\sigma_v}{\sigma_v+\sigma_e}$.

δ means a smaller weight on v, and therefore a smaller information loss. Thus the speculator optimally increases δ when the cost of information loss is larger, i.e., when σ_v^2 is large.

Conclusion 1 *The optimal signal weight δ^* increases in σ_v^2, decreases in σ_e^2, and decreases in γ.*

We turn next to the size of disclosure gains. In particular, we examine how large a cost to disclosure would a speculator be willing to bear while still preferring PBD. Such a cost can be thought of as the opportunity cost to the manager of spending time in a TV studio, of composing and publishing a report, or the monetary cost of making an advertisement. For simplicity, we assume this cost to be a fixed amount c paid by the speculator if she commits to send a signal at $t = -1$.

Proposition 6 suggests that disclosure is always optimal when it is costless. Given a fixed cost c to disclose, we ask the following questions: For what range of γ would the speculator still find it optimal to disclose? How does this range depend on the information environment (σ_v^2 and σ_e^2)?

To answer these questions, let

$$I^\gamma(c, \sigma_v^2, \sigma_e^2, \sigma_z^2) = \{\gamma \in [0,1] | \max_\delta \mathrm{E}\left[W|D=1,\delta\right] - c > \mathrm{E}\left[W|D=0\right]\}.$$

Intuitively, I^γ is the set of γ such that the speculator prefers costly disclosure to no disclosure *ex ante*. Figures 18 and 19 then plot the relation between I^γ and σ_v^2 and σ_e^2, respectively. The two dashed lines represent upper and lower bounds of I^γ, while the solid line represents the width of the interval $[\inf I^\gamma, \sup I^\gamma]$. Note that the direct effect of PBD is to boost the short-term objective by $\gamma \operatorname{Cov}\left(e, \tilde{v}\right) = \gamma \frac{\delta^*(1-\delta^*)\sigma_v^2\sigma_e^2}{\delta^{*2}\sigma_e^2 + (1-\delta^*)^2\sigma_v^2}$, suggesting that the direct gains to disclose is increasing in both σ_v^2 and σ_e^2. This is consistent with Figures 18 and 19. Intuitively, both larger σ_v^2 and larger σ_e^2 increase the scope of the speculator's value function (i.e., short-termism and pumping become more important for it), and therefore can support a larger range of γ for a given fixed disclosure cost c.

Conclusion 2 $(\sup I^{\gamma} - \inf I^{\gamma})$ *is decreasing in c, increasing in* σ_v^2 *and increasing in* σ_e^2*.*

B. Disclosure and Market Liquidity

We now turn to the effect of PBD on market liquidity. As a benchmark, consider first the effect of a public signal of v on the equilibrium depth of an economy where the speculator maximizes exclusively her long-term profit ($\gamma = 0$). Intuitively, any signal of v would reduce the uncertainty about the asset's payoff, hence lowering adverse selection risk and equilibrium price impact (e.g., Pasquariello and Vega 2007; Kahraman and Pachare 2017)—the more so the greater is the initial uncertainty about v. Next, consider the effect of PBT alone on market liquidity, PBT also lowers equilibrium price impact since it induces the speculator to deviate from long-term profit maximization to increase the short-term value of her portfolio—the more so the greater is endowment uncertainty (Bhattacharyya and Nanda 2013).[25] The release of a signal may not only alleviate information asymmetry about v but also reduce uncertainty about e (and PBT), leading to opposing effects on liquidity. Accordingly, we show that disclosing can either increase or decrease the price impact depending on the signal weight δ; yet, price impact is always smaller if PBD is *ex ante* optimal. Equivalently, the effect of s on fundamental uncertainty prevails upon its effect on endowment uncertainty.

Corollary 1 *(1)* λ_1 *increases with* δ*; (2)* $\lambda_1 < \lambda^*$ *if and only if* $\delta < \hat{\delta}$*, where* $\hat{\delta}$ *is given by Eq.* (143)*; (3) In particular, if* δ *is such that* $\mathrm{E}\left[W|D=1,\delta\right] > \mathrm{E}\left[W|D=0\right]$*, then* $\lambda_1 < \lambda^*$*.*

Figure 22 plots equilibrium price impact in the baseline (λ^*, dashed line, left axis) and signaling economies (λ_1, dotted line), as well as their positive difference ($\lambda^* - \lambda_1$ solid line, right axis) with respect to *ex ante* fundamental uncertainty σ_v^2, in correspondence with different combinations of γ, σ_e^2, and σ_z^2, as well as optimal signal weight δ^*. In all graphs and in both economies, equilibrium price impact is increasing in fundamental uncertainty (as in Kyle 1985), since so is the accompanying adverse selection risk faced by the dealership sector when clearing the market. Accordingly, in those circumstances, strategic disclosure

[25] Accordingly, the speculator becomes in effect a partial noise trader.

yields an increasing improvement in equilibrium market depth, (i.e., a greater $\lambda^* - \lambda_1 > 0$), since it mitigates such risk more than the decreasing weight of the speculator's increasingly valuable private fundamental information in her signal (i.e., greater δ^* in s of Eq. (29); see Figure 16) worsens it. We summarize these observations as follows.

Conclusion 3 *The liquidity improvement from optimal disclosure (i.e.,* $\lambda^* - \lambda_1 > 0$*) is increasing in the asset's fundamental uncertainty* σ_v^2*.*

C. Price Efficiency

Our last result concerns price informativeness. We show that the equilibrium price is more efficient in the presence of PBD. Intuitively, to the extent that the signal conveys information regarding asset fundamentals, one would expect that a greater proportion of the speculator's private information will be incorporated into prices; this is indeed the case when a signal is optimally disclosed, as summarized in the following corollary.

Corollary 2 *Denote by* $\mathrm{Var}\left(v|P_1, D=0\right)$ *the portion of the speculator's private information that is not incorporated into prices in the baseline PBT equilibrium of Proposition 4, and by* $\mathrm{Var}\left(v|P_1, D=1, s(\delta)\right)$ *the portion of unincorporated information when the speculator sends a signal with weight* δ*. (1)* $\mathrm{Var}\left(v|P_1, D=0\right) = \frac{1}{2}\sigma_v^2$*. (2) In the second step, less than half of the speculator's remaining private fundamental information is impounded into the price:* $\mathrm{Var}\left(v|P_1, D=1, s(\delta)\right) > \frac{1}{2}\tilde{\sigma}_v^2$*. (3)* $\mathrm{Var}\left(v|P_1, D=1, s(\delta)\right)$ *increases with* δ*. (4)* $\mathrm{Var}\left(v|P_1, D=1, s(\delta)\right) \leq (<) \frac{1}{2}\sigma_v^2$ *if* δ *is such that the speculator ex ante (strictly) prefers disclosure to no disclosure, or equivalently, if* $\mathrm{E}\left[W|D=1,\delta\right] \geq (>)\, \mathrm{E}\left[W|D=0\right]$*.*

Corollary 2 implies that, in the presence of PBD, the equilibrium price incorporates more of the speculator's private information, despite her more cautious trading activity (and less informative order flow).

In Kyle (1985), there is an equivalence between the volatility of price and the amount of private information being impounded.[26] This equivalence is preserved under both the PBT

[26] To see this, note that $\sigma_v^2 = \mathrm{Var}\left(\mathrm{E}\left[v|P_1, D\right]\right) + \mathrm{E}\left[\mathrm{Var}\left(v|P_1, D\right)\right]$, where we can drop the outer expec-

and PBD equilibriums:.

$$\mathrm{Var}\left(P_1|D\right) = \sigma_v^2 - \mathrm{Var}\left(v|P_1, D\right), \tag{45}$$

where $\sigma_v^2 - \mathrm{Var}\left(v|P_1, D\right)$ measures the amount of information incorporated into the price. Therefore optimal PBD implies both greater price informativeness and greater price volatility.

II.2.5 Discussion of Model Assumptions

In delivering our theoretical results, we made two important assumptions: (1) The speculator commits not to deviate, on observing her private information, from her disclosing strategy (which is determined *ex ante*) and (2) the speculator's signal is a convex combination of endowment (e) and fundamentals (v).

In our model, it is crucial that the speculator commits both to disclose and to a predetermined form of disclosure. Were the speculator not bound to disclose exactly $s = \delta e + (1-\delta)v$ *ex post*, she would have a strong incentive to deviate—given the significant gains from signal manipulation when the MM takes the signal at its face value. We discuss the plausibility of these two assumptions below.

On the theoretical side, most existing models in the information transmission literature rely on some commitment by the sender. For instance, Grossman and Stiglitz (1980) and Verrecchia (1982), when modeling economies in which market participants endogenously become informed by acquiring a signal, abstract from the information producer's problem in that each of them not only takes as a given that such a signal is the true fundamental up to an independent noise term but also does not observe it until *after* making the decision to acquire it. Admati and Pfleiderer (1988) study how an informed party sells information to the rest of the market in a model in which the seller can choose signal precision but not signal form and is bounded away from manipulation. Our paper closely resembles Admati and Pfleiderer's

tation because $\mathrm{Var}\left(v|P_1, D\right)$ is constant across all realization of P_1 and s, and $\mathrm{E}\left[v|P_1, D\right] = P_1$ because the equilibrium price is semi-strong form efficient.

(1988) setting in that the informed agent not only transfers her private information, but also trades on her own account. Our paper is also closely related to Kamenica and Gentzkow (2011), in which an information sender is granted the ability to commit to both the form of the signal and truthful revelation of the signal. Kamenica and Gentzkow (2011) derive in their setting the optimal signal that would induce the receiver to take the most favorable actions to the sender. Our model adds to their setting an additional level of complication in that the speculator (the sender) can not only communicate information (disclose a signal), but also take action herself (trade directly on information).

On the empirical side, we note that, in financial markets, *ex post* deviation often entails large penalties. As we argue, either one of the following costs may serve as a commitment device to deter deviation.

The first one is reputation cost. Although our model is a static one, a real-world speculator—be it a fund manager, venture capitalist, or specialist company—is most likely a repeated player. As reputation is generally believed to be of vital importance for any type of financial institution, the gains from "deviation" must be traded-off against the cost of reputation damage when the speculator decides what signal to provide. Therefore, insofar as those gains are not unbounded, reputation concerns arguably constrain the extent to which the speculator may deviate from the committed (agreed-upon) signal disclosure process.[27] Accordingly, Ljungqvist and Qian (2016) find that disclosures by hedge funds with better reputation (e.g., as acquired via prior such disclosures) have a greater impact on the prices of the disclosed stocks.

A second commitment device is financial regulation. Regulators often impose and en-

[27]For instance, one could apply the Folk Theorem to a repeated version of our model where (1) on the equilibrium path, the signaling equilibrium is reached in every stage and (2) once mis-reporting is detected at any time, the players switch to the baseline equilibrium in all subsequent stages. There is only one caveat: In our model, the one-shot gain from deviating could be arbitrarily large. Therefore, one must modify the stage equilibrium to fit in the Folk Theorem framework. One possible modification is as follows. Let $\underline{s}$ and $\bar{s}$ be two threshold values of the signal. If the signal is realized such that $\underline{s} \leq s \leq \bar{s}$ the same equilibrium is reached in the ensuing subgame as before. On the other hand, if s is realized such that $s < \underline{s}$ or $s > \bar{s}$, then the MM will suspect that manipulation is in play and refuse to update his beliefs. Therefore, the ensuing continuation game proceeds with the same common prior as the original one.

force stringent rules regarding disclosure made by fund managers and other key market participants. For instance, in regulating disclosure of financial asset fundamentals, the U.S. Investment Advisor Act of 1940 requires that an advisor has an obligation of "full and fair disclosure of all facts material to the client's engagement of the advisor to its clients, as well as a duty to avoid misleading them." In addition, the SEC prohibits any advisor from "using any advertisement that contains any untrue statement of material fact or is otherwise misleading." Similarly, in regulating any disclosure about a speculator's holdings, the SEC mandates that investment advisors with discretion over \$100 million must file a Form 13(F) on a quarterly basis containing her positions in detail. Although the SEC gives hedge funds the option of delaying reporting on the basis of confidentiality, this confidential treatment is neither trivial nor guaranteed (Agarwal et al. 2013).

Since violating these regulations entail possibly significant punishment ranging from fines to imprisonment, regulations leave the fund manager with little flexibility in her choice of disclosure. In the context of our model, this means the signal weight δ is effectively imposed (or restricted) by the regulators. If the speculator optimally chooses to disclose, she is constrained by regulation to stick to pre-specified signal weights.

Interestingly, this also implies that under some regulatorily imposed signal weights, a speculator may not find it optimal to disclose. Regulation in effect puts the speculators through a screening process; only those who happen to have the right σ_v^2 and σ_e^2 choose to be vocal. To illustrate this observation, Figure 21 plots the speculator's value function in the signaling (solid line) and baseline (dashed line) equilibriums as functions of signal weight δ. Figure 21 shows that, although for the optimal δ releasing a signal is always better than staying silent, there is only a narrow range of δ for which the speculator prefers the signaling equilibrium to the baseline equilibrium. For some speculators, the regulatorily imposed δ may be out of that range.

II.3 Data and Sample Selection

Our model argues that a speculator who cares about the short-term value of her holdings may voluntarily disclose some of her private information. Consistent with our model, Ljungqvist and Qian (2016) show that small hedge fund managers make public their findings about problematic firms after taking large short positions in those companies. Anecdotally, activist investors such as Carl Icahn or Bill Ackman frequently communicate their perspectives to the public through media interviews, Twitter feeds or blogs.[28] Our theory suggests that the use of strategic public disclosure may be even more widespread than what currently reported in the literature, especially among (at least partly) short-term oriented sophisticated financial market participants.

Accordingly, we set to test our model by studying the effect of all voluntary non-anonymous disclosures by mutual funds in the Wall Street Journal (WSJ), the Financial Times (FT), and the New York Times (NYT) on the U.S. stock market. Four observations motivate our choice. First, mutual funds arguably are among the most sophisticated financial market participants (e.g., Wermers 2000; Huang et al. 2011; Kacperczyk et al. 2008). Second, many studies show that mutual fund managers are subject to short-term concerns. For instance, numerous papers find that mutual fund flows are sensitive to past performance (e.g., Ippolito 1992; Sirri and Tufano 1998; Del Guercio and Tkac 2002). Additionally, mutual fund managers exhibit tournament-like behavior (e.g., Brown et al. 1996; Chevalier and Ellison 1999; Chen et al. 2017), consistent with short-term objectives. Third, the large reader base of those three newspapers and their broad coverage of the financial sector grants speculators broad access to investors at large, consistent with our model's notion of the disclosed signal being common knowledge. Fourth, newspaper disclosures leave traceable records, and mutual funds are required by law to regularly report their portfolio compositions; both ensure adequate availability of data to test our theory.[29]

[28] See, for instance, *"Carl Icahn Takes 'Large' Apple Stake"* on CNN Money, available at http://money.cnn.com/2013/08/13/technology/mobile/carl-icahn-apple/.

[29] Investigating strategic disclosure and trading by hedge funds is significantly more challenging in light

II.3.1 Data and Identification Criteria

A. Mutual Fund Holding Data

Our sample spans from 2005 to 2014. We obtain mutual fund holdings data from the CRSP mutual fund database. The database provides portfolio compositions, including both long and short positions, of all open-end mutual funds in the United States. Holdings data is available at the monthly frequency. We use only quarter-end-month data as reporting of portfolio composition is only mandatory quarterly; non-quarter-end month data is missing for most funds. Our theory focuses on strategic disclosures by an active, privately informed speculative sector about assets with non-trivial fundamental uncertainty. Accordingly, we exclude from our sample all index funds, ETFs (given their overwhelmingly passive management style), and fixed income funds. CRSP provides holdings data at the portfolio level. For our tests, however, we consolidate all data to the fund holding company level for two reasons. First, our empirical study involves linking a speculator's disclosure behavior to her incentives to disclose and (as we observe next) most disclosures are only identifiable at the fund holding company level.[30] Second, it is plausible that funds within the same family may coordinate their disclosing strategy to serve the same family-level objective. The fund holding family, therefore, fits more closely with our notion of a sophisticated speculator in the model. We also collect from CRSP the names of all portfolio managers who have worked at each of the fund holding families during our sample period.[31]

For each quarter, we consider as potential disclosure targets all firms that are in the S&P 1500 universe as of the end of the previous quarter. Those firms are the largest in the U.S. stock market, hence presumably the most likely subject of financial media coverage.

of severe data limitations on their managers' identity and portfolio holdings. Accordingly, the unreported analysis of a much smaller sample of hedge funds with viable such data yields qualitatively similar, yet noisier inference.

[30]For example, it is much more likely for a news article to report a quote from "a portfolio manager with T. Rowe Price" rather than a quote from "a portfolio manager at T. Rowe Price Blue Chip Growth Fund."

[31]CRSP reports fund manager names with varying levels of precision. For the majority of fund managers, CRSP reports their first and last names; sometimes all first, middle and last names are available; sometimes CRSP either only reports the last name or states that the fund is "team-managed."

We exclude all financial companies, as most of them are often also classified as speculators in our mutual fund sample. We obtain firm-level balance sheet information from Compustat.

B. Mutual Fund Disclosure Data

Our disclosure data comes from two sources. We obtain WSJ articles from ABI/INFORM and FT and NYT articles from LexisNexis. For each newspaper, we obtain all articles published between 2005 and 2014. We then drop articles that are published in a non-business-related section, letters from readers, or corrections. We parse the news by paragraph to filter out strategic disclosures. Specifically, a paragraph is defined as a (potentially) strategic public disclosure by fund holding company j about target firm i if either one of the following criteria is met:

1. Both names of the target company i and the fund management company j are found. Investment banks are frequently covered in the media together with other firms for reasons unrelated to strategic information disclosure (equity/bond underwriting, market making, mergers/acquisitions, rating assignments, etc.). To avoid confounding our analysis, we exclude investment banks (e.g., Goldman Sachs, Merrill Lynch, Wells Fargo, etc.) from fund management companies, unless one of the following is true:

    - Key words such as "analyst", "portfolio manager", or "strategist" appear in the same sentence as the mention of the fund holding company;
    - Key words such as "securities", "holdings" or "asset management"—which indicate that the disclosure may come from a non-investment banking branch of financial institution j—closely follow the mention of the fund management company (i.e., with no more than one word in between);
    - Name (first name followed by last name) of a portfolio manager associated with fund holding company j is also found in the same paragraph.

2. The name of the target company i is found and either one of the following is true:

- All first, middle, and last names of any portfolio manager at fund holding company j are found;
- First and last names of any portfolio manager at fund holding company j are found, and, in the same sentence, there are such key words as “analyst”, “portfolio manager”, etc.

Importantly, in applying these screenings, we do not separately search for information disclosures about fundamentals (v) versus the speculator’s endowment (e), since, as noted earlier, the two are likely indistinguishable. Plausibly, speculators may provide information to the media with selective emphasis. Upon seeing a disclosure about fundamentals, a reader may rationally infer that the information provider has such a position that she stands to gain if her disclosure is impounded into the price. Second, as sophisticated investors choose their positions endogenously, information about their positions is also likely to be suggestive about fundamentals.

Table 10 reports, for each newspaper, the number of articles so identified as disclosures, as well as the number of articles that are in business-related and non-business-related sections; plots of the total and relative number of these disclosures over our sample period are in Figure 23. Out of the 675,452 articles published in business-related sections of WSJ, FT, and NYT, 11,550 are identified as strategic non-anonymous disclosures between 2005 and 2014, amounting to a plausible and relatively stable 1.7% of their total business coverage. Visual inspection of the identified articles shows that they capture the notion of “strategic disclosure” with reasonable accuracy. Table 11 reports four such paragraphs as examples.

C. Liquidity

We use stock price and trading data to compute a measure that is both commonly used in the literature and broadly consistent with the notion of Kyle’s (1985) lambda in the model: Amihud’s (2002) price impact. For stock i on day t, it is computed as a rolling average of daily price impact:

$$Amihud_{i,t} = \frac{1}{90} \sum_{h=t-90}^{t-1} \frac{|r_{i,h}|}{vol_{i,h}}, \tag{46}$$

where $r_{i,h}$ is the return of stock i on day h and $vol_{i,h}$ is the dollar volume of trading of stock i on day h, obtained by multiplying the number of shares traded by the closing price on that day.

D. Sample Construction and Summary Statistics

The goal of our empirical analysis is to investigate the determinants and liquidity externalities of the aforementioned potentially strategic disclosures by U.S. stock mutual funds between 2005 and 2014. To that end, we merge and filter the firm- and fund-quarter level samples of disclosures, illiquidity, and holdings detailed above in three steps. First, given the preponderance of zeros in the otherwise large raw disclosure and holding samples, we restrict our attention to firm-fund-quarter level observations for which we observe non-zero disclosures, non-zero holdings, or both. Second, we then remove firms that are never disclosed about and funds that never disclose over our sample period. Third, we also exclude, in each quarter, the fund with the largest holdings in a firm—both to minimize the effect of any resulting and potentially non-strategic media access and attention on our measures of firm-fund and firm-level disclosure as well as to mitigate the potentially idiosyncratic impact of extreme such positions on the holding-based, firm-fund and firm-level proxies for short-termism described next; the ensuing inference is unaffected by this exclusion. These criteria yield a final sample of 85,240 firm-fund-quarter level observations for our analysis. Table 12 provides summary statistics for this sample. All reported variables are winsorized at the 2% and 98% levels to further remove extreme realizations. Panel (A) of Table 12 summarizes the sample at holding company-quarter level. Each statistic is reported for the full sample, and for each of the five subsamples for which we restrict the number of disclosures made by the holding company in a quarter to be equal to zero or at least 1, 5, 10 or 15 over the sample period 2005-2014. Disclosing fund holding companies tend to be larger in size and hold less of their assets in equity and cash but more in bonds. There appears to be little variation in the funds' expense ratios.

Summary statistics at the firm-quarter and firm-fund-quarter levels are in Panels (B) and (C) of Table 12, respectively, for the full sample as well as for subsamples defined by the number of strategic disclosures associated with firm-quarters over 2005-2014. On average, disclosure targets tend to be larger in size and hold more intangible assets. There is, however, no clear pattern in firm-level stock market liquidity and return volatility across disclosure subsamples.[32]

II.4 Empirical Results

II.4.1 Strategic Disclosure and Incentives to Disclose

Our theory implies that PBD is optimal for any at least partially short-term oriented speculator. Empirically, we argue that, *ceteris paribus*, fund holding families with stronger short-term incentives disclose more often. The reason is two-fold. First, relative to long-term profit maximizers ($\gamma = 0$) who do not find it optimal to disclose, those with short-term incentives ($\gamma > 0$) clearly disclose more often (e.g., *ceteris paribus* for repeated private information arrival). Second, even among partially short-term oriented financial market participants, some may not find the gains from PBD large enough to justify the cost of doing so. Consequently, we should observe more disclosures being made by those who, *ceteris paribus*, may benefit more from it—i.e., those who have a stronger short-term orientation (larger γ).[33]

[32]Because large numbers of disclosures are rare, the winsorized number of disclosures made about a firm in each quarter is capped at 5 throughout all subsamples in Panel (B). Accordingly, we do not winsorize the number of disclosures at the firm-fund-quarter level in Panel (C), since that number is zero in most firm-fund-quarters.

[33]Note that in our model, the gains from PBD are not monotonic in γ. Figures 18 and 19 suggest that *ex ante* disclosure gains first increase but then decrease as γ increases. Intuitively, as the speculator places less weight on her long-term profit (when γ grows larger), she is less concerned about the cost of PBT; thus she can achieve her short-term objective efficiently enough by PBT alone. As a result, PBD is less valuable to the speculator when γ is sufficiently large. For our empirical tests, however, we ignore the decreasing portion of the gains from PBD (as a function of γ) because a so-behaving speculator would have to trade aggressively to take advantage of PBT. Such overt PBT is, however, unfeasible over our sample period (2005–2014) due to the sharp increase in investor attention and SEC enforcement about portfolio pumping since 2001 (e.g., Gallagher et al. 2009; SEC 2014; Duong and Meschke 2016). With PBT constrained by regulation, it is

We construct two proxies for a fund's short-termism.[34] Our first measure (denoted as $\hat{\gamma}^1_{j,t}$) captures a fund's flow-return sensitivity. As discussed earlier, an important reason mutual funds value their short-term performance is the competition for fund flows (Ippolito 1992; Sirri and Tufano 1998; Chevalier and Ellison 1997). Flow-performance sensitivity reflects the extent to which such competition matters to a fund manager. Additionally, limits to arbitrage also induce short-term concerns (Shleifer and Vishny 1997)—the significance of which arguably depends on a fund's flow-performance sensitivity as well. Accordingly, we argue that funds with greater flow-return sensitivity may be more responsive to their portfolio's short-term valuation. We compute flow-return sensitivity for each fund holding company j in each quarter-end month t in two steps. First, we estimate the following rolling regression of fund flows on contemporaneous and lagged fund returns—for each individual fund k under holding company j—using monthly fund return and flow data over the past year (i.e., from month $m = t - 11$ to $m = t$):

$$\text{Flow}_{k,m} = \alpha_{k,t} + \sum_{h=0}^{2} \zeta^h_{k,t} \text{Ret}_{k,m-h} + \epsilon_{m,t}, \tag{47}$$

where $Flow_{k,m}$ are fund inflows or outflows, and $Ret_{k,m-h}$ are fund portfolio returns.[35] Second, we sum the resulting contemporaneous and lagged estimates of fund-specific flow-performance sensitivity:

$$\hat{\zeta}_{k,t} = \hat{\zeta}^0_{k,t} + \hat{\zeta}^1_{k,t} + \hat{\zeta}^2_{k,t}. \tag{48}$$

plausible that speculators would turn to PBD as a substitute, and the more so the more short-term oriented they are. Consequently, it is plausible that the gains from PBD are increasing for the entire feasible range of γ.

[34]Since our empirical tests aggregate fund information to the fund holding company level, throughout this section we use the terms "fund", "fund holding family/company" and "fund manager" interchangeably—all referring to a fund holding company and its management team. We also use the terms "short-termism", "incentives to disclose/PBD" and "short-term incentives" interchangeably—all referring to the empirical counterpart of our model parameter γ.

[35]So-estimated fund-specific flow-performance sensitivity from time-series data allows us to quantify each fund's potential return to PBT and PBD (i.e., the relative importance of short-termism, γ, in the speculator's value function of Eq. (24)). In the literature on fund flow-performance dependence, this relation is instead typically established in the cross-section (Sirri and Tufano 1998; Gruber 1996), and is found to be strongest among top-performing funds (Sirri and Tufano 1998; Chevalier and Ellison 1997). Unreported tests proxying for flow-performance sensitivity using dummy variables for top-performers in the cross-section of mutual funds based on past performances yield qualitatively similar results as those reported in this paper. Our analysis is also robust to using CAPM- or Fama-French three factor-adjusted returns—instead of raw returns—as measures of fund performance.

for each fund k at each quarter-end month t. We then define our first measure of short-termism from these estimates as the NAV-weighted average of $\hat{\zeta}_{k,t}$ across all individual funds k under holding family j.

Our second measure of a fund's incentives to disclose $(\hat{\gamma}^2_{i,j,t})$ exploits the deviation of a fund's portfolio composition from the market portfolio. Practitioners typically evaluate fund managers by benchmarking their returns to, e.g., the market portfolio. Additionally, PBD in a stock may improve a fund's performance relative to the market only if that fund's percentage holdings in that stock differ from those of the market portfolio; hence the greater is that difference, the more "pivotal" is that stock for the fund's pumping activity. Similarly, a fund manager competing for fund flows would only benefit from PBD in a stock if her percentage holdings in that stock differ from her competitors' holdings. We use that stock's market share as a proxy for its benchmark holdings. To compute $\hat{\gamma}^2_{i,j,t}$, let $H^f_{i,j,t}$ be fund j's percentage holdings of firm i as of the end of quarter t:[36]

$$H^f_{i,j,t} = \frac{\text{Market Value of Firm } i \text{ Shares Held by Fund } j \text{ at the End of Quarter } t}{\text{Market Value of All S\&P 1500 Shares Held by Fund } j \text{ at the End of Quarter } t}, \tag{49}$$

and let $H^m_{i,t}$ be firm i's representation in the S&P 1500 universe:

$$H^m_{i,t} = \frac{\text{Firm } i\text{'s Market Capitalization at the End of Quarter } t}{\text{Market Capitalization of the S\&P 1500 Universe at the End of Quarter } t}; \tag{50}$$

then we define $\hat{\gamma}^2_{i,j,t}$ as:

$$\hat{\gamma}^2_{i,j,t} = \begin{cases} H^f_{i,j,t}/H^m_{i,t}, & \text{if } H^f_{i,j,t} > H^m_{i,t}, \\ H^m_{i,t}/H^f_{i,j,t}, & \text{otherwise.} \end{cases} \tag{51}$$

Importantly, $\hat{\gamma}^2_{i,j,t}$ does not distinguish the direction of the deviation in a fund's portfolio holdings—e.g., a percentage position in firm i that is 50% less than the market portfolio results in the same $\hat{\gamma}^2_{i,j,t}$ as one that is twice the market's share. In our model, it is the intensity of speculative short-termism (γ) to affect both the equilibrium extent of PBD and equilibrium price formation; the specific content of any resulting pre-committed strategic

[36] In a few instances, funds hold short stock positions yielding $H^f_{i,j,t} < 0$. Eliminating these positions from our sample does not affect our empirical analysis.

disclosure (e.g., its "direction") depends on specific, unobservable realizations of fundamental (v) and endowment (e) shocks. Therefore, both $\hat{\gamma}^1_{j,t}$ and $\hat{\gamma}^2_{i,j,t}$ measure exclusively a fund's unsigned incentives to disclose.

Summary statistics for $\hat{\gamma}^1_{j,t}$ and $\hat{\gamma}^2_{i,j,t}$ are in Panel (A) and Panel (C) of Table 12. Fund-flow sensitivity across fund families is non-trivial—e.g., an average standardized change in fund flows of about 0.42 in response to a cumulative one standard deviation shock in current and past fund performance. However, no clear pattern of fund flow-return sensitivity emerges across subsamples of different disclosure intensities. Disclosing funds, however, tend to have larger deviations in their portfolio holdings compared to non-disclosing funds.

To test the dependence of strategic disclosure on mutual fund manager short-termism, we estimate the following OLS model at the firm-fund-quarter level:

$$\#\mathrm{Discl}_{i,j,t} = \beta_0 + \beta_1 \hat{\gamma}^s_{(i,)j,t} + \beta_2 \#\mathrm{Discl}_{-i,j,t} + \beta_3 \#\mathrm{Discl}_{i,-j,t} + \delta_y + \delta_q + \epsilon_{i,j,t}, \quad s = 1,2 \tag{52}$$

where $\#\mathrm{Discl}_{i,j,t}$ is the number of articles in WSJ, FT and NYT identified as strategic disclosures about firm i by fund j during quarter t. All variables in our empirical analysis are standardized to adjust for differences in scale within and across variables and to facilitate the interpretation of the corresponding coefficients of interest; our inference is unaffected by this normalization.

Eq. (52) allows us (1) to test if funds with stronger short-term incentives disclose more frequently, as well as (2) to test if stocks that are more "pivotal" to fund managers become disclosure targets more often. Both (1) and (2) imply that $\beta_1 > 0$. Some fund managers may make more frequent media appearances for reasons unrelated to PBD (e.g., stronger media connections); we control for this possibility by including $\#\mathrm{Discl}_{-i,j,t}$, the number of disclosures made by fund j about all firms except firm i during quarter t; this variable also controls for any fund-level characteristics that induce the fund to disclose about all firms. Some firms may become disclosure targets for reasons unrelated to PBD; for instance, a firm may become more newsworthy in correspondence with important, newsworthy corporate events—e.g., CEO turnover or merger talks. To control for this possibility, we also include

$\#\text{Discl}_{i,-j,t}$, the number of disclosures made about firm i by all funds except fund j during quarter t.[37] This variable also captures firm-level characteristics that may make a stock more newsworthy to all funds. We further include year fixed effects (δ_y) and quarter fixed effects (δ_q) to control for macroeconomic trends as well as seasonality in disclosure patterns (e.g., around quarterly earnings releases). Lastly, to avoid the confounding effects caused by media-initiated disclosures, we exclude, for each firm in each quarter, funds with the largest holdings in that firm's stock from the analysis.[38]

We report estimates of Eq. (52) for both $\hat{\gamma}^1_{j,t}$ and $\hat{\gamma}^2_{i,j,t}$ in Columns (1) and (5), respectively, of Table 14. Consistent with our model, in both cases $\hat{\beta}_1$ is positive and statistically significant—i.e., stronger short-term incentives are associated with higher frequency of disclosures. When proxying for short-termism with $\hat{\gamma}^2_{i,j,t}$, this effect is also economically large—e.g., a one standard deviation increase in short-term incentives corresponds to a more than 22% standard deviation increase in the number of strategic public disclosures—amounting to more than 0.13 additional firm-fund-quarter level disclosures (versus an unconditional mean of 0.2 and median of zero in Panel C of Table 12). Estimates of β_1 are smaller for $\hat{\gamma}^1_{j,t}$. Since $\hat{\gamma}^1_{j,t}$ is a fund-quarter level variable, its effect on disclosure may be subsumed by the control variable $\#\text{Discl}_{-i,j,t}$.

Next, we investigate whether the effect of short-termism on disclosure is more pronounced for subsets of firms whose characteristics may render PBD about them more effective. These tests may enhance our interpretation of the identified disclosures as PBD. We explore three such firm-level characteristics: size, tangibility and return volatility. Intuitively, stock prices may be more sensitive to information disclosure when the issuing firms are smaller, more intangible, or display greater fundamental uncertainty.[39] Plausibly, sophisticated fund man-

[37]Accordingly, in unreported analysis the ensuing inference is qualitatively unaffected by the inclusion of one-way firm or fund or two-way firm-fund fixed effects.

[38]Journalists often contact financial practitioners—typically one of the largest shareholders—for comments when reporting about a firm. Because such reporting involves both the speculator and the firm, it is likely picked up by our screening algorithm but may not represent a strategic disclosure.

[39]For instance, under the two-step formulation of the signaling equilibrium in Section II.2.3.1, the revision in MM's prior is larger in correspondence to the release of a signal when fundamental uncertainty σ^2_v is larger, as shown by Eq. (40).

agers may also have greater informational advantage about firms with these characteristics (larger σ_v^2), making (costly) PBD optimal for a larger number of funds (Figure 18). To examine these effects, we amend the baseline regression of Eq. (52) as follows:

$$\begin{aligned}\#\text{Discl}_{i,j,t} &= \beta_0 + \beta_1 \hat{\gamma}^s_{(i,)j,t} + \beta_2 \text{Suit}_{i,t} + \beta_3 \hat{\gamma}^s_{(i,)j,t} \times \text{Suit}_{i,t} \\ &\quad + \beta_4 \#\text{Discl}_{-i,j,t} + \beta_5 \#\text{Discl}_{i,-j,t} + \delta_y + \delta_q + \epsilon_{i,j,t}, \quad s = 1, 2,\end{aligned} \tag{53}$$

where $Suit_{i,t}$ is the inverse of firm size ($Size_{i,t}$), firm intangibility ($Intan_{i,t}$), or return volatility ($Stdev(Ret)_{i,t}$). Precise definitions of all variables are in Table 13. Since larger realizations of $Suit_{i,t}$ are associated with greater potential gains from PBD, rendering the firms more "suitable" as disclosure targets. we expect that the interaction term $\beta_3 > 0$ for all specifications.

We report estimates of Eq. (53) for $\hat{\gamma}^1_{j,t}$ and $\hat{\gamma}^2_{i,j,t}$ in Columns (2) to (4) and (6) to (8) of Table 14, respectively.[40] As conjectured, $\hat{\beta}_3$ is positive under all specifications and, as earlier, these estimates are statistically significant when $\hat{\gamma}^2_{i,j,t}$ is used, yet not for $\hat{\gamma}^1_{j,t}$. As noted above, this may be due to $\hat{\gamma}^1_{j,t}$ not being firm-specific and so being subsumed by the control variable $\#\text{Discl}_{-i,j,t}$ in Eq. (53). The economic significance of these estimates vary depending on the characteristic under examination. For instance, Columns (6) to (8) show that the effect of short-termism on disclosure is 5% to 40% stronger if the "suitability" of a firm—measured by size, tangibility, or return volatility—is one standard deviation larger than its mean.[41]

II.4.2 Strategic Disclosure and Liquidity

A. Baseline Regression: Liquidity Effect of Disclosure

[40] In these regressions, we use two-way clustering at the firm and fund levels to account for heteroscedasticity and within firm-fund serial correlation (e.g., Petersen 2009). Standard errors clustered at either the firm or the fund level do not meaningfully affect our inference.

[41] Since all variables are standardized in Table 14, $\hat{\beta}_1$ measures the effect of short-termism on disclosure at mean $Suit_{i,t}$, while $\hat{\beta}_1 + \hat{\beta}_3$ measures such effect when $Suit_{i,t}$ is one standard deviation above its mean.

Our model implies that in the presence of optimal PBD (δ^*), market liquidity of the affected asset improves relative to the baseline scenario when only PBT is used (Corollary 1). Thus, we test for the effect of strategic disclosure on the liquidity of the target stock. To that end, we consolidate our sample to firm-quarter level and estimate the following OLS model:

$$\Delta\text{log}(\text{Amihud}_{i,t}) = \beta_0 + \beta_1 \Delta\text{log}(\#\text{Discl}_{i,t}) + \beta_2 \Delta\text{log}(\#\text{Discl}_{-i,t}) + \delta' \Delta \log(X_{i,t}) + \delta_y + \delta_q + \epsilon_{i,t} \quad (54)$$

where $\Delta\text{log}(\text{Amihud})_{i,t}$ is the log change (from the previous to the current quarter) in Amihud's (2002) liquidity measure of firm i's shares, $\Delta\text{log}(\#\text{Discl})_{i,t}$ is the log change in the number of disclosures made (by all sample funds) about firm i, and $\Delta \log(X_{i,t})$ is a vector of log changes in several firm-level control variables including firm size, intangibility, price level, return volatility, and the number of disclosures made about all firms except firm i. First-difference regressions alleviate potential non-stationarity biases due to persistence in firms' level illiquidity (e.g., an average AR(1) coefficient of 0.73 across the funds in our sample; Hamilton 1994). Limitations on data availability (e.g., of measures of short-termism, discussed next) preclude a comprehensive higher-frequency analysis of the liquidity externalities of PBD; nonetheless, the estimation of Eq. (54) and its extensions via an event-study methodology at the daily frequency yields qualitatively similar yet noisier inference; see, e.g., Tables IA-1 and IA-2 of the Internet Appendix. We also include log changes in $\#\text{Discl}_{-i,t}$, the number of disclosures made about all firms except firm i, to control for the possibly contemporaneous release of market-level news. Lastly, we include year fixed effects (δ_y) and quarter fixed effects (δ_q) to control for long-term trends and seasonality.

The coefficient of interest is β_1. Since Eq. (54) is in (log) changes, its estimation is immune from any time-invariant (omitted) factor that may affect both levels of disclosure and liquidity. Our model predicts $\beta_1 < 0$: *ceteris paribus*, an increase in the number of strategic public disclosures should be associated with an improvement in the liquidity of the disclosure target's shares. We report estimates of Eq. (54) in Column (1) of Table

15.[42] Consistent with our model, estimated β_1 is negative and statistically significant. The economic magnitude of this effect, however, is quite small—e.g., a one standard deviation increase in disclosure changes only translates into less than 1% standard deviation increase in liquidity improvement. The lack of economic significance may be due to several reasons. First, strategic disclosure is only one of the many factors influencing stock liquidity (e.g., shocks to ownership structure, equity issuance, changes in credit rating, earnings announcements, institutional trading, changes in trading platforms and specialist companies, etc.), all of which may cause variation in liquidity that mute the effect of PBD. Second, extant literature suggests that the positive effect of *any* public news on financial market quality in general, and liquidity in particular, is both conceptually ambiguous (e.g., Kyle 1985 versus Kim and Verrecchia 1994, 1997) and usually difficult to capture in the data (see, e.g., Green 2004; Pasquariello and Vega 2007).[43] Third, our sample is made of firms in the S&P 1500 universe, all of which are well-established, highly liquid companies, and thus may be the least suitable targets for PBD. The evidence in Ljungqvist and Qian (2016) suggests that more intense PBD may take place—with more pronounced effects—in smaller, more opaque and possibly private firms, for which liquidity is significantly lower and market depth and fund holding data are not readily available. Lastly, newspapers are only one of the venues through which a fund manager may disclose information. Thus, our measure of disclosure may not fully capture the true intensity of PBD, subjecting Eq. (54) to attenuation bias.

B. Liquidity Effect of Disclosure and Short-term Incentives

As noted earlier, information disclosures in general—not just strategic ones (PBD)—may resolve fundamental uncertainty and thus improve liquidity, or otherwise affect both. To distinguish the specific effect of PBD from that of any fundamental information disclosure

[42]In this and all subsequent regressions, robust standard errors are clustered at the firm level.

[43]For instance, the availability of public fundamental information in a Kyle (1985) setting would improve equilibrium market depth by lowering market makers' perceived uncertainty about asset payoff (e.g., λ_1 is increasing in σ_v^2 in Eq. (32); see also Pasquariello and Vega 2007). However, Kim and Verrecchia (1994, 1997) argue that the release of public information may instead increase adverse selection risk and worsen liquidity if it leads to greater information heterogeneity among sophisticated market participants.

on price formation, we test if the estimated liquidity improvement in correspondence with the "potentially strategic" disclosures in our sample is greater when a firm is more "pivotal" to the funds' short-term objectives. [44]To that end, we amend Eq. (54) as follows:

$$\Delta\log(\text{Amihud}_{i,t}) = \beta_0 + \beta_1\hat{\gamma}_{i,t} + \beta_2\Delta\log(\#\text{Discl}_{i,t}) + \beta_3\Delta\log(\#\text{Discl}_{i,t}) \times \hat{\gamma}_{i,t} \quad (55)$$
$$+ \beta_4\Delta\log(\#\text{Discl}_{-i,t}) + \delta'\Delta\log(X_{i,t}) + \delta_y + \delta_q + \epsilon_{i,t},$$

where our "pivotal" measures $\hat{\gamma}_{i,t}$ are meant to capture how well revelation of private information about a firm lines up with mutual funds' short-term incentives. Specifically, since our tests on liquidity are conducted at firm-quarter level, $\hat{\gamma}_{i,t}$ are constructed in two steps to capture the "pivotalness" of firm i to the short-term objective of the mutual fund sector as a whole, not any individual fund. In what follows, we focus on our proxy based on fund-flow performance $\hat{\gamma}^1_{i,t}$.[45] First, we compute a weighted average flow-performance sensitivity across all mutual funds with non-zero holdings in firm i:

$$\overline{\hat{\gamma}^1}_{i,t} = \frac{1}{\sum_j |\text{Shr}_{i,j,t}|} \sum_j |\text{Shr}_{i,j,t}| \times \hat{\gamma}^1_{j,t}, \quad (56)$$

where $\text{Shr}_{i,j,t}$ is the number of firm i shares held by fund j at the end of quarter t, and $\hat{\gamma}^1_{j,t}$ is defined in Eq. (48). Since $\hat{\gamma}^1_{j,t}$ is weighted by the fund's shareholdings, $\overline{\hat{\gamma}^1}_{i,t}$ effectively measures the average flow-return sensitivity across firm i's (mutual fund) shareholders.[46]

[44]In the model with PBT and PBD of Section II.2.2, this is generally the case in equilibrium, except when endowment uncertainty (σ^2_e, unobservable by the econometrician) is "large." For instance, we show in Figure 22 that the improvement in liquidity from PBD, $\lambda^* - \lambda_1$ (solid line, right axis), is increasing in γ when $\sigma^2_e = 0.5$ but decreasing in gamma when $\sigma^2_e = 2$. Intuitively, *ceteris paribus*, a more short-term oriented speculator (higher γ) is willing to disclose more private fundamental information in her signal to pump the equilibrium price in the direction of her endowment e (e.g., lower δ^* in Figure 15), alleviating MM's adverse selection risk more relative to the baseline economy with PBT of Section II.2.1 (greater $\lambda^* - \lambda_1 > 0$). However, such a signal continues to reveal private endowment information as well (i.e., $\delta^* > 0$ in Figure 15), mitigating more the otherwise larger negative impact of more intense PBT on equilibrium market depth in the baseline economy (see, e.g., Proposition 4 and Eq. (43); lower $\lambda^* - \lambda_1 > 0$). The former effect generally prevails on the latter unless σ^2_e is high.

[45]Estimates using $\hat{\gamma}^2_{i,t}$, which is based on deviation of the mutual fund sector's portfolio holdings from the market portfolio, yield quantitatively similar inference, as discussed later in this section.

[46]Absolute share holdings in Eq. (56) allow us to account for the few instances in which funds hold short stock positions; our inference is unaffected by either the removal of these positions from our sample or the use of signed share holdings. In unreported tests, we also consider an alternative weighting scheme in computing

Then, we define $\hat{\gamma}^1_{i,t}$ as

$$\hat{\gamma}^1_{i,t} = \log(1 + \overline{\hat{\gamma}^1}_{i,t}), \tag{57}$$

where the log transformation is to facilitate the interpretation of the corresponding coefficients of interest in Eq. (55); the ensuing inference is robust to this transformation. Estimates of Eq. (55) are in Column (3) of Table 15: The coefficient of interest $\hat{\beta}_3$ is negative, statistically significant, and economically non-trivial (albeit small, in line with the aforementioned prior literature). Intuitively, and consistent with our interpretation of the disclosures in our sample being due to PBD, the negative relationship between liquidity and firm-level strategic disclosures is stronger when such disclosures align more with the funds' short-term objectives; for instance, the liquidity improvement accompanying those disclosures is up to two times larger in correspondence with a one standard deviation increase in measured short-termism from its mean (amounting to 3% of samplewide firm-quarter illiquidity variation).[47]

C. Liquidity Effect of Disclosure, Short-term Incentives and Firm Characteristics

To provide further evidence for PBD, we also explore whether the aforementioned liquidity effects are stronger when certain firm characteristics may make PBD more effective. As before, we focus on three firm characteristics ($Suit_{i,t}$)—size, intangibility, and stock return volatility—capturing the extent of firm-level fundamental uncertainty. According to our model (e.g., see Conclusion 3), the greater is such fundamental uncertainty about an asset (i.e., the higher is σ_v^2), the greater is the improvement in its liquidity stemming from the speculator's strategic disclosure.[48] We amend Eq. (55) to include $Suit_{i,t}$ as an additional

$\overline{\hat{\gamma}^1}_{i,t}$: $\overline{\hat{\gamma}^1}_{i,t} = \frac{1}{\sum_j |H^f_{i,j,t} - H^m_{i,t}|} \sum_j |H^f_{i,j,t} - H^m_{i,t}| \times \hat{\gamma}^1_{j,t}$, where $H^f_{i,j,t}$ and $H^m_{i,t}$ are defined as in Eqs. (49) and (50), respectively. This scheme puts larger weights on funds whose holdings in firm i differ more from the market. As these funds are more likely to benefit from PBD in terms of their performance relative to the market, their short-term incentives (i.e., their flow-return sensitivity) are more likely to affect the gains from revealing private information about firm i. This alternative measure yields similar inference.

[47] Accordingly, Ljungqvist and Qian (2016) find that daily estimates of Amihud's (2002) illiquidity measure for target firms drop and remain persistently low for more than a trading month following the release of detailed negative information about those firms by the boutique short-selling hedge funds in their sample.

[48] Accordingly, in the model with PBT and PBD of Section II.2.2, the aforementioned relation between $\lambda^* - \lambda_1$ and γ is more pronounced when MM's adverse selection risk is more severe (higher σ_v^2; see, e.g., Figure 15).

interaction term, each time reflecting (the log difference of) one of these firm characteristics:

$$\begin{aligned}\Delta\log(\text{Amihud}_{i,t}) &= \beta_0 + \beta_1\hat{\gamma}_{i,t} + \beta_2\text{Suit}_{i,t} + \beta_3\hat{\gamma}_{i,t}\times\text{Suit}_{i,t} + \beta_4\Delta\log(\#\text{Discl}_{i,t}) \\ &+ \beta_5\Delta\log(\#\text{Discl}_{i,t})\times\hat{\gamma}_{i,t} + \beta_6\Delta\log(\#\text{Discl}_{i,t})\times\text{Suit}_{i,t} \\ &+ \beta_7\Delta\log(\#\text{Discl}_{i,t})\times\hat{\gamma}_{i,t}\times\text{Suit}_{i,t} + \beta_8\Delta\log(\#\text{Discl}_{-i,t}) + \delta'\Delta\log(X_{i,t}) + \delta_y + \delta_q + \epsilon_{i,t}.\end{aligned} \tag{58}$$

These estimates are in Columns (6) to (8) of Table 15. Estimated $\hat{\beta}_4$, $\hat{\beta}_5$, $\hat{\beta}_6$ and $\hat{\beta}_7$ are negative and both economically and statistically significant in most specifications, e.g., suggesting that the liquidity improvement associated with strategic non-anonymous disclosures about a firm is at least three times as large ($\hat{\beta}_4 + \hat{\beta}_5$ versus $\hat{\beta}_4$ in Eq. (58), amounting to almost 3% of samplewide firm-quarter illiquidity variation) when mutual funds holding that firm's stocks have stronger short-term incentives, and, in those circumstances, up to more than three times as large ($\hat{\beta}_4 + \hat{\beta}_5 + \hat{\beta}_6 + \hat{\beta}_7$ versus $\hat{\beta}_4 + \hat{\beta}_5$, i.e., for as much as nearly 8% of total illiquidity variation) when PBD about that firm is likely more effective. This evidence is consistent with the model's notion that sophisticated speculators may use PBD to achieve their short-term objectives and, when they do so, the stock market liquidity of the target firm may improve.

D. Liquidity Effects of PBT and PBD

We note in Section II.2.4.B that PBT may also improve the liquidity of the affected stock. As PBD and PBT are correlated, we need to control for PBT in testing for the effect of strategic disclosures on liquidity. As a first step, we examine the effect of PBT alone on liquidity through the following regression:

$$\begin{aligned}\Delta\log(\text{Amihud}_{i,t}) &= \beta_0 + \beta_1\hat{\gamma}_{i,t} + \beta_2\Delta\log(\text{Trading}_{i,t}) + \beta_3\Delta\log(\text{Trading}_{i,t})\times\hat{\gamma}_{i,t} \\ &+ \delta'\Delta\log(X_{i,t}) + \delta_y + \delta_q + \epsilon_{i,t},\end{aligned} \tag{59}$$

where $\Delta\log(\text{Trading})_{i,t}$ is the log change in aggregate percentage trading in firm i by all sample mutual funds, i.e., relative to its shares outstanding.

The baseline model implies that $\beta_2 < 0$ (see Proposition 4). However, the intensity of mutual fund trading may capture not only PBT but also speculative trading in the usual sense (Kyle 1985), which has the opposite effect on liquidity. The sign of β_3 is also ambiguous. Intuitively, in equilibrium, the speculator optimally employs both PBT and PBD to achieve her short-term objective. A stronger short-term objective (larger γ) has two opposing effects on the scale of PBT. First, it increases PBT, as it "pumps up" her short-term portfolio value. Second, stronger short-term incentives also induce the speculator to more aggressive PBD as a partial substitute for costly PBT (in terms of loss of long-term profit from speculative trading).

Estimates of Eq. (59) are in columns (2) and (4) of Table 15. Consistent with models of trading based on Kyle (1985), $\hat{\beta}_2$ is always positive and statistically significant, indicating that the first-order effect of potentially informative trading dominates the mitigating effect of PBT on price impact. Interestingly, the interaction of trading intensity and short-termism is also positive: $\hat{\beta}_3 > 0$ in column (4). This suggests that the aforementioned substitution effect between PBD and PBT dominates any portfolio pumping effect of PBT alone on illiquidity, consistent both with our model and the increasingly strict SEC enforcement of regulation prohibiting pumping by trading over our sample period.

Next, we examine the effect of PBT on the relationship between PBD and stock market liquidity. We do so by amending Eq. (58) to include mutual funds' trading as well as its interactions with short-term incentives and the relevant firm characteristics as follows:

$$
\begin{aligned}
\Delta\log(\text{Amihud}_{i,t}) &= \beta_0 + \beta_1\hat{\gamma}_{i,t} + \beta_2\Delta\log(\#\text{Discl}_{i,t}) + \beta_3\Delta\log(\#\text{Discl}_{i,t}) \times \hat{\gamma}_{i,t} \\
&+ \beta_4\Delta\log(\#\text{Discl}_{i,t}) \times \text{Suit}_{i,t} + \beta_5\Delta\log(\#\text{Discl}_{i,t}) \times \hat{\gamma}_{i,t} \times \text{Suit}_{i,t} + \beta_6\Delta\log(\#\text{Discl}_{-i,t}) \\
&+ \beta_7\Delta\log(\text{Trading}_{i,t}) + \beta_8\Delta\log(\text{Trading}_{i,t}) \times \hat{\gamma}_{i,t} + \beta_9\Delta\log(\text{Trading}_{i,t}) \times \text{Suit}_{i,t} \\
&+ \beta_{10}\Delta\log(\text{Trading}_{i,t}) \times \hat{\gamma}_{i,t} \times \text{Suit}_{i,t} + \beta_{11}\text{Suit}_{i,t} + \beta_{12}\hat{\gamma}_{i,t} \times \text{Suit}_{i,t} \\
&+ \delta'\Delta\log(X_{i,t}) + \delta_y + \delta_q + \epsilon_{i,t}
\end{aligned}
\tag{60}
$$

The signs, statistical significance and economic magnitude of the resulting estimates—in Columns (12) to (14) of Table 15—are very similar to those in Columns (6) to (8). Thus, the effect of funds' strategic disclosure on liquidity is robust to controlling for their strategic trading behavior. For example, relative to the case where both funds' short-term incentives ($\hat{\gamma}^1_{i,t}$) and firms' "suitability" as disclosure targets ($Suit_{i,t}$) are held at their means, the liquidity improvement associated with fund disclosures is between two and five times larger in correspondence with a one standard deviation increase in short-term incentives alone ($\hat{\beta}_2+\hat{\beta}_3$ versus $\hat{\beta}_2$ in Eq. (60), amounting to more than 2% of samplewide firm-quarter illiquidity variation), and between seven and fourteen times larger in correspondence with a one standard deviation increase in both $\hat{\gamma}^1_{i,t}$ and $Suit_{i,t}$ ($\hat{\beta}_2 + \hat{\beta}_3 + \hat{\beta}_4 + \hat{\beta}_5$ versus $\hat{\beta}_2$ in Eq. (60), i.e., for up to 6% of total illiquidity variation).

E. Alternative Measure of Short-term Incentives

Lastly, we consider an alternative proxy for mutual funds' short-term incentives based on $\hat{\gamma}^2_{i,j,t}$ of Section II.4.1. Specifically, and consistent with Eq. (57), we construct $\hat{\gamma}^2_{i,t}$ as the percentage deviation in the mutual fund sector's holdings of firm i from the market:

$$
\hat{\gamma}^2_{i,t} = \begin{cases} \log(\frac{H^f_{i,t}}{H^m_{i,t}}), & \text{if } H^f_{i,t} > H^m_{i,t}, \\ \log(\frac{H^m_{i,t}}{H^f_{i,t}}), & \text{otherwise,} \end{cases} \tag{61}
$$

where $H^f_{i,t} = \frac{\text{Aggregate Holdings of Firm i by All Sample Funds at the End of Quarter t}}{\text{Aggregate Holdings of All S\&P 1500 Firms by All Sample Funds at the End of Quarter t}}$ and $H^m_{i,t} = \frac{\text{Market Cap. of Firm i at the End of Quarter t}}{\text{Total Market Cap. of All S\&P 1500 Firms at the End of Quarter t}}$.

We then run all of the tests in Table 15 using $\hat{\gamma}^2_{i,t}$ instead of $\hat{\gamma}^1_{i,t}$. These estimates, in Table 16, yield qualitatively and quantitatively similar inference. For instance, Column (1) of Table 16 indicates that more disclosures about a firm are accompanied by an improvement in the liquidity of its stock; according to Column (3), this effect is more pronounced when mutual funds are taking larger bets in a firm (i.e., have stronger short-term incentives to PBD)—e.g., about two times larger in correspondence with a one standard deviation increase in $\hat{\gamma}^2_{i,t}$ relative to its mean (amounting to more than 3% of samplewide firm-quarter illiquidity variation). Columns (6) to (8) further show that such effect is even stronger if a firm is a more "suitable" disclosure target—for example, increasing by up to two times ($\hat{\beta}_4 + \hat{\beta}_5 + \hat{\beta}_6 + \hat{\beta}_7$ versus $\hat{\beta}_4 + \hat{\beta}_5$ in Eq. (60), i.e., for more than 6% of total illiquidity variation) when $Suit_{i,t}$ is one standard deviation larger than its mean.

II.5 Conclusions

In this paper, we model and provide evidence of sophisticated speculators' strategic public disclosure of private information. First we develop a model of strategic speculation based on Kyle (1985) and show that when a speculator is (at least partially) short-term oriented, voluntary disclosure of private information is optimal. We model disclosure as a signal that depends positively on two pieces of a speculator's private information—asset fundamentals and her initial endowment in that asset. Intuitively, a positive (negative) endowment shock leads to a more positive (negative) signal realization, which, in turn, may be interpreted by uninformed market participants—the market makers—as a positive (negative) fundamental shock, resulting in equilibrium price changes in the same direction as the endowment shock. Thus, strategic disclosure yields a positive correlation between a speculator's initial endowment in an asset and its short-term price, boosting her portfolio value and her overall value function. Additionally, we show that strategic disclosure has important implications for the affected market. In particular, relative to the non-disclosure case, market depth increases and prices are more efficient, as the adverse selection risk faced by the dealership sector is mitigated.

We provide supportive empirical evidence in the context of the U.S. mutual fund industry. We find that funds' stronger short-term incentives are associated with more frequent non-anonymous disclosures—a pattern that is most pronounced for target firm-level characteristics (namely small size, intangibility, and high return volatility) that likely make strategic disclosure more effective. We also find that (1) these disclosures in target firms are accompanied by liquidity improvements of their stocks and (2) this effect is stronger if the disclosure target is more "pivotal" to the funds' short-term objectives, and is even more so if once again the disclosure is likely more effective—such as when firm-level fundamental uncertainty is greater, consistent with our model.

Overall, our novel analysis has the potential to bridge the gap between the conventional wisdom that information is valuable only if kept private and the not uncommon observation that sophisticated financial market participants voluntarily, non-anonymously, and possibly strategically disclose information to the public. These insights are important both for academics' and practitioners' understanding of the process of price formation in financial markets in the presence of information asymmetry as well as for policy-makers' efforts at regulating the availability of information in those markets.

CHAPTER III

Bank Market Power and Monetary Policy Transmission: Evidence from a Structural Estimation

III.1 Introduction

We examine the quantitative importance of bank market power as a transmission mechanism for monetary policy. This question rests against a backdrop of traditional theories and analysis of monetary policy transmission that largely focus on the impact of regulatory constraints on bank lending (e.g. Bernanke and Blinder, 1988; Kashyap and Stein, 1995). Indeed, the banking industry is often assumed to be perfectly competitive, leaving only regulatory frictions, such as reserve or capital requirements, as a channel through which monetary policy affects loan supply. However, recent research suggests that the industrial organization of the banking sector may also play a role in the transmission of monetary policy (Drechsler et al., 2017; Scharfstein and Sunderam, 2016). While important, this newer literature has been qualitative in nature, leaving open the question of the relative importance of traditional versus market-power channels for the transmission of monetary policy.

Our paper tries to fill this void by constructing and estimating a dynamic banking model with three important frictions: regulatory constraints, financial frictions, and imperfect competition. The estimation allows our data on commercial banks to discipline the model parameters and thus expose the relative magnitude of these three frictions. We find that regulatory frictions restricting bank capital and bank market power both play an important role in monetary policy transmission, while reserve requirements are unimportant. In terms of magnitude, the effect of bank market power is comparable in magnitude to that of bank capital. We also find an interesting interaction between different monetary policy transmission channels. Specifically, we show that bank capital regulation interacts with market power and reverses the sign of monetary policy when the Federal Funds rate is very low. We estimate that when the Federal Funds rate is below 2.27%, further cuts in the policy rates can be contractionary. Moreover, we find external validation of this reversal rate by showing in a simple regression framework that the relation between bank capital and interest rates switches sign at approximately this interest rate.

An understanding of the intuition behind these results requires a deeper description of the model. In the economy, banks act as intermediaries between borrowers and depositors. The lending decision is dynamic because deposits are short-term, while loans are long-term. Monetary tightening enters the picture by increasing banks' funding costs in the deposit market. Because they are not price takers in the deposit and loan market, banks choose how much of a rate increase to pass on to borrowers. The degree of pass-through is influenced by the tightness of regulatory constraints, the degree of financial frictions, and the intensity of competition.

These frictions in our model map into three monetary policy transmission channels emphasized in the literature. The first is the bank reserve channel in which a high Federal Funds rate raises the opportunity cost of holding reserves (Bernanke and Blinder, 1988; Kashyap and Stein, 1995) and thus contracts deposit creation. The second is the bank capital channel in which a rise in the Federal Funds rate exacerbates banks' natural maturity mismatch, thereby lowering bank capital and, consequently, the capacity to lend (Bolton and Freixas, 2000; Van den Heuvel, 2002; Brunnermeier and Sannikov, 2016). The third is the market power channel emphasized by Drechsler et al. (2017) and Scharfstein and Sunderam (2016). Intuitively, after a rate increase, cash becomes less attractive to households relative to deposits. Monopolistically competitive banks can exploit this extra deposit demand by charging higher spreads on deposits. In equilibrium, total deposits fall because households substitute risk-free bonds for deposits. Because banks then need to fund marginal lending in the more expensive debt market, lending contracts.

To gauge the quantitative importance of these transmission channels, we estimate our model using a panel of U.S. commercial banks. Our estimation combines methods used in the industrial organization literature (Berry et al., 1995; Nevo, 2001) with those used in the corporate finance literature (Hennessy and Whited, 2005; Bazdresch et al., 2018). As a first step, we use the demand estimation techniques from industrial organization to obtain the elasticities of substitution in the deposit and loan markets. We then plug these estimates into our model, and use simulated method of moments to obtain estimates of parameters that quantify financial frictions and operating costs. The sequential use of these two techniques is a methodological advance that allows us to consider a rich equilibrium model that would otherwise be intractable to estimate.

To obtain our results on the relative importance of each transmission channel, we then use these parameter estimates to simulate counterfactual experiments in which we subtract each channel from the model one at a time. These counterfactuals also produce our interesting result that rate cuts can be contractionary when rates are already low. Low interest rates depress bank profits by reducing bank market power in the deposit market, as cash becomes less unattractive to households. Lower profits then tighten the capital constraint and result in less lending. This result sheds light on the sluggish bank lending growth post crisis, as an ultra-low rate policy can unintentionally reduce bank profitability, and consequently constrain banks' capacity to lend. Overall, our results suggest that Federal Reserve actions can have complicated effects on bank lending depending on the level of policy rates, the amount of bank capital, and the industrial organization of the banking sector.

Our paper contributes to the literature studying the role of banks in transmitting monetary policy. It is the first to estimate a structural dynamic banking model to quantify various transmission channels.[49] Prior to our work, little has been known about the relative

[49]Xiao (2018) also uses a structural approach, but the main focus is on shadow banks.

importance of different transmission channels, as this type of quantitative exercise is difficult to undertake using reduced form methods.

Second, prior literature usually studies each transmission channel separately, but little is known about the interactions between different channels. Thus, an important contribution of this paper is to provide a unified framework to study these interactions. For example, Drechsler et al. (2017) and Scharfstein and Sunderam (2016) study the market power in the deposit market and loan market separately. We show that the relative importance of the two markets depends on the level of the Federal Funds rate. The deposit market is more important when the Federal Funds rate is low, while the loan market becomes more important when the Federal Funds rate is high. Brunnermeier and Koby (2016) put forth the theoretical possibility that monetary policy can switch sign at a certain threshold referred to as a "reversal rate." Our paper provides an empirical estimation of this threshold.

Third, our paper is related to the literature on external financial frictions. Largely focused on industrial firms, this literature shows that financial frictions significantly affect corporate policies such as investment, cash holding, and dividend payout. We show that banks also face significant financial frictions despite their regular participation in the capital markets. This last result supports the arguments in Kashyap and Stein (1995) that banks' high external financing costs can influence the quantity of bank lending.

III.2 Data

Our main data set is the Consolidated Reports of Condition and Income, generally referred to as the Call Reports. This data set provides quarterly bank-level balance sheet information for U.S. commercial banks, including deposit and loan amounts, interest income and expense, loan maturities, salary expenses, and fixed-asset related expenses. We merge the Call Reports with the FDIC Summary of Deposits, which provides branch-level information for each bank since 1994 at an annual frequency. We follow Egan et al. (2017) by excluding banks with fewer than ten domestic branches. This filter eliminates foreign banks with few U.S. branches and tiny local banks. The resulting sample period is 1994–2017.

Our analysis requires data from several further sources. First, we retrieve publicly listed bank returns from CRSP. We link the stock returns to bank concentration measures using the link table provided by the Federal Reserve Bank of New York. We obtain bank industry stock returns from Kenneth French's website. We collect the Federal Open Market Committee meeting dates from the FOMC Meeting calendar. Finally, we obtain the following time series from FRED (Federal Reserve Economic Data): NBER recession dates, the effective Federal Funds rate, the two-year and five-year Treasury yields, the aggregate amount of corporate bonds issued by U.S. firms, and the aggregate amount of cash, Treasury bonds, and money-market mutual funds held by households.

Table 17 provides summary statistics for this sample, which we use for our demand estimation. The first two lines report the mean, standard deviation, and several percentiles of bank market shares in both the deposit and loan markets. We define the entire United States as a unified market to compute these shares, with the total size of the deposit market defined as the sum of deposits, cash, and Treasury securities held by all U.S. households. The total size of the loan market is defined as the sum of bank loans and corporate bonds borrowed by U.S. firms. Interestingly, mean market shares in both the loan and deposit markets lie near the 90^{th} percentile, indicating a very skewed distribution of market shares in which a few large banks dominate the market.

The next two lines report summary statistics for deposit and loan rates, which we impute by dividing total deposit interest expense by total deposits and total interest income by total loans. The next two lines report summary statistics for two non-rate bank characteristics used in the estimation: the number of branches and the number of employees per branch. While we see little variation in the number of employees per branch, we see both high variance and skewness in the number of branches per bank. The skewness is consistent with the skewness in market shares, as the number of branches is highly correlated with bank size. Lastly, we report summary statistics for the two supply shifters we use in our estimation:

salaries and fixed asset expenses (Ho and Ishii, 2011). Fixed asset expenses include all non-interest expenses stemming from use of premises, equipment, furniture, and fixtures. We scale both supply shifters by total assets.

III.3 Stylized Facts

To motivate our study of the relative importance of various monetary policy transmission channels, we first examine the relation between bank equity returns and monetary policy shocks. The conventional wisdom from the traditional transmission channels is that high interest rate monetary policy should have a negative impact on bank capital. Specifically, the bank capital channel predicts that because bank-loan maturity exceeds deposit maturity, an increase in interest rates reduces the value of assets more than the value of liabilities, so bank equity falls. The bank reserve channel predicts that a high Fed Funds rate increases the opportunity cost of holding reserves because reserves bear no interests. Therefore, a high interest rate leads to less deposit taking and less lending, which lowers banks' profits and consequently, bank capital.

We verify this prediction by regressing bank equity returns on the change in the two-year Treasury yield on Federal Open Market Committee (FOMC) meeting days. We focus on FOMC days following Hanson and Stein (2015), who use daily changes in the two-year Treasury yield surrounding FOMC meetings to measure monetary policy shifts. The advantage of examining the two-year Treasury yield instead of the Federal Funds rate is that the former captures the effects of "forward guidance" in the FOMC announcement, which has become increasingly important in recent years (Hanson and Stein, 2015).[50] The identifying assumption is that unexpected changes in interest rates in a one-day window surrounding scheduled Federal Reserve announcements arise from news about monetary policy. While our sample period runs from 1994 to 2017, we exclude the burst of dot-com bubble (2000–2001) and the subprime financial crisis (2007–2009) because in these crisis times, monetary policy can be

[50] We also use 1-year Treasury yield and the results are robust.

strongly influenced by the stock market rather than by inflation or economic growth (Cieslak and Vissing-Jorgensen, 2017).

Table 18 reports the regression estimates. We find the conventional wisdom is generally true when the startling level of the Fed Funds rate is above 2%. As shown in the regression in column 1, an increase in the short-term interest rates reduces bank equity value. However, we find that the negative relation between interest rates and bank equity reverse sign if the starting level of the Fed Funds rates are below 2%. As shown in column 2, an increase in the two-year Treasury yield is associated with positive significant returns for bank equity. In other words, the market expects that an increase in interest rates leads to an increase in bank capital. This low-interest-rate result stands in contrast to the conventional wisdom that monetary tightening reduces bank capital. This result is not driven by a steepening of the term structure, as we control for the change in the five-year term spread over two-year Treasury, where we pick the five-year spread to match the average maturity of bank loans in our sample, which is five years. As shown in Figure 24, the contrast between the results in Columns 1 and 2 can be seen in a simple scatter plot of bank industry excess returns against the change in the two-year Treasury yield. Moreover, in the Online Appendix, we examine returns for all 49 Fama-French industries. We find that the banking industry is the *only* industry exhibiting a switch from a negative interest sensitivity to positive interest sensitivity in the low interest environment. In summary, we find that monetary policy has a nonmonotonic effect on bank capital. When the Federal Funds rate is high, the relation between the short-term rates and bank capital seems be to negative, but when the Federal Funds rate is low, this relation becomes negative. As far as we know, this paper is the first to document this empirical relation.

To delve into the mechanism behind this basic result, we estimate a non-parametric relationship between the Fed Funds rates and the average deposit spread of the U.S. banks. The deposit spread is defined the difference between the Fed Funds rates and the deposit rates, which measures the price that banks charge for their depository services. One would expect a constant deposit spread that equals marginal costs of providing depository services if there is no market power or other frictions. However, we find a positive relation between the deposit spread and the Fed Funds rate, which becomes even stronger when the Fed Funds rate is close to zero. In other words, banks are able to charge higher prices for their depository services when the Fed raises interest rates. This pattern is consistent with the idea that banks have market power as suggested by Drechsler et al. (2017). In presence of market power, high Fed Funds rate allows banks to raise the markups above marginal costs because an important outside option for depositors, cash, becomes more costly to hold. Therefore, banks make more profits in the deposit market when the Fed raises short-term rates. This effect is particular strong when the Fed Funds rate is close to zero when banks face intense competition from cash.

To verify this explanation, in Columns 3 and 4 of Table 18, we interact the change in the interest rate with a measure of bank market power, the Herfindahl-Hirschman index of the local deposit market in which the bank operates, where we define a local deposit market as a Metropolitan Statistical Area (MSAs). If a bank operates in several MSAs, the bank-level HHI is the weighted average of local HHIs, weighted by the deposits of the bank in the local market. We find that when the Federal Funds rate is below 2%, banks with greater market power in the deposit market experienced larger positive returns.

This evidence provides a possible explanation on the sluggish lending growth in the recent economy recovery. Figure 26 plots average U.S. bank loan-to-deposit ratios following the five recessions from 1973 to 2017. The loan-to-deposit ratio usually falls when a recession starts, as both loan demand and supply fall. In the first three recessions during this period, the loan-to-deposit ratio recovered three to four years after the start of the recession. However, the recoveries after the 2001 and 2008 recessions are notably slower. The loan-to-deposit ratio took six to seven years to recover after the 2001 recession, and this ratio still has not yet recovered 10 years after the 2008 recession. This sluggishness is surprising given that both recessions ended within two years.[51]

Although many factors such as regulatory changes could be driving the lengthy recovery in bank lending, one feature that these two episodes share is protracted periods in which the Federal Reserve lowered short term interest rates to near zero. As such, loose monetary policy is a possible culprit. As argued above, extreme low short-term rates may depress banks' profitability and slow down the capital accumulation. Since banks want to maintain certain level of capital ratio, a lower capital accumulation will constrain the lending growth.[52]

III.4 Model

While the facts documented in the previous section point to interesting interactions between bank capital, bank, competition and interest rates, this time-series evidence cannot help us understand the various mechanisms that drive these patterns in the data. To move in this direction, we next consider an infinite-horizon, equilibrium model with three sectors: households, firms, and banks. Banks act as intermediaries between households and firms by taking short-term deposits from households and providing long-term loans to firms. We model the households and firms as solving straightforward static discrete choice problems in which they choose from a variety of saving and financing vehicles. The richness of the model lies in the banking sector, as a variety of frictions imply that monetary policy affects the amount of intermediation that banks provide. These frictions are important because in a frictionless world where bank loans and bonds are perfect substitutes, bond market interest rates summarize monetary policy and banks are simply pass-through entities. However, if bank loans and bonds are imperfect substitutes (Bernanke and Blinder, 1988), the supply of bank loans matters for monetary policy in its own right.

Since Bernanke and Blinder (1988), researchers have identified many frictions that affect

[51]One concern with the results in Figure 26 is that they may be driven largely by an increase in the denominator—deposits. To address this concern, in the Online Appendix, we plot the amount of loans following the onset of each recession and the result still holds.

[52]In the Online Appendix further separate banks into two groups according to their capital ratios. We find that banks with below-median capital ratios experience much lower loan growth following the recession. The gap between poorly-capitalized and well-capitalized banks is particularly large in 2001 and 2008 recessions.

monetary transmission through banks. Our model incorporates the following prominent channels featured in the literature. First, access to non-deposit external financing is more costly than taking deposits. This friction implies that shocks to the quantity of deposits are transmitted to the supply of bank loans, as banks cannot costlessly replace deposits with non-reservable borrowing. Second, competition in the deposit and loan markets is imperfect. With market power, banks strategically choose deposit and loan rates to maximize their profits. This profit maximizing behavior, in turn, determines how monetary policy transmits through the banking system. Third, banks are subject to reserve regulation and capital regulation. Reserve regulation links the opportunity cost of taking deposits to the prevailing Federal Funds. Capital regulation incentivizes banks to optimize their loan supply intertemporally with an eye to preserving excess equity capital as a buffer against future capital inadequacy.

III.4.1 Households

At each time t, the economy contains W_t households, each of which is endowed with one dollar. Hereafter, we drop the time subscript for convenience, so aggregate household wealth is then W. Households choose among the following investment options for their endowments: cash, corporate bonds, and bank deposits, where the deposits of each individual bank constitute a differentiated product. If we index each option by j, the households' choice set is given by $\mathcal{A}^d = \{0, 1, \ldots, J, J+1\}$, with option 0 representing cash, option $J+1$ representing short-term bonds, and options $1, \ldots, J$ representing deposits in each bank. We further assume that each depositor can choose only one option. This one-dollar, one-option assumption is without loss of generality. For example, we can interpret this setting as if households make multiple discrete choices for each dollar that they have, and the probability of choosing each of the options can be interpreted as portfolio weights.

Each option is characterized by a yield, r_j^d, and a quality value, q_j^d. The yield on cash is 0, and the yield on bonds is the Federal Funds rate, f. q_j^d captures the convenience of option j to a depositor. For a bank, q_j^d can reflect the bank's number of branches or the number of employees per branch. For the other options, q_j^d can capture the ease with which the household can use the option as a medium of transaction. We assume q_j^d varies only with banks and not with households, so different households cannot ascribe a different quality value to the same option. We allow households to belong to a finite set of types, indexed by $i \in 1, 2, \ldots, I$. A household's utility from choosing option j is given by $u_{i,j} = \alpha_i^d r_j^d + q_j^d + \epsilon_{i,j}^d$, where α_i^d is the yield sensitivity and $\epsilon_{i,j}^d$ is a relationship specific shock for the choice of option j by household i. We assume $\epsilon_{i,j}^d$ follows a generalized extreme value distribution with a cumulative distribution function given by $F(\epsilon) = \exp(-\exp(-\epsilon))$. This distributional assumption is standard in the structural industrial organization literature and allows for a closed-form solution for the consumer's probability of making each choice.

The decision of each household is then to choose the best option to maximize its utility:

$$\max_{j \in \mathcal{A}^d} u_{i,j} = \alpha_i^d r_j^d + q_j^d + \epsilon_{i,j}^d. \tag{62}$$

The solution to (62) implies that the demand for the deposits of bank j is given by the following formula:

$$s_j^d\left(r_j^d\right) = \sum_{i=1}^{I} \mu_i^d \frac{\exp\left(\alpha_i^d r_j^d + q_j^d\right)}{\sum_{m \in \mathcal{A}^d} \exp\left(\alpha_i^d r_m^d + q_m^d\right)}, \tag{63}$$

where μ_i^d is the fraction of total wealth (W) held by households of type i. The quantity of deposits is then given by the market share multiplied by total wealth, $D_j = s_j^d W$.

III.4.2 Firms

There are K firms, each of which wants to borrow one dollar, so aggregate borrowing demand is K. Firms can borrow by issuing long-term bonds or taking out bank loans. We assume that each individual bank is a differentiated lender, where this assumption is motivated by such factors as geographic location or industry expertise. Letting each option be indexed by j, the firms' choice set is given by $\mathcal{A}^l = \{0, 1, \ldots, J, J+1\}$, where option 0 represents bonds, option $1, \ldots, J$ represents loans from each bank, and option $J+1$ is the option not to borrow at all.[53] Each option is characterized by a lending rate, r_j^l, and a vector of product characteristics, x_j^l. As above, these characteristics can include the number of branches or employees per branch.

For tractability, we assume that both bonds and bank loans have the following repayment schedule. Each period the firm has to pay back a fraction, μ, of its outstanding debt, where μ includes both interest accrued over the last period, as well as some amortized principal. For instance, if the firm borrow a nominal value of one dollar, the repayment stream, starting in the next period, is $\mu, (1-\mu)\mu, (1-\mu)^2\mu, \ldots$. Accordingly, all firm debt has an average maturity of $\frac{1}{\mu}$ periods. This construction saves us from having to track the entire age distribution of a bank's loan portfolio. Thus, a sufficient statistic for the future repayment schedule is just the total amount outstanding.

We assume that the interest rate on the long-term bond ($\bar{f}_t$) is set according to:

$$\sum_{n=0}^{\infty} \frac{\mu(1-\mu)^n}{(1+\bar{f}_t)^{n+1}} = \frac{\mu}{1+f_t} + \mathbb{E}_t \left[\sum_{n=1}^{\infty} \frac{\mu(1-\mu)^n}{\prod_{m=0}^{n}(1+f_{t+m})} \right] \tag{64}$$

Put differently, $\bar{f}_t$ is the fixed rate that produces the bond's fair present value when used to discount the bond's cash flows. Fair present value, in turn, is simply this expected value of this cash flow stream discounted at the (non-constant) Federal Funds rate, f_t. Each of the firm's financing option's is characterized by a rate, r_j^l, and a quality value, q_j^l, which reflects the effort a firm must exert to borrow via option j. In case of a bank loan, q_j^l can include the number of branches or the number of employees per branch. In the case of the corporate bond, q_j^l can capture the cost of hiring an underwriter. We assume q_j^l varies only with banks and not with firms, where, as in the case of the households, we allow firms to belong to a finite set of types, indexed by $i \in 1, 2, \ldots, I$.

The profit for firm i from choosing option j is given by $\pi_{i,j} = \alpha_i^l r_j^l + q_j^l + \epsilon_{i,j}^l$, where α_i^l is

[53]Our index choices recycle the notation i to index firms and j to index the firm's borrowing options.

the yield sensitivity, and $\epsilon^l_{i,j}$ is an idiosyncratic relationship shock when a firm i borrows from bank j. We assume $\epsilon^l_{i,j}$ follows a generalized extreme value distribution with a cumulative distribution function $F(\epsilon) = \exp(-\exp(-\epsilon))$. Each firm's decision is to choose the best option to maximize its profit, as follows:

$$\max_{j \in \mathcal{A}^l} \pi_{i,j} = \alpha^l_i r^l_j + q^l_j + \epsilon^l_{i,j}. \tag{65}$$

The solution to (65) implies that the demand for the loans of bank j is given by:

$$s^l_j\left(r^l_j\right) = \sum_{i=1}^{I} \mu^l_i \frac{\exp\left(\alpha^l_i r^l_j + q^l_j\right)}{\sum_{m \in \mathcal{A}^l} \exp\left(\alpha^l_i r^l_m + q^l_m\right)}, \tag{66}$$

where μ^l_i is the fraction of type i firms. Loan quantity is given by the market share multiplied by the total market size, $B_j = s^l_j K$.

III.4.3 The Banking Sector

Given the Federal Funds rate, f_t, each bank simultaneously sets its deposit rate, $r^d_{j,t}$, and its loan rate $r^l_{j,t}$, thereby implicitly choosing the quantities of deposits to take from households and credit to extend to firms. For example, given each bank j's choice of $r^d_{j,t}$, households solve their utility maximization problem described above, which yields the quantity of deposits supplied to bank j, $D_j(r^d_{j,t})$. Similarly, given each bank j's choice of $r^l_{j,t}$, firms solve their profit maximization problem, which yields the quantity of loans borrowed from bank j, $B_j(r^l_{j,t})$. To simplify notation, in what follows, we suppress the dependence of loans and deposits on the relevant interest rates, denoting them simply as D_t and B_t.

This lending activity involves a maturity transformation. Let $L_{i,t}$ denote the amount of loans that the bank currently holds. In each period, as in the case of bonds, a fraction, μ, of a bank's outstanding loans matures, with principle plus interest payments equal to $\mu \times L_{i,t}$. This assumption about long-term loans captures a traditional maturity transformation role for banks, in which they convert one-period deposits into long-term bank loans with maturity $\frac{1}{\mu}$. As noted above, banks can also issue new loans with an annualized interest rate of $r^l_{j,t}$. The new loans, once issued, have the same maturity structure as the existing ones, with a fraction $\mu B(r^l_{j,t})$ becoming due each year. As such, a bank's outstanding loans evolve according to:

$$L_{j,t+1} = (1-\mu)(L_{j,t} + B_{j,t}), \tag{67}$$

We assume that a random fraction of loans, $\delta_t \in [0,1]$, falls delinquent in each period, with delinquency occurring when a loan comes due but the borrower fails to pay. Although we assume that delinquent payments are written off by the bank, with charge-offs equal to $\mu L_t \times \delta_t$, defaulting on a payment in one period does not exonerate the borrower from payments in future periods. Therefore, delinquency does not affect the evolution of loans in (67).

We denote by $P(B_{j,t}, r^l_{j,t})$ the amount bank j extends to firms. Fair pricing implies that this quantity is simply the discounted the payment stream at the constant loan rate $r^l_{j,t}$:

$$P(B_{j,t}, r^l_{j,t}) = \sum_{m=0}^{\infty} \frac{(1-\mu)^m \mu B_{j,t}}{(1+r^l_{j,t})^{m+1}} = \frac{\mu}{r^l_{j,t} + \mu} B_{j,t} \tag{68}$$

Notice that if the loan rate $r_{j,t}$ is set to 0, then equation (68) simplifies to $P(B_{i,t}, r^l_{i,t}) = B_{i,t}$, showing that the amount the bank gives to firms at the present period simply equals the sum of all future payments. If μ is set to one, then debt has a maturity of one year, and the interest income from lending is $B_{j,t} - P_{j,t} = \frac{r^l_{j,t}}{1+r^l_{j,t}} B_{j,t} \approx r^l_{j,t} B_{j,t}$.

We summarize the rest of the bank's activities in the balance sheet given in Table 19, where we suppress the subscript for bank identity, j, for convenience. Here, we see that the banks assets consist of existing plus new loans, reserves, and holdings of government securities. Its liabilities consist of deposits, borrowing not subject to reserve requirements. The difference is then bank equity. We now go through these items in detail.

In each period, the bank can rely on deposits or internal retained earnings to finance its new loans, B_t. When the supply of funds falls short of loan demand, the bank can also borrow via non-reservable securities, N_t. A typical example of non-reservable borrowing is large denomination CDs. As argued by Kashyap and Stein (1995), because non-reservable borrowing is not insured by FDIC deposit insurance, purchasers of this debt must concern themselves with the default risk of the issuing bank. These considerations make the marginal cost of non-reservable borrowing an increasing function of the amount raised, and motivate our next assumption, which is that non-reservable borrowing incurs a quadratic financing cost beyond the prevailing Federal Funds rate, as follows:

$$\Phi^N(N_t) = \phi^N N_t^2. \tag{69}$$

This assumption embodies two important frictions, the first of which is deposit insurance. Because a large fraction of deposits are insured, depositors are willing to accept a rate of interest that does not reflect default risk. The second friction is deadweight default losses, which affect the rate of return on non-reservable securities, which are subject to bank default risk.

Banks also incur operating costs, such as rents and wages. We assume that costs are linear in the amount of deposits:

$$\Phi^d(D_t) = \phi^d D_t. \tag{70}$$

Similarly, we also assume that lending activity itself incurs separate costs, such as the labor input necessary to screen loans or maintain client relationships. Again, we assume a linear functional form as follows:

$$\Phi^l(B_t) = \phi^l B_t. \tag{71}$$

If the total supply of funds exceeds the demand from the lending market, the bank can invest in government securities, G_t, where the return is the Federal Funds rate, f_t. The bank's holdings of loans, government securities, deposits, reserves, and non-reservable borrowing must satisfy the standard condition that assets equal liabilities plus equity:

$$L_t + P(B_t, r_t) + R_t + G_t = D_t + N_t + E_t, \tag{72}$$

where R_t denotes bank reserves and E_t is the bank's begin-of-period book equity. E_t itself evolves according to:

$$E_{t+1} = E_t + \Pi_t \times (1 - \tau) - C_t \tag{73}$$

where τ denote the linear tax rate, and Π_t is the bank's total operating profit from its deposit taking, security investments, and lending decisions. This identity ends up being a central ingredient in the model, as it links bank competition, which is reflected in profits, with bank capital regulation.

The profits in (73) are in turn given by:

$$\Pi_t = B_t - P(B_t, r_t^l) - D_t \times r_t^d + G_t \times f_t - \Phi^l(B_t) - \Phi^d(D_t) - \Phi^N(N_t) - \mu L_t \times \delta_t. \tag{74}$$

Finally, C_t in equation (73) represents the cash dividends distributed to the bank's shareholders. We assume that a bank can only increase its inside equity via retained earnings, that is, there is no new equity issuance, so:

$$C_t \geq 0 \quad \forall t. \tag{75}$$

This constraint reflects a bank's limited liability, which prevents it from obtaining any external equity financing from shareholders. This constraint represents an important friction because in its absence, banks could always raise equity capital to fund any shortfall in the loanable funds market. This activity would disconnect banks' deposit taking decisions from their lending decisions, so changes in the Federal Funds rate would not have an impact on lending. Equation (75) implies that model cannot capture the equity issuances we see in the data. However, given that banks' equity issuances are both tiny and rare, we view this drawback of our model as minor.

We now introduce the capital requirement and the reserve requirement:

$$E_{t+1} \geq \kappa \times L_{t+1} \tag{76}$$

$$R_t \geq \theta \times D \tag{77}$$

Equation (76) implies that the bank's book equity at the beginning of the next period has to be no smaller than a fraction, κ, of the loans outstanding. Equation (77) is the bank's reserve requirement, which says that the bank has to keep θ of its deposits in a non-interest bearing account with the central bank. Zero interest on reserves implies that the bank has no incentive to hold excess reserve, so equation (77) holds with equality.

To close the model, we assume that the law of motion for the bank loan charge-offs and the Federal Funds rate is given by:

$$\begin{bmatrix} \ln \delta_{t+1} \\ \ln f_{t+1} \end{bmatrix} = \begin{bmatrix} \rho_\delta & \rho_{\delta f} \\ 0 & \rho_f \end{bmatrix} \cdot \begin{bmatrix} \ln \delta_t \\ \ln f_t \end{bmatrix} + \begin{bmatrix} \sigma_\delta & 0 \\ 0 & \sigma_f \end{bmatrix} \cdot \mathcal{N}_2, \tag{78}$$

where $\mathcal{N}_2$ stands for the density function of a standard bi-variant normal distribution.

III.4.4 Bank's problem and equilibrium

Figure 27 summarizes the sequence of events in a typical time period. The bank enters the period and observes the Federal Funds rate, f_t, and the realization of the default fraction, δ_t. At that point, it takes the corresponding charge-offs. Next, banks interact with households and firms by setting the loan and deposit spreads, receiving the corresponding amount of deposits from households, and extending the corresponding amount of loans to firms. Depending on the extent of these activities, the banks adjust their reserves, holdings of government securities, and non-reservable borrowing. Finally, at the end of the period, a fraction μ of the loans matures, and banks collect profits and distribute dividends to shareholders.

As discussed above, loan and deposit demand depend on the rates put forth by all banks in the economy. Accordingly, when each bank chooses its own deposit and loan rates (r_t^d and r_t^l), as well as its non-reservable borrowings (N_t), and investment in government securities (G_t), it rationally takes into account the choices made by other banks in both the current and future periods. As such, all of a bank's optimal choices depend on the composition of the banking sector, that is, the cross-sectional distribution of bank states, which we denote by Γ_t. Letting P^Γ denote the probability law governing the evolution of Γ_t, we can express the evolution of Γ_t as:

$$\Gamma_{t+1} = P^\Gamma(\Gamma_t). \tag{79}$$

Every period, after observing the Federal Funds rate (f_t) and the random fraction of defaulted loans (δ_t), the banks choose the optimal policy to maximize its discounted cash dividends to shareholders:

$$V(f_t, \delta_t, L_t, E_t \big| \Gamma_t) = \max_{\{r_t^l, r_t^d, G_t, N_t, R_t\}} \left\{ C_t + \frac{1}{1+\gamma} \mathbb{E} V(f_{t+1}, \delta_{t+1}, L_{t+1}, E_{t+1} \big| \Gamma_{t+1}) \right\} \tag{80}$$

$$s.t. \qquad (69),\ (70),\ (71),\ (72),\ (73),\ (79),$$

where γ is the bank's discount factor.

We define equilibrium in this economy as follows.

Definition 1 *A stationary equilibrium occurs when:*

1. *All banks solve the problem given by* (80)*, taking as given the other banks' choices of loan and deposit rates.*
2. *All households and firms maximize their utilities given the list of rates put forth by banks.*
3. *Each period, the deposit and loan markets clear.*
4. *The probability law governing the evolution of the industry, P^Γ, is consistent with banks' optimal choices.*

One of the state variables for bank's problem (Γ_t) is an object whose dimension depends on the number of banks in the economy. This dimensionality poses a challenge for numerically solving the banks' problem. To simplify the model solution, we follow Krusell and Smith (1998) by considering a low-dimensional approximation of Γ_t. Specifically, we postulate that all information about Γ_t relevant to banks' optimization can be summarized by the contemporaneous Federal Funds rate (f_t). Accordingly, we define the equilibrium "average" loan and deposit rates $\bar{r}^l_t(f_t)$ and $\bar{r}^d_t(f_t)$, respectively) as,

$$\exp(\alpha^d_i \bar{r}^d_t + q^d_i) \equiv \mathbb{E}\Big[\exp(\alpha^d_i r^d + q^d_i)\Big], \tag{81}$$

and

$$\exp(\alpha^l_i \bar{r}^l_t + q^l_i) \equiv \mathbb{E}\Big[\exp(\alpha^l_i r^l + q^l_i)\Big]. \tag{82}$$

With a reasonably large number of banks, $\bar{r}^l_t(f_t)$ and $\bar{r}^d_t(f_t)$ approximately summarizes the choices of other banks, thereby allowing each bank to derive its deposit and loan demand functions. In solving the model, we ensure that $\bar{r}^l_t(f_t)$ and $\bar{r}^d_t(f_t)$ are consistent with equilibrium bank choices by iterating over their values until convergence. As $\bar{r}^l_t(f_t)$ and $\bar{r}^d_t(f_t)$ are functions of f_t only, we drop Γ_t from banks' value functions in (80).

III.4.5 Monetary policy transmission

In this section, we use a simplified version of the model to illustrate the key transmission mechanisms.

A. Frictionless benchmark

First, we examine how the economy behaves in a frictionless benchmark model. By frictionless, we mean a simplified version of our model with the following five features: (1) the bank has no market power in either the deposit or the loan market, i.e., the deposit and loan demand elasticities are infinite; (2) there are no frictions related to non-reservable borrowing;

(3) the bank faces no capital requirement, $\kappa = 0$; (4) there is no reserve requirement, $\theta = 0$; and (5) there is no maturity transformation. These features imply that the bank's problem can be viewed as a static problem.

In this static frictionless model, banks choose deposit rates, r^d, and loan rates, r, to maximize one-period profits

$$\Pi = \max_{\{r^l, r^d\}} r^l B\left(r^l\right) - r^d D\left(r^d\right) - \phi^l B\left(r^l\right) - \phi^d D\left(r^d\right) - f\left(B\left(r^l\right) - D\left(r^d\right)\right). \tag{83}$$

When deposits fall short of loans, the bank can make up any funding shortfall, $B - D$, with non-reservable borrowing at a cost equal to the Federal Funds rate, f. There are no additional financing costs associated with non-reservable borrowing. When there are excess deposits, the bank can invest any this surplus, $D - B$, in government securities and earn the Federal Funds rate, f.[54] In the absence of a balance sheet friction, the bank can optimize its choices for deposit and loan amounts (B and D) separately.

The optimal lending rates are given by the Federal Funds rate plus the marginal cost and the markup:

$$r^l = f + \phi^l + \left(-\frac{B'}{B}\right)^{-1},$$

and the optimal deposit rates are given by the Federal Funds rate minus the marginal cost and the markup:

$$r^d = f - \phi^d - \left(\frac{D'}{D}\right)^{-1}.$$

When there is perfect competition among banks, the demand elasticities, $-\frac{B'}{B}$ and $\frac{D'}{D}$, become infinite and the markups converge to zero. Deposit and lending rates converge to the Federal Funds rate minus or plus the marginal cost, as follows:

$$r^d \to f - \phi^d,\ r^l \to f + \phi^l \tag{84}$$

[54] In reality, the Federal Funds rate is slightly higher than the risk-free Treasury yield because of the default risk of the bank. However, we assume there is no default by the bank, so these two rates are equal.

Under the frictionless benchmark, banks function as the bond market, passing through the interest rate changes to the exact same degree.

B. Imperfect competition

When competition is imperfect, market power creates a wedge between the Federal Funds rate and the rates at which banks borrow and lend. Monetary policy can affect the market power of banks by influencing the attractiveness of bank deposits or loans relative to other outside options available to households or firms.

In the model, bank deposits face competition from both bonds and cash. Investors get higher returns from investing in bonds but endure low liquidity. On the contrary, cash holdings offer high liquidity but zero return. Bank deposits are somewhere in between, offering investors both liquidity and some non-zero return. When the interest rate is high, the opportunity cost of holding cash increases and investors move out of cash and into bank deposits and bonds. Consequently, banks enjoy an outward shift in their deposit demand function and they can charge larger markup on deposits (e.g., Drechsler et al., 2017), so:

$$\frac{\partial \left(\frac{D'}{D}\right)^{-1}}{\partial f} > 0. \tag{85}$$

In the lending market, an increase in the Federal Funds rate makes bank loans less attractive to firms relative to the outside option of not borrowing. Therefore, total lending shrinks and banks optimally lower the markups they on loans to mitigate the effect of lower lending demand.

$$\frac{\partial \left(-\frac{B'}{B}\right)^{-1}}{\partial f} < 0 \tag{86}$$

C. Balance sheet frictions

In the frictionless benchmark, the deposit market and loan market are entirely separable because the bank can costlessly use non-reservable borrowing and government securities as buffers. Now consider the case in which banks face balance sheet frictions, so they incur additional costs when using non-reservable borrowing. In this case, the banks' optimization problem becomes:

$$\Pi = \max_{\{r^l, r^d\}} r^l B\left(r^l\right) - r^d D\left(r^d\right) - \phi^l B\left(r^l\right) - \phi^d D\left(r^d\right) - f\left(B\left(r^l\right) - D\left(r^d\right)\right) - \Phi(N),$$

where $\Phi(N)$ is the cost of non-reservable borrowing or investing excess funding and $N = B - D$ is the funding imbalance. In the presence of balance sheet frictions, the bank cannot costlessly replace any lost deposits with wholesale borrowing. Therefore, shocks to deposits will be transmitted to loans.

D. Reserve requirement

Now consider the case in which banks face reserve regulation that requires that for every dollar of deposits, the bank needs to keep a fraction, θ, of these deposits as reserves. Assuming that the interest on reserves is zero, banks' optimization becomes

$$\Pi = \max_{\{r^l, r^d\}} r^l B\left(r^l\right) - r^d D\left(r^d\right) - \phi^l B\left(r^l\right) - \phi^d D\left(r^d\right) - f\left(B\left(r^l\right) + R - D\left(r^d\right)\right)$$

$$s.t.\ R \geq \theta D\left(r^d\right)$$

Because the interest rate on reserves is zero, the reserve constraint is binding. We can solve for the optimal deposit rate as

$$r^d = f - \phi^d - \left(\frac{D'}{D}\right)^{-1} - \theta f. \tag{87}$$

Here we see that higher Federal Funds rates increase the opportunity cost of holding reserves, θf, which lowers deposit rates. Lower deposit rates, in turn, reduce the quantity of deposits and optimal supply of loans.

E. Capital regulation

Now consider the case in which banks face capital regulation that requires bank capital to exceed a certain fraction of bank assets. In this case, the banks' optimization problem becomes:

$$\Pi = \max_{\{r^l, r^d\}} r^l B\left(r^l\right) - r^d D\left(r^d\right) - \phi^l B\left(r^l\right) - \phi^d D\left(r^d\right) - f\left(B\left(r^l\right) - D\left(r^d\right)\right),$$

$$s.t.\ E_0 + (1-\tau_c)\Pi \geq \kappa B\left(r^l\right).$$

In the presence of capital regulation, shocks to bank capital affect lending capacity. One way that monetary policy affects bank capital is through maturity mismatch. Because deposits are short-term, an increase in the Federal Funds rate raises the rate that the bank has to pay on all deposits. However, loans are long-term, so only a fraction of loans matures, with the remaining outstanding loans commanding a lower rate. Hence, an increase in the Federal Funds rate temporarily reduces bank capital and tightens the bank capital constraint in equation (76).

Another way that monetary policy affects bank capital is through market power. When the Federal Funds rate increases, bank profits from the deposit market increase, as the competition from cash lessens, but bank profits from the loan market decrease as borrowers are less willing to borrow at higher rates. The effect from the deposit market is likely to dominate the loan market effect when rates are very low, and especially, when rates are near the zero lower bound, leading to a tighter capital constraint in this region.

III.5 Estimation

III.5.1 Estimation procedure

We divide the estimation procedure into two stages. In the first stage, we estimate the demand elasticities and liquidity values for deposits and loans following Berry et al. (1995).

In the second stage, we estimate the remaining parameters describing banks' balance sheet frictions using simulated method of moments (SMM).

We first parameterize the quality of each option as a function of characteristics, $q_j^k = \beta^k x_j + \xi_j^k$, $k = d,\ l$, where x_j is a vector of bank characteristics that includes the number of branches, the number of employees per branch, banks fixed effects, and time fixed effects. ξ_j^k is an unobservable demand shock associated with product j. Next, we allow for heterogeneity in rate sensitivity in the deposit market, so each individual depositor's rate sensitivity can be written as a mean rate sensitivity and a deviation from the mean, $\alpha_i = \alpha + \sigma_\alpha v_i$, where v_i follows a uniform distribution. We assume the sensitivity to non-rate characteristics is homogeneous across both borrowers and depositors. Taken together, the demand functions for bank deposits and loans are characterized by the preference parameters, $\left(\alpha^k, \beta^k, \sigma_\alpha^k\right)$, where $k = d,\ l$. For simplicity, we drop the superscript indicating the deposit or loan market in the following discussion.

We use the methods from Berry et al. (1995) to estimate the demand parameters, $\Theta = (\alpha, \beta, \sigma_\alpha)$. First, we divide the parameters into linear parameters, (α, β), and non-linear parameters, σ_α. Second, for a given value of σ_α, there is a relation between mean utility, $E\left[u_{ij}\right] = u_j = \alpha r_j + \beta x_j + \xi_j$, and the observed market share, s_0, given by $s\left(u|\sigma_\alpha\right) = s_0$, where $s\left(.\right)$ is the market share, which is defined by equations (63) and (66). Third, we solve for the implicit function, $s^{-1}\left(.\right)$, using the nested fixed-point algorithm described in Nevo (2001). Fourth, using this implicit function, we can solve for the unobservable demand shocks as functions of the observable market share and the demand parameters, as follows:

$$\xi\left(\Theta\right) = s^{-1}\left(s_0|\sigma_\alpha\right) - \left(\alpha r_j + \beta x_j\right)$$

A key challenge in identifying the demand parameters is the natural correlation between deposit rates and unobservable demand shocks, ξ_j. Following the industrial organization literature (Nevo, 2001), we use a set of supply shifters, c_j, as instrumental variables. Our particular instruments are bank salaries and non-interest expenses related to the use of fixed assets. Our identifying assumption is that these supply shifters are orthogonal to unobservable demand shocks and thus shift the supply curve along the demand curve, allowing us to trace out the slope of the demand curve.

Formally, define $Z = [x, c]$, where x is a vector of bank characteristics and c is a vector of supply shifters. The moment condition for this estimation is the orthogonality condition between the unobservable demand shocks, ξ_j and the exogenous variables, z_j, as follows:

$$\mathbb{E}\left[\xi_j z_j\right] = 0.$$

Define W as a consistent estimate of $\mathbb{E}\left[Z'\xi\xi'Z\right]$. The GMM estimator of the demand parameters is then given by:

$$\hat{\Theta} = \arg\min_{\Theta} \xi\left(\Theta\right)' Z' W^{-1} Z \xi\left(\Theta\right).$$

The data used for the deposit demand estimation include each bank's deposit market share, the proportions of cash and bonds in the household portfolio, non-rate bank characteristics such as the number of branches and the number of employees per branch, and each bank's deposit rate, where we use a weighted average of deposit rates for different types of deposits, where the weights are the relative quantities of each deposit type. We also include bank and time fixed effects. The data used for the loan demand estimation include loan market shares for each bank, the corporate bonds market share, each bank's lending rate, and any non-rate characteristics.

We then plug the first-stage estimates of the deposit and loan demand functions into our model of the banking sector in Section III.4.3 for the second stage SMM estimation. For this stage, we have to make one further simplification. Our data contain a large number of very small banks. This feature of the data poses a challenge because solving a model with a number of banks equal to the number of banks in our data would intractable. Therefore, we solve for an equilibrium with $\hat{J}$ ex ante symmetric representative banks, where the number of representative banks $\hat{J}$ is calibrated to match the HHI in the data. Because the size distribution has a heavy left tail, this approach substantially reduces the number of banks in the model while keeping the market concentration similar to that in the data. An alternative approach is to limit the sample to the largest banks. Our results are robust to the alternative approach.

Next, because we have a large number of non-rate bank characteristics that enter linearly in the utility function, we summarize these non-rate characteristics with a composite index that we interpret as "quality." For simplicity, we assume quality is the same for all the representative banks. The quality value can be calculated as follows:[55]

$$\hat{q} = \log\left(\frac{1}{\hat{J}}\sum_{j=1}^{J}\exp(x_j\hat{\beta})\right). \tag{88}$$

With the quality value in hand, we parameterize the deposit and loan demand functions as:

$$D_j(r_j^d|f) = \sum_{i=1}^{I}\mu_i^d\frac{\exp\left((\hat{\alpha}^d+\hat{\sigma}_\alpha^d v_i)r_j^d+\hat{q}_j^d\right)}{\sum_{m\in\mathcal{A}}\exp\left((\hat{\alpha}^d+\hat{\sigma}_{\alpha^d}^d v_i)r_m^d+\hat{q}_m^d\right)}W \tag{89}$$

$$B_j(r_j^l|f) = \sum_{i=1}^{I}\mu_i^l\frac{\exp\left((\hat{\alpha}^l+\hat{\sigma}_\alpha^l v_i)r_j^l+\hat{q}_j^l\right)}{\sum_{m\in\mathcal{A}}\exp\left((\hat{\alpha}^l+\hat{\sigma}_{\alpha^l}^l v_i)r_m^l+\hat{q}_m^l\right)}K, \tag{90}$$

in which $\hat{\alpha}$ and $\hat{\sigma}_\alpha$ are the mean and standard deviation of the deposit or loan rate sensitivities, which are estimated from the first stage. Correspondingly, v_i and μ_i, $i = 1, 2, \ldots, I$ are a discrete approximation of a uniform distribution, and q_j is the quality value associated with option $j \in 0, 1, \ldots, J+1$. In the deposit market, we normalize the quality value of cash to zero, and we denote by q_d^d and q_b^d the quality values of bank deposits and short-term bonds, respectively. In the loan market, we normalize the quality of bonds to zero, and we

[55] Alternatively, we can directly use the characteristics of the N largest banks in the data and ignore the smaller banks. This alternative approach biases the HHI in the model upwards, but the magnitude of the bias becomes quite small if N is larger than 10. The small bias occurs because the 10 largest banks in the United States account for a disproportionately large market share, so ignoring the small banks has a limited impact on the market equilibrium in the national market.

denote by q_l^l and q_n^l the quality values of loans and not borrowing, respectively. Note that the quality value of not borrowing cannot be estimated from the demand estimation because we do not observe its share. Therefore, we relegate this parameter to SMM.

The final plug-in problem consists of inserting (89) and (90) into the definition of bank profits given by (74) before solving and simulating the bank model for the SMM estimation. This plug-in problem operationalizes the notion that banks set deposit and loan rates facing the demand for deposits and loans, banks set deposit and loans rates. It is important to note that, the pricing decision is dynamic because deposits are short-term, while loans are long-term.

In the second stage, we estimate five additional parameters using simulated method of moments (SMM), which chooses parameter values that minimize the distance between the moments generated by the model and their analogs in the data. We use eight moments to identify the remaining five model parameters. Parameter identification in SMM requires choosing moments whose predicted values are sensitive to the model's underlying parameters. Our identification strategy ensures that there is a unique parameter vector that makes the model fit the data as closely as possible.

First, we use banks' average non-reservable borrowing as a fraction of their deposits to identify the cost of holding non-reservables (ϕ^N). Intuitively, larger financing costs induce banks to finance loans mainly through deposits, and less via borrowing. Next, we use the average deposit and loan spreads to identify banks' marginal costs of generating deposits (ϕ^d) and servicing loans (ϕ^l). Deposit spreads are defined as the difference between the Federal Funds rate and deposit rates, while loan spreads are the difference between loan rates and Treasury yields matched by maturity. In our model, banks with market power optimally choose to pass a fraction of their operating costs onto the depositors and borrowers. Hence, higher operating costs lead to monotonically higher spreads that banks charge in the deposit and lending markets. In addition, banks' market power also determines the fraction of banks' marginal costs that get passed onto customers. Market power depends critically the Federal

Funds rate, as the attractiveness to households of alternative investments, as such cash and long-term bonds, changes with the Federal Funds rate. Therefore, we also include the correlation between the Federal Funds rate and both loan and deposit spreads to ensure that our model captures this important mechanism. Next, we use banks' average dividend yield to identify the discount rate, γ. Intuitively, a high discount rate makes the banks impatient, so they pay out a larger fraction of their profit to shareholders instead of retaining it to finance future business. Finally, to identify the value of firms' outside option of not borrowing, q_n^l, we include banks' average loan to deposit ratio and the sensitivity of total corporate borrowing to the Federal Funds rate. These two moments suit this purpose because when the outside option becomes less valuable, its market share remains low regardless of the current Federal Funds rate. Thus, the sensitivity of the aggregate corporate borrowing to the Federal Funds rate should fall as q_n^l falls. In addition, a high loan-to-deposit ratio should be inversely related to q_n^l because when aggregate borrowing from the corporate sector is high, bank loans face proportionally higher demands.

III.5.2 Estimation Results

Table 20 presents the point estimates for the 22 model parameters. In Panel A, we start with the parameters that we can directly quantify in the data. Specifically, we set the corporate tax rate to its statutory rate of 35%. Capital regulation stipulates that banks keep no less than 6% of their loans as book equity. Reserve regulation requires a 10% reserve ratio for transaction deposits, 1% for saving deposits, and 0% otherwise. In our model, we only have one type of deposit, so our estimate of the deposit ratio is a weighted average of these three requirements, where the weights are the shares of a particular type of deposit in total deposits. We model the Federal Funds rate and the bank-level loan default rate as log AR(1) processes, and we directly calculate their means, standard deviations, and autocorrelations from the data. Finally, we set the maturity of loans in our model to average loan maturity in the data, which is approximately five years.

Panel B in Table 20 presents the demand parameters from the first stage BLP estimation.[56] Not surprisingly, we find that depositors react favorably to high deposit rates while borrowers react negatively to high loan rates. Both yield sensitivities are precisely estimated, and the economic magnitudes are significant as well. A 1% increase in the deposit rate increases the market share of a bank by approximately 0.8%, while a 1% increase in the loan rates decreases bank market share by 0.9%. We also find that depositors exhibit significant dispersion in their rate sensitivity. Finally, we estimate depositors' and borrowers' sensitivities to non-rate bank characteristics such as the number of branches and the number of employees per branch. The estimates are also both statistically and economically significant. A 1% increase in the number of branches increases bank market share by 0.868% in the deposit market and 1.117% in the loan market. In comparison, the sensitivity to the number of employees per branch is smaller. A 1% increase in the number of employees per branch increases bank market share by 0.587% in the deposit market and 0.694% in the lending market. Using these estimates combined with bank and time fixed effects, we can calculate the implied quality parameter using (88), which we plug into the second-stage SMM estimation.

Panel C in Table 20 presents the balance sheet parameters from our second stage SMM estimation. We find that banks have a subjective discount rate of 5%, which is only slightly higher than the average Federal Funds rate observed in the data. Given the discount rate, banks pay out 2.6% of their equity value as dividends. We also find the cost of non-reservable borrowing both statistically and economically significant. At the average amount of non-reservable borrowing (30%), a marginal dollar of non-reservable borrowing costs the bank 0.6 cents above the cost implied by the prevailing Federal Funds rate. Note that the average deposit spread is 0.8%. Because banks equate the marginal costs of their funding sources, these numbers imply the marginal cost of expanding deposit averages 1.4%, suggesting a large role for deposit market power.[57] This result implies that banks cannot easily replace

[56] Detailed estimation results are presented in Table 22.

[57] The marginal cost of non-reservable borrowing is $\frac{\partial \Phi}{\partial N} = 2\phi^N N = 2 \times 0.05 \times 0.3 = 0.03$.

deposits with other funding sources. Therefore, shocks to bank deposits are likely to be transmitted to bank lending. Finally, we find that banks incur a 0.7% cost of maintaining deposits and a 0.9% cost of servicing their outstanding loans.

Table 21 compares the empirical and model-implied moments. The model is able to match closely the banks' market shares, average spreads, and the sensitivity of the Federal Funds rate to the deposit spread. In both the data and the model, banks borrow non-reservable securities, which amount to 30% of their total deposit intake. The spread that banks charge in the deposit market is significantly lower than the spread they receive in the loan market. This result arises because as the Federal Funds rate approaches zero, bank deposits face increasing competition from cash. Thus, banks market power falls and deposit spreads become compressed. A 1% decrease in the Federal Funds rate decreases the deposit spread by 30 basis points. However, as the Federal Funds rate falls lower, loan demand rises. A 1% decrease in the Federal Funds rate increases loan spreads by 25 basis points. These results are consistent with our intuition and the data.

III.6 Counterfactuals

III.6.1 Decomposing Monetary Policy Transmission

Now we examine the quantitative forces that shape the relation between monetary policy, as embodied in changes in the Federal Funds rate, and aggregate bank lending. To this end, we start with the baseline model in row (1) of Table 23, where we see that on average in our model, a one percent change in the Federal Funds rate translates into a 3.88% decrease in aggregate lending. In the column labeled "Aggregate Lending," we have normalized lending to 100% for this baseline case.

We proceed by eliminating the banks' local market power and the regulatory constraints one by one to examine the cumulative effect of removing these frictions. As such, we analyze how the absence of each model ingredient influences aggregate lending in the economy and the transmission of the Federal Reserve's monetary policy.

Row (2) presents the results from a version of the model without a reserve requirement. The nearly identical results imply that the reserve regulation has a minimal effect on banks' lending decisions.

In row (3), we remove from the model banks' market power in the deposit market. In this case, banks receive a fixed lump-sum profit equal to their oligopolist profit in the baseline case, and they use marginal cost pricing for deposit-intake decisions. Namely, they set the deposit rate equal to the Federal Funds rate minus the bank's marginal cost of servicing deposits, and they take as many deposits as depositors offer, given that deposit rate. If deposit market power is in place, when the Federal Funds rate increases, banks enjoy higher market power in the deposit market because consumers place less value on cash as an investment option. Put differently, the competitiveness of cash relative to deposits falls. Banks react by charging higher deposit spreads and consequently lowering the amount of deposit intake. Banks' lending decisions partially echo this decline in deposit in-take because when the amount of lending exceeds deposits, banks need to use expensive non-reservable borrowing to finance their loans. Thus, the bank's market power, combined with the non-reservable borrowing cost, contribute to a negative relation between banks' lending and the Federal Funds rate. Our results confirm this intuition. Once we eliminate market power in the deposit market, bank lending becomes less sensitive to change in the Federal Funds rate. A 1% increase in the Federal Funds rate causes a 2.57% decrease in aggregate lending. This sensitivity is 30% smaller than the 3.81% sensitivity observed in the baseline case. Finally, this result is important in that it highlights the interconnectedness of banks' deposit taking and lending businesses. Banks' market power in the deposit market gets passed on to the loan market and contributes to the sensitivity of bank lending to the Federal Funds rate.

Does the above result imply that bank market power plays a quantitative important monetary policy transmission, relative to other candidate transmission mechanisms? To answer this question, we compare the magnitudes in line (3) to the effects of relaxing the capital requirement, the results of which are in line (4). We find that without a capital requirement, the sensitivity of bank loans to the Federal Funds rate drops sharply, with a change in the Federal Funds rate translating almost one-to-one into a change in bank loans. A comparison of the results in lines (3) and (4) shows that the capital requirement enhances monetary policy transmission by 1.62% (2.57% − 0.95%). This effect is roughly 25% larger than the effect of deposit market power. Of course, this 1.62% magnitude captures both the effects of the capital requirement itself and also of its interaction with bank market power. More specifically, when the Federal Funds rate goes up, bank capital takes a hit because of the maturity mismatch. The profit resulting from bank's market power also changes, thus interacting with the capital requirement.

Finally, we turn to banks' market power in the lending market. Our results show that having market power in the lending market has a large impact on the quantity of aggregate lending. The magnitude is consistent with the sizable spread that banks charge. In both the data and our baseline model, banks charge an average loan spread of 2.7%, which is significantly higher than the expected default cost plus the marginal cost of servicing loans. Once the banks switch to marginal cost pricing, the aggregate amount of lending in the economy goes up by 34%, from 128% of the baseline to 193% of the baseline. At the same time, removing banks' loan market power also makes the aggregate quantity of loans more sensitive to the Federal Funds rate. This sensitivity goes up from −0.95% in the case in which loan market power is present to −1.38% in the case in which banks use marginal cost pricing in both the deposit and loan markets.

III.6.2 Reversal Rate

In our previous analysis, we did not break down the effects of changes in the Federal Funds rate as a function of the rate level. We now turn to this question in Figure 28, which shows the amount of bank lending for different levels of the Federal Funds rate. Overall, and as expected, there is a negative relationship between the Federal Funds rate and the amount of lending. However, the negative relation is reversed in the region where the Federal Funds rate is close to zero.

To understand this pattern, we also plot in Figure 28 the level of bank capital and the optimal amount of bank lending in a world with no capital requirements. We find that aggregate bank capital in the economy is inversely U-shaped. When the Federal Funds rate is above the 2.27% threshold, an increase in the Federal Funds rate has the usual effect of tightening lending. However, when the Federal Funds rate is below the 2.27% threshold, an increase in the Federal Funds rate actually has the opposite effect of expanding lending. We call the region in which the Federal Funds rate is below 2.27% a “reversal rate” environment.

The pattern in bank capital is central to answering the question of why monetary policy, as embodied in changes in the Federal Funds rate, has opposite signs on the two sides of the threshold. To understand this connection, note that optimal lending is the smaller of two quantities: desired lending and feasible lending. The former is the optimal amount of lending in the absence of a capital requirement, and the latter is maximal lending permitted by bank's equity capital. In equilibrium, desired lending is always decreasing in the Federal Funds rate, as high funding costs deter firms from borrowing. Hence, in high-rate regions, the capital requirement is slack, and the actual quantity of lending is the desired amount. On the other hand, when the Federal Funds rate is low, desired lending exceeds that allowed by the bank's equity. Thus, the capital requirement binds, and the actual lending tracks the bank's equity capital, which increases in the Federal Funds rate. Figure 28 confirms this intuition. When the Federal Funds rate is above 2.27%, actual lending and desired lending closely track each other, whereas when the Federal Funds rate is below this threshold, actual lending falls short of the desired quantity.

The excess of desired over capital-constrained lending makes sense given firms' equilibrium high demand for loans in a low interest rate environment. However, the question remains of the forces behind the positive relation between bank equity and the Federal Funds rate when the latter is low. This result stems from the relative magnitudes of profits from lending and deposit taking. First, changes in the Federal Funds rate have opposite effects on bank profits in the deposit and lending markets. When the Federal Funds rate is high, holding cash is highly unattractive from the depositors' point of view, and banks face consistent weak competition from cash in the deposit market. Hence, bank profit from the deposit market increases in the Federal Funds rate. In contrast, bank profit from lending decreases in the Federal Funds rate, as higher funding costs makes the firms' outside option of not investing more appealing. Our parameter estimates imply that when the Federal Funds rate is low, the effect on profits from the deposit market dominate the effects from the lending market. Thus, an increase in the Federal Funds rate leads to higher bank profits, which in turn feed into the equity capital base, as banks find it optimal to shore up capital to deflect future financing costs by not paying out all of their profits to shareholders.

To understand more fully the dynamic response of bank lending to monetary policy shocks, in Figure 29, we simulate the response of bank lending to a shock to the Federal Funds rate. The economy starts at time zero in an initial steady state with the Federal Funds rate equal to the inflection point of 2.27%. At time one, the Federal Funds rate either increases or decreases by two standard deviations, and it stays at that level afterwards until the economy reaches a new steady state. Each variable in the graph is scaled by its level in the old steady state, that is, when the Federal Funds rate is 2.27%.

The top panel depicts the response to an increase in the Federal Funds rate. In this case, banks faces less competition from households' demand for cash in the deposit market. Thus, they can behave more like monopolists by charging higher spreads and cutting the amount of deposits. Lower deposit intake increases the banks' marginal cost of lending because when their lending exceeds their capital plus deposit intake, they must turn to the market for non-reservable borrowing, in which they face increasing marginal external financing costs. A positive shock to the Federal Funds rate also increases the cost of capital in corporate sector, making firms more likely to switch to the outside option of not borrowing. Both effects shrink the amount of lending. Because deposits have shorter duration than loans, deposits drop sharply and converge almost instantaneously to the new steady state. Non-reservable borrowing increases to fill the gap between deposits and loans. In contrast, loan quantity first overshoots and then reverts slowly back to the new steady state. Intuitively, the bank's equity takes a hit with a positive shock to the Federal Funds rate because of the maturity mismatch on its balance sheet. It takes time for the bank to restore its capital stock by retaining profits. Loan quantity converges even more slowly as the bank only replaces a fraction, μ, of its long-term loans each period.

The bottom panel depicts the response to a decrease in the Federal Funds rate. As it approaches the zero lower bound, banks face increasingly intense competition from cash in the deposit market. As a result, the spread that banks can charge in the deposit market is squeezed, leading to a sharp drop in banks' profits. Given the high persistence in the Federal Funds rate, this lower profit translates into slower retained earnings accumulation over time and leads to decreased bank capital. In the new steady state, banks take large deposits in the deposit market, which can support increased lending. However, banks cannot lend more because their capital requirements tighten in the extremely low Federal Funds rate environment. Because total lending decreases, the banks face less of a need to seek external financing, and they use less non-reservable borrowing. As before, loan quantity initially overshoots because the longer maturity of bank loans induces a temporary relaxation in the capital requirement.

It is interesting to note that in the two graphs in Figure 29, the loan amount decreases when the Federal Funds rate changes in either direction. Although the loan amount moves in the same direction, the driving force is different in the two cases. When the Federal Funds rate increases, loans fall because higher spreads in the deposit market discourage households from making deposits. Banks turn to non-reservable borrowing to fund loans, and because of increasing costs in this market, the amount of lending is highly dependent on the quantity of deposits. Instead, when the Federal Funds rate decreases, the loan amount decreases because of the binding capital requirement, which in turn echoes changes in the banks' profit accumulation. The distinct driving forces underlying the above two plots are also reflected by the differential trends in banks' deposit quantity and non-reservable borrowing.

III.6.3 Heterogeneous Monetary Transmission across Regions

There are significant cross-region variations in banking market concentration in the U.S. In 2017, the 10th percentile MSA has 2 banks while the 90th MSA has 238 banks. Such variations in market concentration may rise to heterogeneous monetary transmission across regions.

The effect of market concentration on monetary transmission may be quite complicated because of two opposing forces. On one hand, Drechsler et al. (2017) argue that an increase in market concentration in the deposit market enhances monetary transmission. On the other hand, Scharfstein and Sunderam (2016) argue that an increase in market concentration in the loan market dampens monetary transmission. The net effect of these two forces, however, is unclear.

Our structural model is able to speak to this issue. In Table 24, we consider three scenarios with different level of market concentration. We first calculate the overall effect of monetary policy for each scenario and then decompose the overall effect by each channel of transmission. There are two takeaways from this table. First, when market concentration increases, monetary policy transmission becomes stronger because the enhancing effect of the deposit market dominates the dampening effect from the lending market. Second, when the market becomes more concentrated, the bank capital channel becomes weaker because banks are able to charge higher spreads in both the deposit and the lending markets, which makes capital regulation less binding.

III.6.4 Heterogeneous Monetary Transmission across Banks

Monetary transmission may also be heterogeneous across banks. Kashyap and Stein (1995) find that the impact of monetary policy on lending is stronger for small banks. They suggest that small banks are not able to frictionlessly raise wholesale funding to replace deposits.

Therefore, shocks to deposits from monetary tightening are more likely to be transmitted to the supply of bank loans. However, Kashyap and Stein (1995) face a major challenge which is they do not directly measure the cost of external financing. They only have the size of the bank as a proxy which may affect many other things at the same time. This opens up alternative interpretations of their results. For instance, some may argue that small banks lend to small firms, whose credit demand is more cyclical. Therefore, the larger sensitivity of smaller bank lending is driven by the demand side rather than the financing friction in the supply side.

Our structural model sheds light on this issue because we are able to directly estimate the cost of external financing for each type of banks. Specifically, we re-estimate the balance sheet parameters for large and small banks separately using the data moments for each subsample. The results are reported in Table 25. We find that the largest difference between large versus small banks lies in their external financing cost. Note that we do not use bank size to estimate this parameter. Instead, this parameter is identified off the fraction of assets financed by nonreservables. This additional data moment lends support to the Kashyap and Stein (1995) argument that large and small banks mainly differ in the dimension of external financing costs. In addition, in the simulation exercise, we are also able to hold the loan demand constant to isolate the effect of the financing friction, which is hard to do with reduced-form approaches. Overall, we find that lending in small banks is more sensitive to the FFR. This is consistent with the hypothesis proposed by Kashyap and Stein (1995) that different external financing costs across large and small banks leads to heterogeneous transmission of monetary policy to credit supply.

III.7 Conclusion

The U.S. banking sector has experienced an enormous amount of consolidation. The market share of the top five banks has increased from less than 15% in the 1990s to over 45% as of 2017. This consolidation begs the question of whether bank market power has a quantitatively important effect on the transmission of monetary policy. We study this question by formulating and estimating a dynamic banking model with regulatory constraints, financial frictions, and imperfect competition. This unified framework is useful because it allows us to gauge the relative importance of different monetary policy transmission channels.

In our counterfactuals, we show that the channel related to reserve requirements has minor quantitative importance. In contrast, we find that channels related to bank capital requirements and to market power are very important. We also find an interesting interaction between the market power channel and the bank capital channel. If the Federal Funds rate is low, depressing it further can actually contract bank lending, as the drop in bank profits in the deposit market has a negative impact on bank capital. Lastly, we show that financial frictions on banks' balance sheet play an important role in transmitting shocks from bank deposits to bank loans.

Our work contributes to the historical debate between the "money view" and the "lending view" of banking monetary policy transmission (Romer and Romer, 1990; Kashyap and Stein, 1995). The "money view" postulates that the quantity of deposits matters for economic activity as a medium of exchange and that monetary policy influences deposit quantity through bank reserves. While our results do not negate the premise that the quantity of deposits matters, we show that the channel through which monetary policy affects bank deposits is increasingly through the market power channel rather than the reserve channel, at least after the 1990s.

An alternative view of monetary transmission is the "lending view", which rests on the idea that monetary policy also has a separate effect on the supply of loans by influencing the quantity of deposits. Romer and Romer (1990) argue that the "lending view" is unlikely to be important because banks can always easily replace deposits with external financing. In contrast, Kashyap and Stein (1995) argues that the banks can face costly external financing. Our study sheds new light on this debate, as the structural estimation approach allows us to infer the degree of the bank financing costs from the relative size of their non-reservable borrowing and deposit taking. We find the magnitude of this cost is economically significant and frictions related to bank balance sheets play an important role in the transmission of monetary policy.

TABLES AND FIGURES

Table 1: Variable and Parameter Definitions

Variable	**Model Counterpart**	**Construction from Compustat Items**
Capital Stock	K	Total assets (AT)
Profit	$\big(y - q - \chi(\Delta s)\big) \times K$	Operating income before depreciation ($OIBDP$)
Net Dividends	$d \times K$	Cash dividends on common stock ($CDVC$) + cash dividends on preferred/preference stock ($PDVC$) + purchase of common stock ($PRSTKCC$, if non-missing) + Purchase of Preferred/Preference Stock ($PRSTKPC$, if non-missing) − sale of common and preferred stock ($SSTK$, if non-missing)
Net Cash Holdings	$a_{beg} \times K$	Cash and short-term investments (CHE) − debt in current liabilities (DLC) − long-term debt ($DLTT$)
Leverage	$\max\{-a_{beg}, 0\}$	The negative part of capital scaled net cash holdings.
Tobin's Q	$v - a_{beg}$	Market value of equity less net cash holdings, divided by capital stock.
R&D Expenses	$q \times K$	Research and Development Expenses (XRD)
Patent Stock	$s \times K$	Patent stock is computed by cumulating patent grants, expirations, purchases and sales. Each patent is weighted by its adjusted citations, which is the number of citations divided by average number of citations received by all patents granted in the same year and technology class. Specifically, I define: $$\textit{Pat. Stock} = \left(\sum_{j \in \mathbb{Q}_{i,t}^{\text{grant}}} - \sum_{j \in \mathbb{Q}_{i,t}^{\text{expire}}} + \sum_{j \in \mathbb{Q}_{i,t}^{\text{buy}}} - \sum_{j \in \mathbb{Q}_{i,t}^{\text{sell}}} \right) \frac{C_j}{\hat{\mathbb{E}}\Big[C_k \Big| Y_k = Y_j, T_k = T_j\Big]},$$ where $\mathbb{Q}_{i,t}^{\text{grant}}$, $\mathbb{Q}_{i,t}^{\text{expire}}$, $\mathbb{Q}_{i,t}^{\text{buy}}$, and $\mathbb{Q}_{i,t}^{\text{sell}}$ denote the set of patents granted, expired, bought, and sold up until quarter t. Y_j and T_j are the grant year and technology class of patent j, and C_j is the patent's citation count.
Patent Purchase	$\max\{\Delta s, 0\} \times K$	The citation-weighted number of patents bought, where I adjust citations in the same way as when I compute *Patent Stock*. Specifically, I define *Patent Purchase* $= \sum_{j \in \mathbb{P}_{i,t}^{\text{buy}}} \frac{C_j}{\hat{\mathbb{E}}\big[C_k \big| Y_k = Y_j, T_k = T_j\big]}$, where $\mathbb{P}_{i,t}^{\text{buy}}$ is the set of patents bought by firm i in quarter t.
Patent Sales	$\max\{-\Delta s, 0\} \times K$	Defined analogously as *Patent Puchase*.
Patent Trade (Net Buy)	$\Delta s \times K$	*Patents Purchase* − *Patents Sales*
Trade Volume	$\frac{1}{2}\lvert\Delta s\rvert \times K$	$\frac{1}{2}\big[$*Patents Purchase* + *Patents Sales*$\big]$

Parameters

r_f	The risk-free rate	δ	Productivity depreciation rate	π	Productivity depreciation probability
τ	Corporate tax rate	λ	Equity issuance cost	$-\underline{a}$	Debt capacity
η	Project maturing rate	μ_i	Mean seed inflow	χ_j	Trading costs, $j = 0, 1, 2$
ψ	Productivity improvement per unit of maturing projects			c_f	Fixed cost of operation

Table 2: Summary Statistics

This table reports key summary statistics and the industry composition of the sample and the Compustat universe. The sample spans 1980–2010 and contains all firms that own at least one patent during this period. Panel A reports summary statistics at the firm-quarter level. All variable definitions are in Table 1. Panel B reports the fraction of firms in each SIC sector. I also include industries (at the 3-digit SIC code level) with pronounced differences in their representations in the sample and the Compustat universe.

Variable	**Sample**					**Compustat Universe**				
	Mean	Percentiles 25	50	75	#OBS	Mean	Percentiles 25	50	75	#OBS
Panel A: Summary Statistics										
Assets	1.470	0.026	0.119	0.672	395,437	0.864	0.015	0.077	0.406	793,113
Net Buy	0.018	0.000	0.000	0.000	395,437	0.009	0.000	0.000	0.000	793,113
Trading Volume	0.458	0.000	0.000	0.000	395,437	0.228	0.000	0.000	0.000	793,113
R&D/Assets	0.017	0.000	0.000	0.017	395,209	0.012	0.000	0.000	0.000	791,559
Equity Iss./Assets	0.007	0.000	0.000	0.000	395,209	0.006	0.000	0.000	0.000	791,559
Net Cash/Assets	-0.050	-0.292	-0.098	0.174	394,680	-0.112	-0.345	-0.135	0.120	790,457
Payout/Assets	0.001	0.000	0.000	0.000	793,113	0.002	0.000	0.000	0.000	793,113
Profit/Assets	0.006	-0.000	0.029	0.049	321,313	0.000	-0.007	0.026	0.047	653,033
Patent Stock	108.944	0.000	4.342	32.401	395,437	54.318	0.000	0.000	4.291	793,113
$\mathbb{1}\{\textit{Trading Volume} \neq 0\}$	0.053				395,437	0.027				793,113
$\mathbb{1}\{\textit{Equity Iss.} \neq 0\}$	0.012				395,209	0.011				791,559
$\mathbb{1}\{\textit{Payout} \neq 0\}$	0.292				330,613	0.248				673,777
$\textit{Net Buy}\,\vert\,\textit{Trade}\neq 0$	0.337	-2.818	0.203	3.525	21,075	0.337	-2.818	0.203	3.525	21,075
$\textit{Equity Iss.}\,\vert\,\textit{Equity Iss.}\neq 0$	0.627	0.112	0.313	0.744	4,557	0.561	0.110	0.280	0.655	8,983
$\textit{Payout}\,\vert\,\textit{Payout}\neq 0$	0.007	0.002	0.004	0.008	96,581	0.009	0.002	0.004	0.009	167,409
Panel B: Industry Composition										
Agriculture, Forestry, Fishing	0.003					0.005				
Mining	0.028					0.124				
Gold & silver ores	0.003					0.022				
Crude petroleum & natural gas	0.011					0.062				
Construction	0.008					0.014				
Manufacturing	0.719					0.441				
Drugs	0.099					0.053				
Compute & office equipments	0.050					0.027				
Communications equipments	0.038					0.022				
Elec. components & accessories	0.053					0.027				
Lab apparatus etc.	0.037					0.018				
Surgical, medical, & dental instr.	0.066					0.031				
Transportation, Public Utilities	0.033					0.079				
Telephone communications	0.012					0.023				
Wholesale Trade	0.025					0.045				
Retail Trade	0.020					0.072				
Eating & drinking places	0.004					0.017				
Services	0.163					0.221				

Table 3: Parameters Estimated Outside the Main Model Estimation

This table reports parameters estimated outside the main model estimation.

Parameter	Value	Data Moment Used for Estimation
r_f	0.025	The average U.S. Treasury Bill rate from 1980 to 2010, adjusted to annual frequency.
$\delta \times \pi$	0.080	The estimated depreciation rate of R&D capital and organization capital in Grabowski and Mueller (1978) and McGrattan and Prescott (2010).
τ	0.350	US corporate tax rate.
λ	0.052	Average issuance fee per dollar raised through equity.
$\underline{a}$	-0.720	Estimated upper bound on debt ratio from DeAngelo et al. (2011).

Table 4: SMM Estimation Results with $\alpha = 0.50$

This table reports the estimation results. Panel A contains the sample moments and the corresponding moments simulated from the model solution. Panel B reports the parameter estimates with standard errors in parentheses. I set $\alpha = 0.50$; the other parameters that I set outside the main model estimation are in Table 3.

Panel A: Moments

		Data Mmt.	Siml. Mmt.
Mean capital scaled R&D expense	$\mathbb{E}(q - \Delta s)$	0.0699	0.0669
Variance of capital scaled R&D expenses	$\mathbb{V}(q - \Delta s)$	0.0112	0.0057
Corr. b/w capital scaled R&D expenses and leverage	$\text{Corr}(q - \Delta s, \max\{-a_{beg}, 0\})$	0.0649	0.1771
Mean capital scaled profit	$\mathbb{E}(y - q - \chi(\Delta s))$	0.0252	0.0278
Variance of capital scaled profit	$\mathbb{V}(y - q - \chi(\Delta s))$	0.0418	0.0162
Patent Trading Frequency	$\mathbb{E}(\mathbb{1}\{\Delta s \neq 0\})$	0.2133	0.2288
Patent trading volume/patent stock	$\mathbb{E}(\frac{1}{2}\lvert\Delta s\rvert)/\mathbb{E}(s)$	0.0182	0.0220
Variance of net patent purchase/patent stock squared	$\mathbb{V}(\Delta s)/\mathbb{E}(s)^2$	0.1900	0.0372
Corr. b/w net patent purchase and leverage	$\text{Corr}(\Delta s, \max\{-a_{beg}, 0\})$	-0.0118	-0.0553
Corr. b/w net patent purchase and patent stock	$\text{Corr}(\Delta s, s)$	-0.0396	-0.0879

Panel B: Parameter Estimates

η	μ_i	π	χ_0	χ_1	χ_2	ψ	c_f
0.2767	0.0330	0.1712	0.1110	2.1057	1.6950	0.7004	0.1759
(0.0012)	(0.0002)	(0.0062)	(0.0009)	(0.207)	(0.0134)	(0.0057)	(0.0010)

Table 5: SMM Estimation Results with $\alpha = 0.75$

This table reports the estimation results. Panel A contains the sample moments and the corresponding moments simulated from the model solution. Panel B reports the parameter estimates with standard errors in parentheses. I set $\alpha = 0.75$; the other parameters that I set outside the main model estimation are in Table 3.

Panel A: Moments

		Data Mmt.	Siml. Mmt.
Mean capital scaled R&D expense	$\mathbb{E}(q - \Delta s)$	0.0699	0.0657
Variance of capital scaled R&D expenses	$\mathbb{V}(q - \Delta s)$	0.0112	0.0089
Corr. b/w capital scaled R&D expenses and leverage	$\mathrm{Corr}(q - \Delta s, \max\{-a_{beg}, 0\})$	0.0649	0.2051
Mean capital scaled profit	$\mathbb{E}(y - q - \chi(\Delta s))$	0.0252	0.0286
Variance of capital scaled profit	$\mathbb{V}(y - q - \chi(\Delta s))$	0.0418	0.0264
Patent Trading Frequency	$\mathbb{E}(\mathbb{1}\{\Delta s \neq 0\})$	0.2133	0.1932
Patent trading volume/patent stock	$\mathbb{E}(\frac{1}{2}\lvert\Delta s\rvert)/\mathbb{E}(s)$	0.0182	0.0237
Variance of net patent purchase/patent stock squared	$\mathbb{V}(\Delta s)/\mathbb{E}(s)^2$	0.1900	0.0306
Corr. b/w net patent purchase and leverage	$\mathrm{Corr}(\Delta s, \max\{-a_{beg}, 0\})$	-0.0118	-0.0095
Corr. b/w net patent purchase and patent stock	$\mathrm{Corr}(\Delta s, s)$	-0.0396	0.0246

Panel B: Parameter Estimates

η	μ_i	π	χ_0	χ_1	χ_2	ψ	c_f
0.2520	0.0391	0.0839	0.1407	2.3709	0.4819	1.0398	0.0689
(0.0001)	(0.0001)	(0.0003)	(0.0001)	(0.0003)	(0.0021)	(0.0001)	(0.0798)

Table 6: Patent Trading and R&D in Subsamples Sorted by Firm Sizes and Net Cash Holdings

This table shows patent trading and R&D patterns by subsamples. In each year, I first sort all sample firms into five quintiles based on book assets. Next, I sort each quintile into yet another five quintiles by book-assets-scaled net cash holdings. For each of the resulting 25 subsamples, I compute four statistics as follows. Panel A reports the average book-assets-scaled net patent purchase. Net patent purchase is constructed by aggregating the firm's signed trades in the quarter, where each trade is weighted by its adjusted citation count. Panel B reports the frequency of patent trading, defined as $\hat{\mathbb{E}}(\mathbb{1}\{Trade\})$. The dummy variable $\mathbb{1}\{Trade\}$ equals one if a firm buys or sells at least one patent in the quarter. Panel C reports the average book-assets-scaled net patent purchase conditioning on that the firm trades. Finally, Panel D reports book-assets-scaled R&D expenses.

	Net Cash/Assets											
	Low	2	3	4	High	All	Low	2	3	4	High	All
Assets	**Panel A: *Net Buy/Assets***						**Panel C: *Net Buy/Assets* $\vert\mathbb{1}\{Trade\}$=1**					
Small	-1.232	-1.312	-0.618	0.512	0.399	-0.450	-94.390	-101.440	-50.004	36.402	29.496	-34.158
	(0.596)	(0.500)	(0.536)	(0.545)	(0.551)	(0.244)	(45.321)	(38.106)	(43.357)	(38.773)	(40.837)	(18.523)
2	-0.322	0.033	0.630*	1.061***	1.023***	0.484***	-20.622	1.746	32.256*	47.508***	47.232***	24.648***
	(0.341)	(0.325)	(0.355)	(0.346)	(0.368)	(0.155)	(21.865)	(16.935)	(18.136)	(15.323)	(16.833)	(7.879)
3	0.029	0.309*	1.064***	0.375	0.495**	0.454***	1.260	11.250*	32.857***	11.069	14.390**	14.928***
	(0.205)	(0.181)	(0.212)	(0.228)	(0.196)	(0.091)	(8.649)	(6.572)	(6.419)	(6.730)	(5.661)	(3.000)
4	0.079	-0.152	0.104	0.342*	0.426***	0.159**	2.270	-3.049	1.835	6.171*	7.334***	3.120**
	(0.100)	(0.175)	(0.149)	(0.188)	(0.151)	(0.069)	(2.876)	(3.511)	(2.621)	(3.396)	(2.599)	(1.364)
Large	-0.020	-0.066	-0.000	0.048	0.218***	0.036	-0.232	-0.491	-0.002	0.277	1.166***	0.237
	(0.068)	(0.068)	(0.068)	(0.092)	(0.078)	(0.033)	(0.780)	(0.505)	(0.392)	(0.524)	(0.416)	(0.221)
All	-0.292	-0.237	0.236*	0.468***	0.512***	0.137**	-8.374	-4.845	4.007*	7.765***	8.140***	2.573**
	(0.145)	(0.130)	(0.139)	(0.143)	(0.142)	(0.062)	(4.156)	(2.659)	(2.361)	(2.374)	(2.258)	(1.175)
Assets	**Panel B: $\mathbb{1}\{Trade\}$**						**Panel D: *R&D/Assets***					
Small	0.013***	0.012***	0.012***	0.014***	0.013***	0.016***	0.040***	0.020***	0.029***	0.040***	0.059***	0.038***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
2	0.015***	0.019***	0.019***	0.022***	0.021***	0.019***	0.009***	0.012***	0.019***	0.031***	0.046***	0.023***
	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
3	0.023***	0.027***	0.032***	0.033***	0.034***	0.030***	0.004***	0.006***	0.011***	0.018***	0.028***	0.013***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
4	0.034***	0.050***	0.057***	0.055***	0.058***	0.051***	0.002***	0.003***	0.004***	0.007***	0.017***	0.007***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Large	0.087***	0.135***	0.174***	0.175***	0.187***	0.152***	0.001***	0.002***	0.003***	0.004***	0.011***	0.004***
	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
All	0.034***	0.048***	0.059***	0.060***	0.062***	0.053***	0.011***	0.009***	0.013***	0.020***	0.032***	0.017***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)

Table 7: Patent Trading and R&D in Subsamples Sorted by Firm Sizes and Patent Stocks

This table shows patent trading and R&D patterns by subsamples. In each year, I first sort all sample firms into five quintiles based on book assets. Next, I sort each quintile into yet another five quintiles by book-assets-scaled patent stocks. Patent stock is computed by accumulating the firm's patent grants, expirations, and transactions, where each patent is weighted by its adjusted citation count. For each of the resulting 25 subsamples, I compute four statistics as follows. Panel A reports the average book-assets-scaled net patent purchase. Net patent purchase is constructed by aggregating the firm's signed trades in the quarter, where each trade is weighted by its adjusted citation count. Panel B reports the frequency of patent trading, defined as $\hat{\mathbb{E}}(\mathbb{1}\{Trade\})$. The dummy variable $\mathbb{1}\{Trade\}$ equals one if a firm buys or sells at least one patent in the quarter. Panel C reports the average book-assets-scaled net patent purchase conditioning on that the firm trades. Finally, Panel D reports book-assets-scaled R&D expenses.

	Patent Stock											
	Low	2	3	4	High	All	Low	2	3	4	High	All
Assets	**Panel A: *Net Buy/Assets***						**Panel C: *Net Buy/Assets* $\vert\mathbb{1}\{Trade\}=1$**					
Small	0.144	0.796	0.422	-1.096	-1.956	-0.450	11.946	85.480	38.426	-84.648	-107.477	-34.158
	(0.363)	(0.692)	(0.403)	(0.513)	(0.755)	(0.244)	(30.159)	(73.872)	(36.713)	(39.289)	(41.094)	(18.523)
2	1.093***	0.713***	0.764***	0.751***	-1.140	0.484***	89.868***	61.838***	50.166***	35.569***	-29.902	24.648***
	(0.233)	(0.242)	(0.223)	(0.288)	(0.571)	(0.155)	(18.497)	(19.922)	(14.358)	(13.559)	(14.948)	(7.879)
3	0.500***	0.097	0.403***	0.503***	0.615*	0.454***	38.881***	8.760	19.089***	13.355***	8.870*	14.928***
	(0.111)	(0.097)	(0.137)	(0.187)	(0.362)	(0.091)	(8.354)	(8.697)	(6.444)	(4.941)	(5.222)	(3.000)
4	0.280**	0.144**	0.165***	0.189	-0.008	0.159**	17.702**	10.689**	4.826***	2.699	-0.069	3.120**
	(0.115)	(0.073)	(0.059)	(0.172)	(0.259)	(0.069)	(7.235)	(5.356)	(1.713)	(2.462)	(2.118)	(1.364)
Large	0.143**	0.045*	0.015	0.011	-0.039	0.036	7.888**	1.389*	0.144	0.046	-0.110	0.237
	(0.064)	(0.026)	(0.043)	(0.067)	(0.131)	(0.033)	(3.515)	(0.812)	(0.397)	(0.271)	(0.368)	(0.221)
All	0.444***	0.225***	0.350***	0.072	-0.505	0.137**	32.351***	12.099***	8.822***	0.927	-4.178	2.573**
	(0.118)	(0.064)	(0.085)	(0.128)	(0.210)	(0.062)	(8.616)	(3.445)	(2.149)	(1.650)	(1.743)	(1.175)
Assets	**Panel B: $\mathbb{1}\{Trade\}$**						**Panel D: *R&D/Assets***					
Small	0.012***	0.009***	0.010***	0.012***	0.018***	0.016***	0.034***	0.033***	0.035***	0.036***	0.050***	0.038***
	(0.000)	(0.001)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)
2	0.012***	0.011***	0.015***	0.021***	0.038***	0.019***	0.018***	0.021***	0.023***	0.026***	0.031***	0.023***
	(0.000)	(0.001)	(0.000)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
3	0.012***	0.011***	0.021***	0.037***	0.069***	0.030***	0.010***	0.008***	0.012***	0.016***	0.020***	0.013***
	(0.000)	(0.001)	(0.001)	(0.001)	(0.002)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
4	0.015***	0.013***	0.034***	0.070***	0.122***	0.051***	0.003***	0.002***	0.006***	0.009***	0.013***	0.007***
	(0.000)	(0.001)	(0.001)	(0.002)	(0.002)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Large	0.018***	0.032***	0.109***	0.248***	0.356***	0.152***	0.000***	0.001***	0.003***	0.006***	0.010***	0.004***
	(0.001)	(0.001)	(0.002)	(0.003)	(0.003)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
All	0.013***	0.018***	0.039***	0.078***	0.120***	0.053***	0.016***	0.008***	0.015***	0.019***	0.025***	0.017***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)

Table 8: Patent Sales and Past Returns

This table reports the dependence of the patent sale frequency on past returns. The following regression is estimated:

$$\mathbb{1}\{\Delta s_{i,t} < 0\} = \beta_0 + \beta_1 \sum_{h=1}^{12} r_{i,t-h} + \beta_2 a_{i,t-1} + \beta_3 a_{i,t-1} \times \sum_{h=1}^{12} r_{i,t-h} + \nu_{i,t},$$

where $\mathbb{1}\{\Delta s_{i,t} < 0\}$ is an indicator variable that equals one if firm i sells patents in month t, $r_{i,t}$ is the firm's stock return in month t, and $a_{i,t-1}$ is the firm's net cash holdings as of the end of the latest quarter. Columns (1)–(3), (4)–(6), and (7)–(9) report regression results using raw, CAPM adjusted, and Fama-French three-factor model adjusted returns, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
VARIABLES				$\mathbb{1}\{\text{Sales} \neq 0\}$					
		Ret = Raw Ret.			*Ret = CAPM Adjusted Ret.*			*Ret = FF Adjusted Ret.*	
$\sum_{h=1}^{12} \text{Ret}_{m-h}$	-0.0037***	-0.0025***	-0.0016***	-0.0022***	-0.0011***	-0.0002	-0.0022***	-0.0012***	-0.0004
	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)
Net Cash		-0.0143***	-0.0099***		-0.0133***	-0.0103***		-0.0133***	-0.0103***
		(0.0007)	(0.0012)		(0.0008)	(0.0013)		(0.0008)	(0.0013)
Net Cash $\times \sum_{h=1}^{12} \text{Ret}_{m-h}$		-0.0015*	0.0004		-0.0023**	0.0010		-0.0023**	0.0007
		(0.0009)	(0.0008)		(0.0010)	(0.0010)		(0.0010)	(0.0010)
Constant	0.0328***	0.0315***	0.0010***	0.0341***	0.0328***	0.0017***	0.0341***	0.0328***	0.0017***
	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)
Firm FE	No	No	Yes	No	No	Yes	No	No	Yes
Observations	437,816	412,869	412,869	390,216	369,000	369,000	390,216	369,000	369,000

Table 9: Decomposition of Speculator's Ex Ante Expected Value Function

	Actions	**Short-term Objective**		**Long-term Objective**	
		D=0	D=1	D=0	D=1
Stage 1	PBD	0	$\frac{1}{2}\gamma\tilde{\sigma}_v\tilde{\sigma}_e$	0	0
Stage 2	PBT	$\frac{\gamma\beta}{2}\lambda^*\sigma_e^2$	$\frac{\gamma\beta}{2}\lambda_1\tilde{\sigma}_e{}^2$	$(1-\gamma)\lambda^*\sigma_z^2$	$(1-\gamma)\lambda_1\sigma_z^2$

Table 10: Summary Statistics of WSJ/NYT/FT Data

This table summarizes our disclosure data. Our sample spans from 2005 to 2014 and covers all articles published in the Wall Street Journal, the Financial Times and the New York Times. To identify a strategic disclosure, we apply the following criteria: An article is defined to be a disclosure made by fund holding company j about target firm i, if there exists a paragraph in it such that either one of the following is satisfied.

1. Both names of the target company i and the fund management company j are found. Because investment banks are frequently covered in the media together with other firms for reasons unrelated to strategic information disclosure (equity/bond underwriting, grading assignments, etc.), to avoid confounding our analysis, we exclude investment banks (e.g. Goldman Sachs, Merrill Lynch, Wells Fargo, etc.) from fund management companies, unless (i) key words such as "analyst", "portfolio manager" or "strategist" appear in the same sentence as the mention of the fund holding company; (ii) key words such as "securities", "holdings" or "asset management", which indicates the disclosure comes from a non-investment banking branch of j, closely follow the mention of the fund management company (with no more than one word in between); or (iii) name (first name followed by last name) of a portfolio manager associated with fund holding company j is also found in the same paragraph.
2. The name of the target company i is found and either (i) all first, middle, and last names of any portfolio manager at fund holding company j is found, or (ii) first and last names of any portfolio manager at fund holding company j is found, and, in the same sentence, there is key word such as "analyst", "portfolio manager", etc.

For each of the three newspapers, we count separately the number of articles which we identify as disclosures, which we do not identify as disclosures but are published in a business-related section, and which are published in a non-business-related section such as leisure, art or food.

	# Articles			
	FT	NYT	WSJ	All
Disclosures	3,531	2,886	5,133	11,550
Business Related	189,472	133,191	352,789	675,452
Business Unrelated	405,769	872,169	4,678	1,282,616
All	595,275	1,005,363	357,476	1,958,114

Table 11: Examples of Identified Disclosures

This table lists sample paragraphs—one for each newspaper—with which a journal article is identified as a strategic disclosure using our screening techniques.

Time Warner's Cable Plan Is Attracting Bargain Hunters

Julia Angwin

The Wall Street Journal, Mar. 3rd, 2005

Time Warner plans to pay for Adelphia partly by issuing stock in the new Time Warner cable company. "I'm not the biggest cable bull in the world, but I'm positive on the speculated deal terms," said Henry Ellenbogen, an analyst with T. Rowe Price, which owned a 1.2% stake in Time Warner as of Dec. 31, according to FactSet Research. Mr. Ellenbogen believes the new cable stock likely would trade at a higher multiple than Time Warner shares do currently, indicating that it would be fast-growing. It would "showcase the growth and quality of cable operation and show that Time Warner's high-quality, albeit moderate-growth, media assets trade at a significant discount to their peers," he said.

How Often to Trade? It's Tricky for Funds, Too

Norm Alster

The New York Times, Jan. 8th, 2012

But even low-turnover funds can be tempted by the bargains created in sharp downturns. "The volatility provides an opportunity to enter stocks that the market may have unduly punished," said Aram Green, one of four portfolio managers of the Legg Mason ClearBridge Mid Cap Growth fund. Though generally slow to turn over its portfolio, the fund managers did some selective nibbling during recent market sell-offs. One buy was F5 Networks, a computer networking company whose stock peaked above $140 early last year, but by August had dipped below $70. The fund stepped in, and the stock has since rebounded.

Reed Krakoff Seals $50M Buyout

Elizabeth Paton

The Financial Times, Sept. 3rd, 2013

Henry Ellenbogen, portfolio manager at T Rowe Price, a mutual fund that has invested in US luxury retail companies such as Tory Burch and Michael Kors, said: "We have an extremely strong record in the sector and see this business as a future force to be reckoned with on a global scale."

Investors Question the Track Record of US Media

Aline van Duyn

The Financial Times, Aug. 8th, 2005

Larry Haverty, portfolio manager at Gabell & Co, which owns Time Warner shares, said: "Increasing leverage is not sensible in an environment in which interest rates can go up and given the uncertainties in the media sector, such as growing competition from the internet."

Table 12: Summary Statistics of Sample Firms and Fund Holding Companies

This table provides summary statistics for our sample firms and fund holding companies. Panel (A) summarizes the sample at holding company-quarter level. The first three rows (*Equity*, *Bond* and *Cash*) report the holding companies' asset allocation—measured as percentage holdings—in three (non-exhaustive) broad asset classes. *NAV* measures the combined net asset values of all funds managed by a holding company. *Expense Ratio* is the sum of 12b-1 fees and operating expenses, expressed as a percentage of a fund's net asset value and averaged (weighted by each individual fund's NAV) across all funds under the same holding company. $\hat{\gamma}^1_{j,t}$ is a measure of a holding company j's overall flow-return sensitivity. To obtain $\hat{\gamma}^1_{j,t}$, we first estimate the following rolling regressions (Eq. (47)) for each fund k under holding company j at each quarter-end t using monthly fund return and flow data in the past year (i.e., $m = t-11, t-10, ..., t$):

$$\text{Flow}_{k,m} = \alpha_{k,t} + \sum_{h=0}^{2} \zeta^h_{k,t} \text{Ret}_{k,m-h} + \epsilon_{m,t}. \tag{47}$$

where $Flow_{k,m}$ are fund inflows or outflows, and $Ret_{k,m-h}$ are fund portfolio returns. We sum the resulting coefficients $\zeta^0_{k,t}$, $\zeta^1_{k,t}$ and $\zeta^2_{k,t}$ to obtain the flow-return sensitivity for each fund k at each quarter-end month t. $\hat{\gamma}^1_{j,t}$ is then defined as the NAV weighted average flow-return sensitivity of all funds managed by holding company j at month t. *#Disclosures* is the number of disclosures made by the fund holding company about all sample firms during a quarter. *Age* is defined as the NAV weighted average of each of the holding company's individual fund's age (number of days since the first time a fund is offered). Panel (B) summarizes the sample at firm-quarter level. We report the sample firms' market capitalization, Amihud's (2002) measure of illiquidity, number of disclosures made about a firm by all sample funds during a quarter, stock volatility *Stdev(Ret)* (measured as the annualized standard deviation of daily stock return in the quarter), and asset intangibility (measured as intangible assets as a percentage of total assets). Panel (C) summarizes the sample at firm-fund-quarter level. *#Disclosures* is the number of strategic disclosures made by a fund holding company about a firm in the current quarter. $\hat{\gamma}^2_{i,j,t}$ is the deviation of a fund's percentage holdings of a firm from the benchmark. To get $\hat{\gamma}^2_{i,j,t}$, we first define $H^f_{i,j,t} = \frac{V_t(\text{Holding Company j's Holdings of Firm i})}{V_t(\text{Holding Company j's Holdings of All S\&P 1500 Firms})}$ and let $H^m_{i,t} = \frac{V_t(\text{Firm i})}{V_t(\text{All S\&P 1500 Firms})}$; we then compute (Eq. (51))

$$\hat{\gamma}^2_{i,j,t} = \begin{cases} H^f_{i,j,t}/H^m_{i,t}, & \text{if } H^f_{i,j,t} > H^m_{i,t}, \\ H^m_{i,t}/H^f_{i,j,t}, & \text{Otherwise.} \end{cases} \tag{51}$$

For each of the characteristics, we report its mean and median in the full sample, and in each of the five subsamples characterized by the number of strategic disclosures. All variables are winsorized at the 2% and 98% levels, with the sole exception of the number of disclosures at the firm-fund-quarter level in Panel (C).

Table 12 Continued

	Mean						Median					
	Full	#Discl					Full	#Discl				
	Sample	= 0	≥ 1	≥ 5	≥ 10	≥ 15	Sample	= 0	≥ 1	≥ 5	≥ 10	≥ 15
Panel (A) Fund-Quarter Level												
Equity (%)	72.2	73.1	69.5	65.4	64.8	65.0	76.5	78.3	72.9	70.2	69.4	69.4
Bond (%)	5.3	4.7	7.1	8.0	8.1	7.9	0.0	0.0	0.0	0.2	1.1	1.5
Cash (%)	4.3	4.5	3.6	3.3	3.2	3.3	3.0	3.1	2.8	2.8	2.9	2.9
NAV ($B)	0.928	0.624	1.852	3.076	3.360	3.474	0.146	0.109	0.653	2.233	2.662	2.820
Expense Ratio (%)	1.1	1.1	1.1	1.1	1.1	1.1	1.2	1.2	1.1	1.1	1.1	1.1
$\hat{\gamma}^{1}_{j,t}$	0.428	0.466	0.311	0.286	0.311	0.305	0.121	0.127	0.107	0.116	0.124	0.110
# Disclosures	1.0	0.0	4.2	11.4	15.2	16.8	0	0	2	11	17	17
Age (Days)	3,111.3	3,174.5	2,919.3	2,950.7	2,929.4	2,960.8	2,992.5	3,032.6	2,900.7	3,017.2	3,059.7	3,056.8
Observations	10,932	8,226	2,706	709	401	270	10,932	8,226	2,706	709	401	270
Panel (B) Firm-Quarter Level												
Market Cap ($B)	13.362	8.988	30.726	63.035	83.546	94.148	3.966	3.277	12.342	59.109	117.485	117.485
Amihud	1.678	1.837	1.047	1.200	2.527	4.517	0.329	0.418	0.105	0.028	0.017	0.015
# Disclosures	0.4	0.0	2.0	5.0	5.0	5.0	0	0	1	5	5	5
Stdev(Ret) (%)	35.4	35.7	34.3	32.7	37.4	43.0	30.0	30.5	27.8	24.4	25.3	31.3
Intangibility (%)	22.5	22.2	23.6	25.4	28.1	33.0	16.9	16.6	18.0	17.8	17.6	21.8
Observations	28,094	22,441	5,653	666	168	57	28,094	22,441	5,653	666	168	57
Panel (C) Firm-Fund-Quarter Level												
$\hat{\gamma}^{2}_{i,j,t}$	48.6	41.7	91.8	96.2	91.5	67.8	6.5	5.0	130.6	130.6	130.6	70.8
# Disclosures	0.2	0.0	1.3	7.1	13.8	20.0	0	0	1	6	12	18.5
Observations	85,240	73,472	11,768	198	29	8	85,240	73,472	11,768	198	29	8

Table 13: Variable Definitions

Variable	Interpretation/Construction
	Key Variables Used in Testing the Effect of Short-termism on Disclosures
$\hat{\gamma}^1_{j,t}$	For each fund k managed by holding company j and each quarter-end month t, we first estimate the following regressions over a rolling twelve-month window: $\text{Flow}_{k,m} = \alpha_{k,t} + \sum_{h=0}^{2} \zeta^h_{k,t} \text{Ret}_{k,m-h} + \epsilon_{k,m}$, where $Flow_{k,m}$ and $Ret_{k,m}$ are monthly fund flows and returns, respectively. Each regression is estimated over twelve months of data, i.e., $m = t-11, t-10, ..., t$. We next define $\hat{\zeta}_{k,t} = \hat{\zeta}^0_{j,t} + \hat{\zeta}^1_{j,t} + \hat{\zeta}^2_{j,t}$. Lastly, we compute $\hat{\gamma}^1_{j,t}$ as the NAV-weighted average of those $\hat{\zeta}_{k,t}$ across all funds k under holding company j in quarter-end month t.
$\hat{\gamma}^2_{i,j,t}$	$\hat{\gamma}^2_{i,j,t} = \begin{cases} H^f_{i,j,t}/H^m_{i,t}, & \text{if } H^f_{i,j,t} > H^m_{i,t}, \\ H^m_{i,t}/H^f_{i,j,t}, & \text{Otherwise} \end{cases}$, where $H^f_{i,j,t}$ and $H^m_{i,t}$ are defined in (49) and (50), respectively.
$\#\text{Discl}_{i,j,t}$	Number of disclosures made by fund j about firm i during quarter t.
$\#\text{Discl}_{-i,j,t}$	Number of disclosures made by fund j about all firms except firm i during quarter t.
$\#\text{Discl}_{i,-j,t}$	Number of disclosures made by all funds except fund j about firm i during quarter t.
	Key Variables Used in Testing the Effect of PBT/PBD on Liquidity
$\text{Amihud}_{i,t}$	Amihud's (2002) measure of liquidity. For each firm i and quarter t, $\text{Amihud}_{i,t}$ is computed as $$\frac{1}{N_t}\sum_d \frac{\lvert r_{i,d}\rvert}{\text{Dvol}_{i,d}}$$ where $r_{i,d}$ and $\text{Dvol}_{i,d}$ denote, respectively, daily return and dollar trading volume for firm i shares on day d. The sum is taken over all trading days d in quarter t, with a total of N_t days.
$\hat{\gamma}^1_{i,t}$	$\hat{\gamma}^1_{i,t} = \log(1 + \frac{1}{\sum_j \text{Shr}_{i,j,t}} \sum_j \text{Shr}_{i,j,t} \times \hat{\gamma}^1_{j,t})$, where $\text{Shr}_{i,j,t}$ is the number of firm i shares held by fund j at the end of quarter t.
$\hat{\gamma}^2_{i,t}$	$\hat{\gamma}^2_{i,t} = \begin{cases} \log(\frac{H^f_{i,t}}{H^m_{i,t}}), & \text{if } H^f_{i,t} > H^m_{i,t}, \\ \log(\frac{H^m_{i,t}}{H^f_{i,t}}), & \text{Otherwise} \end{cases}$, where $H^f_{i,t} = \frac{\text{Value of Firm i Shares Held by All Sample Funds at the End of Quarter t}}{\text{Value of S\&P 1500 Firms Held by All Sample Funds at the End of Quarter t}}$ and $H^m_{i,t} = \frac{\text{Market Cap. of Firm i at the End of Quarter t}}{\text{Market Cap. of All S\&P 1500 Firms at the End of Quarter t}}$.
$\#\text{Discl}_{i,t}$	Number of disclosures made by all sample funds about firm i during quarter t.
$\#\text{Discl}_{-i,t}$	Number of disclosures made by all sample funds about all firms except firm i during quarter t.
$\text{Trading}_{i,t}$	Percentage trading by all sample mutual funds, defined as: $\text{Trading}_{i,t} = \frac{\lvert \text{Shr}_{i,t} - \text{Shr}_{i,t-1}\rvert}{\text{ShrOut}_{i,t-1}}$, where $\text{Shr}_{i,t}$ is the total number of shares held by all sample mutual funds at the end of quarter t and $\text{ShrOut}_{i,t}$ is firm i's number of shares outstanding as of the end of quarter t.
	Control and Conditioning Variables
$Size_{i,t}$	Market capitalization of firm i as of the end of quarter t.
$Intan_{i,t}$	$Intan_{i,t} = \frac{\text{Firm i's Intangible Asset at the End of Quarter t}}{\text{Firm i's Total Asset at the End of Quarter t}}$.
$Stdev(Ret)_{i,t}$	Standard deviation of firm i's stock return computed using daily return data in quarter t.
$\overline{Price}_{i,t}$	Firm i's average price computed using daily closing price in quarter t.

Table 14: Strategic Disclosure and Short-termism

This table reports test results on the effect of short-termism on mutual fund disclosures. We estimate, in part or in full, the following regression model of Eq. (53):

$$\begin{aligned}\#\text{Discl}_{i,j,t} =& \beta_0 + \beta_1 \hat{\gamma}^s_{(i,)j,t} + \beta_2 \text{Suit}_{i,t} + \beta_3 \hat{\gamma}_{i,j,t} \times \text{Suit}_{i,t} + \beta_4 \#\text{Discl}_{-i,j,t} \\ &+ \beta_5 \#\text{Discl}_{i,-j,t} + \delta_q + \delta_y + \epsilon_{i,j,t}, \quad s = 1, 2,\end{aligned} \tag{53}$$

where $\#\text{Discl}_{i,j,t}$ is the number of disclosures made by fund holding company j about firm i during quarter t (as defined in Section II.3.1) and $\hat{\gamma}^1_{j,t}$ measures the flow return sensitivity of fund holding company j. To obtain $\hat{\gamma}^1_{j,t}$, we first estimate the following rolling regressions (Eq. (47)) for each fund k under holding company j at each quarter-end t using monthly fund return and flow data in the past year (i.e., $m = t-11, t-10, ..., t$):

$$\text{Flow}_{k,m} = \alpha_{k,t} + \sum_{h=0}^{2} \zeta^h_{k,t} \text{Ret}_{k,m-h} + \epsilon_{m,t}. \tag{47}$$

where $Flow_{k,t}$ are fund inflows or outflows, and $Ret_{k,t}$ are fund portfolio returns. We next sum the resulting coefficients $\zeta^0_{k,t}$, $\zeta^1_{k,t}$ and $\zeta^2_{k,t}$ to obtain flow-return sensitivity for each fund k at each quarter-end month t. We then define $\hat{\gamma}^1_{j,t}$ as the NAV-weighted average flow-return sensitivity of all funds k managed by holding company j at month t. $\hat{\gamma}^2_{i,j,t}$ measures the "pivotalness" of a position (firm) i to a fund holding company j at the end of quarter t as the deviation of j's percentage holding of i from the market's. That is, define $H^f_{i,j,t} = \frac{V_t(\text{Fund j's Holdings of Firm i})}{V_t(\text{Fund j's Holdings of All S\&P 1500 Firms})}$ and let $H^m_{i,t} = \frac{V_t(\text{Firm i})}{V_t(\text{All S\&P 1500 Firms})}$; then define (Eq. (51))

$$\hat{\gamma}^2_{i,j,t} = \begin{cases} H^f_{i,j,t}/H^m_{i,t}, & \text{if } H^f_{i,j,t} > H^m_{i,t}, \\ H^m_{i,t}/H^f_{i,j,t}, & \text{Otherwise.} \end{cases} \tag{51}$$

$Suit_{i,t}$, the conditioning variable, is defined in Table 13 as either the inverse of firm size (measured as market capitalization, $Size_{i,t}$), intangibility (proportion of intangible asset of total asset, $Intan_{i,t}$), or standard deviation of stock i's past returns ($Stdev(Ret)_{i,t}$)—as indicated in the bottom row of this table. $\#\text{Discl}_{-i,j,t}$ is the number of disclosures made by fund j about all S&P 1500 firms except firm i during quarter t; $\#\text{Discl}_{i,-j,t}$ is the number of disclosures about firm i made by all sample funds except fund j. For each quarter and each firm, we exclude the largest holder fund from the regressions. In all specifications, we include year fixed effects (δ_y) and quarter fixed effects (δ_q). All variables are winsorized at the 2% and 98% levels and standardized. Standard errors in parentheses are heteroscedasticity-robust and two-way clustered by firm-fund.

Table 14 Continued

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
LHS Var.				$\#\text{Discl}_{i,j,t}$				
	$\hat{\gamma}^1$= Flow-Return Sensitivity				$\hat{\gamma}^2$=Pivotal			
$\hat{\gamma}$	0.015***	0.010**	0.015***	0.013**	0.222***	0.205***	0.222***	0.218***
	(0.006)	(0.005)	(0.006)	(0.006)	(0.008)	(0.006)	(0.008)	(0.008)
$\text{Suit}_{i,t}$		0.118***	0.019***	0.069***		0.041***	0.009	0.035***
		(0.018)	(0.007)	(0.010)		(0.011)	(0.006)	(0.008)
$\hat{\gamma} \times \text{Suit}_{i,t}$		0.013	0.005	0.004		0.082***	0.012*	0.042***
		(0.012)	(0.005)	(0.007)		(0.014)	(0.007)	(0.008)
$\#\text{Discl}_{-i,j,t}$	0.225***	0.221***	0.225***	0.223***	0.217***	0.214***	0.217***	0.216***
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
$\#\text{Discl}_{i,-j,t}$	0.103***	0.117***	0.103***	0.107***	0.108***	0.111***	0.107***	0.108***
	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)
Constant	-0.029**	-0.044***	-0.028**	-0.010	-0.053***	-0.075***	-0.053***	-0.047***
	(0.013)	(0.012)	(0.013)	(0.014)	(0.012)	(0.011)	(0.012)	(0.013)
Observations	85,240	85,240	85,240	85,240	85,240	85,240	85,240	85,240
R-squared	0.064	0.078	0.065	0.068	0.109	0.122	0.110	0.113
$\text{Suit}_{i,t}$		$1/Size_{i,t}$	$Intan_{i,t}$	$Stdev(Ret)_{i,t}$		$1/Size_{i,t}$	$Intan_{i,t}$	$Stdev(Ret)_{i,t}$

Table 15: PBT, PBD and Market Liquidity with $\hat{\gamma}^1_{i,t}$

This table reports test results on the effect of PBT and PBD on market liquidity. In each specification, we test—in part or in full—the following regression model of Eq. (60):

$$\begin{aligned}\Delta\log(\text{Amihud}_{i,t}) =& \beta_0 + \beta_1\hat{\gamma}^1_{i,t} + \beta_2\text{Suit}_{i,t} + \beta_3\hat{\gamma}^1_{i,t} \times \text{Suit}_{i,t} + \beta_4\Delta\log(\#\text{Discl}_{i,t}) + \beta_5\Delta\log(\#\text{Discl}_{i,t}) \times \hat{\gamma}^1_{i,t} \\ &+ \beta_6\Delta\log(\#\text{Discl}_{i,t}) \times \text{Suit}_{i,t} + \beta_7\Delta\log(\#\text{Discl}_{i,t}) \times \hat{\gamma}^1_{i,t} \times \text{Suit}_{i,t} + \beta_8\Delta\log(\text{Trading}_{i,t}) \\ &+ \beta_9\Delta\log(\text{Trading}_{i,t}) \times \hat{\gamma}^1_{i,t} + \beta_{10}\Delta\log(\text{Trading}_{i,t}) \times \text{Suit}_{i,t} \\ &+ \beta_{11}\Delta\log(\text{Trading}_{i,t}) \times \hat{\gamma}^1_{i,t} \times \text{Suit}_{i,t} + \delta'\Delta\log(\text{X}_{i,t}) + \delta_y + \delta_q + \epsilon_{i,t}.\end{aligned} \tag{60}$$

The sample we use to test this model is constructed at firm-quarter level, as indexed by i and t, respectively. $\Delta\log(\text{Amihud}_{i,t})$ measures the log change in Amihud's (2002) liquidity. $\hat{\gamma}^1_{i,t}$ is a proxy for funds' incentives to disclose about stock i in quarter t (short-termism) and is constructed as follows. In each quarter, we construct each holding company j's flow-return sensitivity—labeled $\hat{\gamma}^1_{j,t}$—by first estimating, for each fund k under the holding company, a rolling regression of its fund flows on its contemporaneous as well as past fund returns (Eq. (47)) and then computing $\hat{\zeta}_{k,t}$ as the sum of the resulting contemporaneous and lagged estimates of flow-performance sensitivity coefficients (Eq. (48)). We then define $\hat{\gamma}^1_{j,t}$ as the NAV-weighted average $\hat{\zeta}_{k,t}$ of all funds k managed by holding company j at quarter t. For each stock i in each quarter t, we then compute a weighted average of $\hat{\gamma}^1_{j,t}$ across all holding companies with non-zero holdings in that stock using the absolute value of the corresponding number of its shares held as weights. We denote this weighted average by $\overline{\hat{\gamma}^1}_{i,t}$ (Eq. (56)):

$$\overline{\hat{\gamma}^1}_{i,t} = \frac{1}{\sum_j |\text{Shr}_{i,j,t}|} \sum_j |\text{Shr}_{i,j,t}| \times \hat{\gamma}^1_{j,t}. \tag{56}$$

We then define $\hat{\gamma}^1_{i,t}$ as $\log(1 + \overline{\hat{\gamma}^1}_{i,t})$. $\Delta\log(\#\text{Discl}_{i,t})$ is the log change in the number of disclosures about firm i from quarter $t-1$ to quarter t. $\Delta\log(\text{Trading}_{i,t})$ is the log change in the percentage trading by all sample mutual funds; percentage trading is defined as $\text{Trading}_{i,t} = \frac{|\text{Shr}_{i,t} - \text{Shr}_{i,t-1}|}{\text{ShrOut}_{i,t-1}}$, where $\text{Shr}_{i,t}$ is the total number of shares held by all sample funds at the end of quarter t and $\text{ShrOut}_{i,t}$ is firm i's number of shares outstanding as of the end of quarter t. $Suit_{i,t}$, the conditioning variable, is defined in Table 13 as the log change in either the inverse of firm size (measured as market capitalization, $Size_{i,t}$), intangibility (proportion of intangible asset of total asset, $Intan_{i,t}$), or standard deviation of stock i's past returns ($Stdev(Ret)_{i,t}$)—as indicated in the bottom row of this table. In all specifications, we include in the control vector $\Delta\log(X_{i,t})$ the following variables: The log change in firm size, intangibility, and stock return volatility—whenever either is not also used as a measure of a firm's suitability ($\text{Suit}_{i,t}$); the log change in its average price level; and $\Delta\log(\#\text{Discl}_{-i,t})$, the log change in the number of disclosures made about all firms except firm i, whenever $\Delta\log(\#\text{Discl}_{i,t})$ is also included. In all specifications, we include year fixed effects (δ_y) and quarter fixed effects (δ_q). All variables are winsorized at the 2% and 98% levels and standardized. Standard errors in parentheses are heteroscedasticity-robust and clustered by firm.

Table 15 Continued

	(1)	(2)	(3)	(4)	(5)
LHS Var.			Δlog(Amihud)		
$\hat{\gamma}^1$			0.027***	0.024***	0.022***
			(0.009)	(0.008)	(0.008)
Δlog(#Discl)	-0.008*		-0.010**		-0.009*
	(0.005)		(0.005)		(0.005)
Δlog(#Discl) $\times \hat{\gamma}^1$			-0.020**		-0.018**
			(0.009)		(0.008)
Δlog(Trading)		0.023**		0.015*	0.013
		(0.009)		(0.009)	(0.009)
Δlog(Trading) $\times \hat{\gamma}^1$				0.023***	0.019**
				(0.008)	(0.008)
Observations	28,094	28,094	28,094	28,094	28,094
R-squared	0.514	0.513	0.515	0.514	0.516

	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
LHS Var.					Δlog(Amihud)				
$\hat{\gamma}^1$	-0.014**	0.026***	0.022***	-0.011**	0.021***	0.010*	-0.011**	0.020***	0.009*
	(0.006)	(0.009)	(0.007)	(0.005)	(0.008)	(0.005)	(0.005)	(0.007)	(0.005)
$\text{Suit}_{i,t}$	0.326***	-0.001	-0.025	0.347***	-0.005	-0.051**	0.345***	-0.006	-0.052**
	(0.043)	(0.005)	(0.022)	(0.047)	(0.005)	(0.020)	(0.048)	(0.005)	(0.021)
$\hat{\gamma}^1 \times \text{Suit}_{i,t}$	-0.005	0.013	0.046***	-0.000	0.008	0.010	-0.002	0.006	0.002
	(0.011)	(0.009)	(0.015)	(0.008)	(0.007)	(0.009)	(0.008)	(0.007)	(0.009)
Δlog(#Discl)	-0.001	-0.009**	-0.008**				-0.002	-0.007*	-0.005*
	(0.003)	(0.004)	(0.003)				(0.003)	(0.004)	(0.003)
Δlog(#Discl) $\times \hat{\gamma}^1$	-0.008**	-0.018***	-0.016***				-0.009**	-0.017***	-0.012**
	(0.004)	(0.006)	(0.005)				(0.004)	(0.006)	(0.005)
Δlog(#Discl) $\times \text{Suit}_{i,t}$	-0.002	-0.011	-0.017**				-0.002	-0.009	-0.012*
	(0.005)	(0.007)	(0.007)				(0.005)	(0.006)	(0.006)
Δlog(#Discl) $\times \hat{\gamma}^1 \times \text{Suit}_{i,t}$	-0.016***	-0.029***	-0.036***				-0.016***	-0.027**	-0.028***
	(0.006)	(0.011)	(0.009)				(0.006)	(0.011)	(0.008)
Δlog(Trading)				-0.009*	0.013	0.014*	-0.011**	0.011	0.012
				(0.005)	(0.009)	(0.008)	(0.005)	(0.009)	(0.008)
Δlog(Trading) $\times \hat{\gamma}^1$				-0.009*	0.021***	0.022***	-0.013***	0.017**	0.018***
				(0.005)	(0.007)	(0.006)	(0.005)	(0.007)	(0.006)
Δlog(Trading) $\times \text{Suit}_{i,t}$				0.005	-0.001	0.063***	0.007	-0.002	0.061***
				(0.005)	(0.007)	(0.019)	(0.005)	(0.007)	(0.019)
Δlog(Trading) $\times \hat{\gamma}^1 \times \text{Suit}_{i,t}$				-0.010	0.023***	0.052***	-0.011	0.020**	0.049***
				(0.009)	(0.009)	(0.013)	(0.009)	(0.008)	(0.012)
Observations	28,094	28,094	28,094	28,094	28,094	28,094	28,094	28,094	28,094
R-squared	0.543	0.517	0.521	0.541	0.515	0.525	0.544	0.518	0.528
$\text{Suit}_{i,t}(\Delta\text{log})$	$1/Size_{i,t}$	$Intan_{i,t}$	$Stdev(Ret)_{i,t}$	$1/Size_{i,t}$	$Intan_{i,t}$	$Stdev(Ret)_{i,t}$	$1/Size_{i,t}$	$Intan_{i,t}$	$Stdev(Ret)_{i,t}$

Table 16: PBT, PBD and Market Liquidity with $\hat{\gamma}^2_{i,t}$

This table reports test results on the effect of PBT and PBD on market liquidity. In each specification, we test—in part or in full—the following regression model of Eq. (60):

$$
\begin{aligned}
\Delta\log(\text{Amihud}_{i,t}) =& \beta_0 + \beta_1\hat{\gamma}^2_{i,t} + \beta_2\text{Suit}_{i,t} + \beta_3\hat{\gamma}^2_{i,t}\times\text{Suit}_{i,t} + \beta_4\Delta\log(\#\text{Discl}_{i,t}) + \beta_5\Delta\log(\#\text{Discl}_{i,t})\times\hat{\gamma}^2_{i,t} \\
&+ \beta_6\Delta\log(\#\text{Discl}_{i,t})\times\text{Suit}_{i,t} + \beta_7\Delta\log(\#\text{Discl}_{i,t})\times\hat{\gamma}^2_{i,t}\times\text{Suit}_{i,t} + \beta_8\Delta\log(\text{Trading}_{i,t}) \\
&+ \beta_9\Delta\log(\text{Trading}_{i,t})\times\hat{\gamma}^2_{i,t} + \beta_{10}\Delta\log(\text{Trading}_{i,t})\times\text{Suit}_{i,t} \\
&+ \beta_{11}\Delta\log(\text{Trading}_{i,t})\times\hat{\gamma}^2_{i,t}\times\text{Suit}_{i,t} + \delta'\Delta\log(\text{X}_{i,t}) + \delta_y + \delta_q + \epsilon_{i,t}.
\end{aligned} \tag{60}
$$

The sample we use to test this model is constructed at firm-quarter level, as indexed by i and t, respectively. $\Delta\log(\text{Amihud}_{i,t})$ measures the log change in Amihud's (2002) liquidity. $\hat{\gamma}^2_{i,t}$ is a proxy for a fund's incentives to disclose (short-termism) and is constructed as follows. For each firm i in each quarter t, we define $\hat{\gamma}^2_{i,t}$ as the deviation of the mutual fund sector's holdings of firm i from firm i's market share. Specifically, let $H^f_{i,t} = \frac{\text{Value of Firm i Shares Held by All Sample Funds at the End of Quarter t}}{\text{Value of All S\&P 1500 Firms Held by All Sample Funds at the End of Quarter t}}$ and let $H^m_{i,t} = \frac{\text{Market Cap. of Firm i at the End of Quarter t}}{\text{Market Cap. of All S\&P 1500 Firms at the End of Quarter t}}$, then define (Eq. (61))

$$
\hat{\gamma}^2_{i,t} = \begin{cases} \log(\frac{H^f_{i,t}}{H^m_{i,t}}), & \text{if } H^f_{i,t} > H^m_{i,t}, \\ \log(\frac{H^m_{i,t}}{H^f_{i,t}}), & \text{Otherwise.} \end{cases} \tag{61}
$$

$\Delta\log(\#\text{Discl}_{i,t})$ is the log change in the number of disclosures about firm i from quarter $t-1$ to quarter t. $\Delta\log(\text{Trading}_{i,t})$ is the log change in the percentage trading by all sample mutual funds; percentage trading is defined as $\text{Trading}_{i,t} = \frac{|\text{Shr}_{i,t} - \text{Shr}_{i,t-1}|}{\text{ShrOut}_{i,t-1}}$, where $\text{Shr}_{i,t}$ is the total number of shares held by all sample funds at the end of quarter t and $\text{ShrOut}_{i,t}$ is firm i's number of shares outstanding as of the end of quarter t. $Suit_{i,t}$, the conditioning variable, is defined in Table 13 as the log change in either the inverse of firm size (measured as market capitalization, $Size_{i,t}$), intangibility (proportion of intangible asset of total asset, $Intan_{i,t}$), or standard deviation of stock i's past returns ($Stdev(Ret)_{i,t}$)—as indicated in the bottom row of this table. In all specifications, we include in the control vector $\Delta\log(X_{i,t})$ the following variables: The log change in firm size, intangibility, and stock return volatility—whenever either is not also used as a measure of a firm's suitability ($\text{Suit}_{i,t}$); the log change in its average price level; and $\Delta\log(\#\text{Discl}_{-i,t})$, the log change in the number of disclosures made about all firms except firm i, whenever $\Delta\log(\#\text{Discl}_{i,t})$ is also included. In all specifications, we include year fixed effects (δ_y) and quarter fixed effects (δ_q). All variables are winsorized at the 2% and 98% levels and standardized. Standard errors in parentheses are heteroscedasticity-robust and clustered by firm.

Table 16 Continued

	(1)	(2)	(3)	(4)	(5)
LHS Var.			Δlog(Amihud)		
$\hat{\gamma}^2$			0.036**	0.028**	0.027**
			(0.015)	(0.012)	(0.012)
Δlog(#Discl)	-0.008*		-0.011**		-0.010*
	(0.005)		(0.005)		(0.005)
Δlog(#Discl) $\times\ \hat{\gamma}^2$			-0.021**		-0.019**
			(0.009)		(0.009)
Δlog(Trading)		0.023**		0.010	0.008
		(0.009)		(0.006)	(0.006)
Δlog(Trading) $\times\ \hat{\gamma}^2$				0.035***	0.031***
				(0.009)	(0.009)
Observations	28,094	28,094	28,094	28,094	28,094
R-squared	0.514	0.513	0.516	0.515	0.517

	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
LHS Var.					Δlog(Amihud)				
$\hat{\gamma}^2$	-0.023***	0.035**	0.028**	-0.021***	0.026**	0.007	-0.021***	0.025**	0.007
	(0.005)	(0.015)	(0.011)	(0.005)	(0.012)	(0.006)	(0.005)	(0.012)	(0.007)
Suit$_{i,t}$	0.304***	-0.002	-0.046***	0.303***	-0.006	-0.073***	0.300***	-0.007*	-0.076***
	(0.039)	(0.006)	(0.018)	(0.038)	(0.005)	(0.015)	(0.040)	(0.004)	(0.015)
$\hat{\gamma}^2 \times$ Suit$_{i,t}$	0.020***	0.009	0.085***	0.020***	0.002	0.031***	0.019***	0.000	0.028***
	(0.006)	(0.010)	(0.020)	(0.006)	(0.008)	(0.008)	(0.006)	(0.008)	(0.009)
Δlog(#Discl)	-0.003	-0.008**	-0.008**				-0.003	-0.007*	-0.006**
	(0.003)	(0.004)	(0.003)				(0.003)	(0.004)	(0.003)
Δlog(#Discl) $\times\ \hat{\gamma}^2$	-0.011***	-0.019***	-0.015***				-0.012***	-0.017***	-0.013***
	(0.004)	(0.006)	(0.005)				(0.004)	(0.006)	(0.005)
Δlog(#Discl) $\times$ Suit$_{i,t}$	-0.001	-0.009	-0.011**				-0.001	-0.008	-0.009
	(0.005)	(0.006)	(0.006)				(0.005)	(0.006)	(0.005)
Δlog(#Discl) $\times\ \hat{\gamma}^2 \times$ Suit$_{i,t}$	-0.013**	-0.027***	-0.028***				-0.012**	-0.026***	-0.022***
	(0.006)	(0.010)	(0.008)				(0.006)	(0.010)	(0.007)
Δlog(Trading)				-0.009*	0.009	0.008	-0.010**	0.007	0.006
				(0.005)	(0.006)	(0.005)	(0.005)	(0.006)	(0.005)
Δlog(Trading) $\times\ \hat{\gamma}^2$				-0.003	0.034***	0.030***	-0.007*	0.030***	0.026***
				(0.004)	(0.009)	(0.006)	(0.004)	(0.010)	(0.006)
Δlog(Trading) $\times$ Suit$_{i,t}$				-0.001	-0.001	0.032***	0.001	-0.002	0.032***
				(0.005)	(0.006)	(0.007)	(0.005)	(0.006)	(0.007)
Δlog(Trading) $\times\ \hat{\gamma}^2 \times$ Suit$_{i,t}$				0.006	0.018**	0.072***	0.006	0.015*	0.069***
				(0.005)	(0.009)	(0.011)	(0.005)	(0.008)	(0.011)
Observations	28,094	28,094	28,094	28,094	28,094	28,094	28,094	28,094	28,094
R-squared	0.544	0.517	0.526	0.541	0.516	0.532	0.544	0.519	0.535
Suit$_{i,t}$(Δlog)	$1/Size_{i,t}$	$Intan_{i,t}$	$Stdev(Ret)_{i,t}$	$1/Size_{i,t}$	$Intan_{i,t}$	$Stdev(Ret)_{i,t}$	$1/Size_{i,t}$	$Intan_{i,t}$	$Stdev(Ret)_{i,t}$

Table 17: Summary Statistics

This table reports summary statistics of the sample for BLP estimation. The sample period is from 1994 to 2017. Deposit share and loan share are computed taking the entire United States as a unified market. The total size of the deposit market is defined as the sum of deposits, cash, and bonds held by all the U.S. households. The total size of the loan market is defined as the sum of bank loans and corporate bonds issued by the U.S. firms. Deposit and loan rates are imputed using the interest expense and income from Call report. Expense of fixed assets and salary are scaled by total assets. Deposit share, loan share, deposit rates, loan rates, expense of fixed assets and salary are reported in percentage. The data is from Call report and FDIC Summary of Deposits.

	mean	sd	p10	p25	p50	p75	p90
Deposit Share	0.086	0.535	0.004	0.005	0.010	0.024	0.088
Loan Share	0.028	0.160	0.001	0.001	0.002	0.006	0.027
Deposit Rates	1.774	1.275	0.117	0.562	1.667	2.883	3.546
Loan Rates	6.521	1.629	4.416	5.269	6.383	7.813	8.682
# of Branches	80.963	342.600	12.000	14.000	20.000	40.000	115.000
# Employees per Branch	17.443	16.131	9.063	11.015	13.905	18.571	26.533
Expenses of Fixed Assets	0.458	0.153	0.271	0.342	0.437	0.564	0.729
Salary	1.683	0.451	1.065	1.343	1.634	1.990	2.493

Table 18: Monetary Policy Shocks and Bank Equity Returns on FOMC Days

This table reports the estimates of the relation between bank equity returns and monetary policy shocks on FOMC Days. Monetary shocks are measured by the daily change in the two-year Treasury yield on FOMC days. HHI is the the Herfindahl-Hirschman index of the local deposit market in which the bank operates. A local deposit market is defined as a Metropolitan Statistical Area (MSAs). If a bank operates in several MSAs, the bank-level HHI is the weighted average of local HHI, weighted by the deposits of the bank in the local market. The sample includes all publicly traded U.S. banks from 1994 to 2017. We exclude observations during the burst of dot-com bubble (2000-2001) and the subprime financial crisis (2007-2009). The standard errors are clustered by time.

	(1)	(2)	(3)	(4)
	FFR $>$ 2%	FFR $\leq$ 2%	FFR $>$ 2%	FFR $\leq$ 2%
Δ 2-year Yield	-1.292**	2.202**	-0.639	-1.393
	[0.615]	[0.879]	[0.653]	[0.852]
HHI*Δ 2-year Yield			-0.134	0.562***
			[0.145]	[0.153]
Δ Term Spread	-0.634	2.336*	-0.667	1.827
	[1.265]	[1.350]	[1.257]	[1.293]
Market Return	0.297***	0.730***	0.295***	0.733***
	[0.072]	[0.070]	[0.071]	[0.070]
Observations	27,257	33,805	27,257	33,805
Adj, R-squared	0.015	0.123	0.016	0.125

Table 19: Bank Balance Sheet

This table illustrates the balance sheet of a typical bank at the beginning of the period.

Assets		Liabilities	
Existing loans	L_t	Deposits	D_t
New loans	$P\left(B_t, r_t^l\right)$	Non-reservable borrowings	N_t
Reserves	R_t	Equity	E_t
Government securities	G_t		
Total Assets	$L_t + P\left(B_t, r_t^l\right) + R_t + G_t$	*Total Liabilities and Equity*	$D_t + N_t + E_t$

Table 20: Parameter Estimates

This table reports the model parameter estimates. Panel A presents results for parameters that represent statutory rates. Panel B presents results from parameters that can be calculated as simple averages or by simple regression methods. Panel C presents results from parameters estimated via BLP. Panel C presents results from parameters estimated via SMM.

Statutory Parameters			
τ_c	Corporate tax rate	0.35	
θ	The reserve ratio	0.022	
κ	The capital ratio	0.06	
Parameters Estimated Separately			
μ	Average loan maturity	5	
$\bar{f}$	Log Federal Funds rate mean	0.60	
σ_f	Log Federal Funds rate variance	0.65	
ρ_f	Log Federal Funds rate persistence	0.91	
$\bar{\delta}$	Log loan chargeoffs mean	-0.89	
σ_δ	Log loan chargeoffs variance	1.24	
ρ_δ	Log loan chargeoffs persistence	0.50	
$\hat{J}$	Number of representative banks	14	
Parameters Estimated via BLP			
α^d	Depositors' sensitivity to deposit rates	0.80	[0.16]
σ_{α^d}	The dispersion of depositors' sensitivity to deposit rates	1.58	[0.44]
α^l	Borrowers' sensitivity to loan rates	-0.90	[0.16]
q_d^d	Convenience of holding deposits	0.95	[0.19]
q_b^d	Convenience of holding bonds	-0.10	[0.16]
q_l^l	Convenience of borrowing through loans	-0.10	[0.59]
Parameters Estimated via SMM			
γ	Banks' discount rate	0.052	
ϕ^N	Cost function of non-reservable borrowing	0.010	
ϕ^d	Bank's cost of taking deposits	0.007	
ϕ^l	Bank's cost of servicing loans	0.009	
q_n^l	The value of firms' outside option	-6.493	

Table 21: Moment Conditions

This table reports the moment conditions in the simulated method of moment (SMM) estimation.

	Actual Moment	**Simulated Moment**
Dividend yield	2.53%	2.64%
Non-reservable borrowing share	30%	30.8%
Deposit spread	1.46%	1.66%
Loan spread	2.78%	2.77%
Loan/Deposit Ratio	0.96	0.978
Corporate Borrowing-FFR Sensitivity	-0.50	-0.562
Deposit spread - FFR sensitivity	0.30	0.285
Loan spread - FFR sensitivity	-0.25	-0.241

Table 22: Demand Estimation

This table reports the estimated parameters of the deposit and loan demand. The first column reports parameters of deposit demand. The second column reports parameters of loan demand. Yield sensitivity (α) refers to the average sensitivity of the depositors (firms) to deposit rates (loan rates). Log No. of Branches (β_1) refers the sensitivity of the depositors (firms) to log number of branches that each bank has. Log No. of Employees (β_1) refers the sensitivity of the depositors (firms) to log number of employees per branch. Yield sensitivity (σ_α) refers to the dispersion in the sensitivity of the depositors to deposit rates (the dispersion is set to 0 for firms). The sample includes all the U.S. commercial banks from 1994 to 2017 with domestic branches higher than 10. The data is from the Call report and the Summary of Deposits.

	Deposit	Loan
Yield sensitivity (α)	0.800***	-0.904***
	[0.158]	[0.163]
Log number of branches (β_1)	0.868***	1.117***
	[0.009]	[0.000]
Log number of employees (β_2)	0.587***	0.694***
	[0.016]	[0.031]
Yield sensitivity dispersion (σ_α)	1.579***	
	[0.439]	
Sector F.E.	Y	Y
Time F.E.	Y	Y
Observations	15575	15575
Adj. Rsq	0.982	0.867

Table 23: Determinants of Monetary Policy Transmission

This table depicts a series of counterfactual experiments in which we examine the cumulative effect of removing frictions from our model on two important quantities. The first is the sensitivity of loans to the Federal Funds rate (FFR), and the second is the aggregate amount of borrowing, which is normalized to 100% in the baseline case. Each line of the table presents the results from eliminating the corresponding friction.

		Sensitivity of Loans to FFR ($\frac{\Delta(l)}{\Delta f}$)	Aggregate Bank Loans
(1)	Baseline	−3.88%	100%
(2)	− Reserve Regulation	−3.81%	101%
(3)	− Deposit Market Power	−2.57%	118%
(4)	− Capital Constraint	−0.95%	128%
(5)	− Loan Market Power	−1.38%	193%

Table 24: High versus Low Market Concentration

This table illustrates how the monetary policy transmission is influenced by different frictions under three economic regimes: high bank concentration, median bank concentration, and low bank concentration. Bank concentration is measured by the number of competing banks, N, in the local market. Monetary policy transmission is captured by the sensitivity of loans to the Federal Funds rate (FFR). Each line of the table presents the results from eliminating the corresponding friction.

	Concentration		
	Low, $N = 200$	Median, $N = 14$	High, $N = 2$
(1) Baseline	-3.52%	-3.88%	-5.21%
(2) − Deposit Market Power	-3.18%	-2.57%	-3.27%
(3) − Capital Constraint	-0.96%	-0.95%	-0.93%
(4) − Loan Market Power	-1.35%	-1.38%	-1.59%

Table 25: Large versus Small Banks

This table presents the parameter estimates and the degree of monetary policy transmission in subsamples of large and small banks. ϕ^d and ϕ^l are banks' marginal costs of intaking deposits and servicing loans, respectively, and ϕ^N is the quadratic cost of borrowing non-reservables. The last column reports the sensitivity of loans to the Federal Funds rate (FFR), which is a measure of monetary policy transmission. Standard errors clustered at the firm level are in parentheses under the parameter estimates.

	Parameters Estimates					Sensitivity of Loans to FFR($\frac{\Delta(l)}{\Delta f}$)
	γ	q_n^l	ϕ^N	ϕ^d	ϕ^l	
Full Sample	0.052	-6.439	0.004	0.008	0.006	-2.48
Big Banks	0.052	-6.439	0.004	0.008	0.005	-2.31
Small Banks	0.052	-6.439	0.003	0.009	0.012	-3.24

Figure 1: Sequence of Events for a Typical Firm

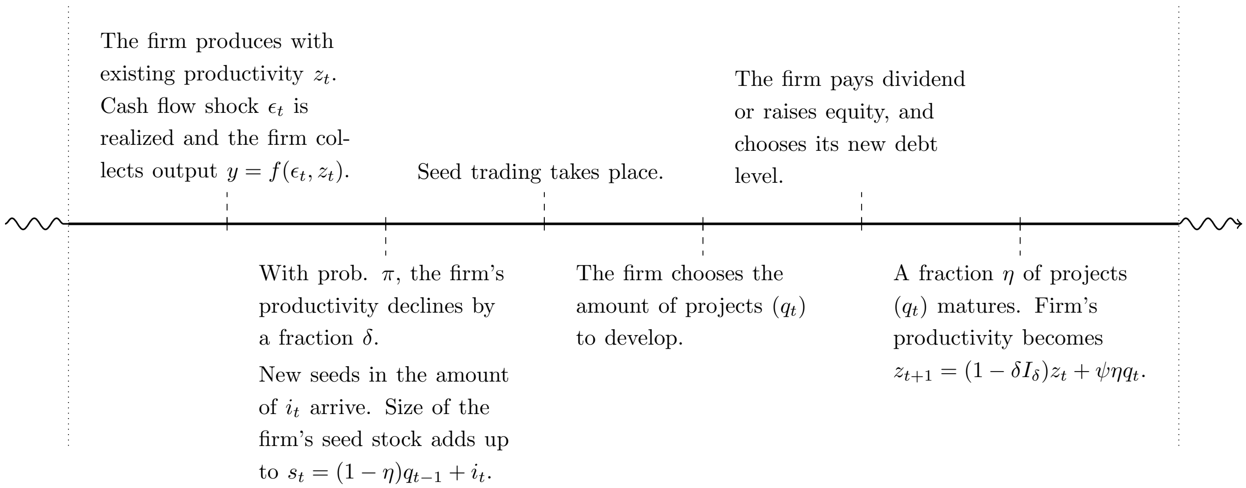


Figure 1 shows the sequence of events in a typical time period t for a typical firm.

Figure 2: Empirical and Fitted Distributions of Quarterly Patent Grants

This figure plots the empirical and fitted distributions of quarterly patent grants. The empirical distribution is estimated non-parametrically. I measure the quarterly patent grant as the citation-weighted number of patents issued to firm i in quarter t:

$$n_{i,t}^{g} = \sum_{j \in \mathbb{Q}_{i,t}^{\text{grant}}} \frac{C_j}{\hat{\mathbb{E}}\left[C_k \middle| Y_k = Y_j, T_k = T_j\right]},$$

where $\mathbb{Q}_{i,d}^{\text{grant}}$ is the set of patents issued to firm i in quarter t, C_j is the number of citations received by Patent j, and $\hat{\mathbb{E}}\left[C_k \middle| Y_k = Y_j, T_k = T_j\right]$ is the average number of citations received by all patents granted in the same year and in the same technology field as patent j. The solid lines are the kernel density estimations of $n_{i,t}^{g}$, and the dashed lines are the fitted exponential distributions. The three panels show the quarterly patent grant distributions for the full sample, small firms and large firms, respectively. Small (large) firms are defined as those with capital stocks below (above) the sample median.

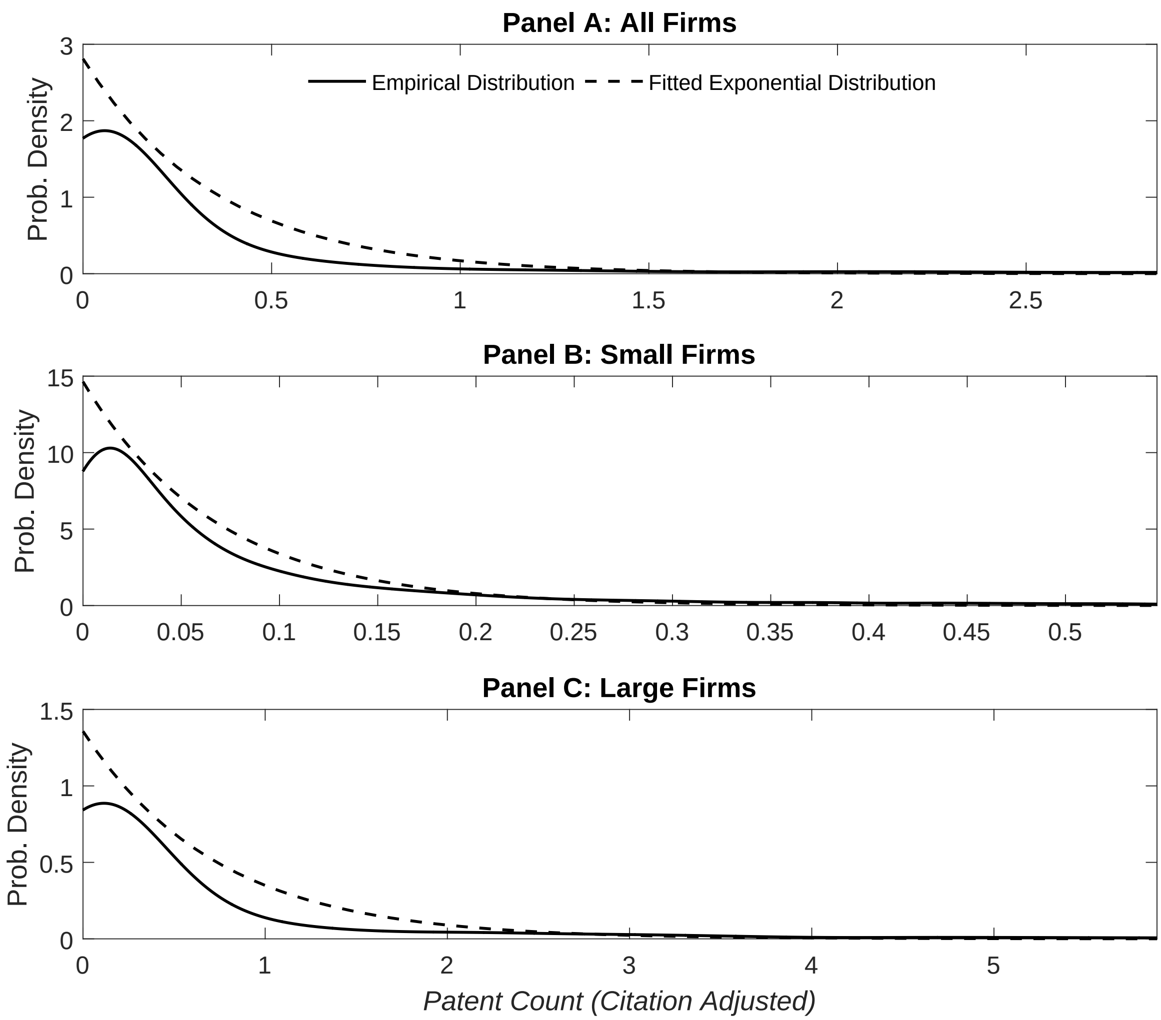


Figure 3: Numerical Policy Functions

This figure presents the numerical policy functions. Panels A and B show the dependences of the real policies, net seed purchase Δs and the number of projects developed q, on the beginning-of-period net cash holdings, a_{beg}. Panels C and D are the firm's financial policies, net payout d and end-of-period savings a_{end}. Panels E and F show how net seed purchase Δs varies with the firm's other two state variables, current productivity z and seed stock s. In all figures, the solid lines are the policy functions of an individual firm; when moving along the x-axis, one state variable is varied while the others are fixed. The dashed lines are the equilibrium averages of the policies conditioning on the state variable in the x-axis.

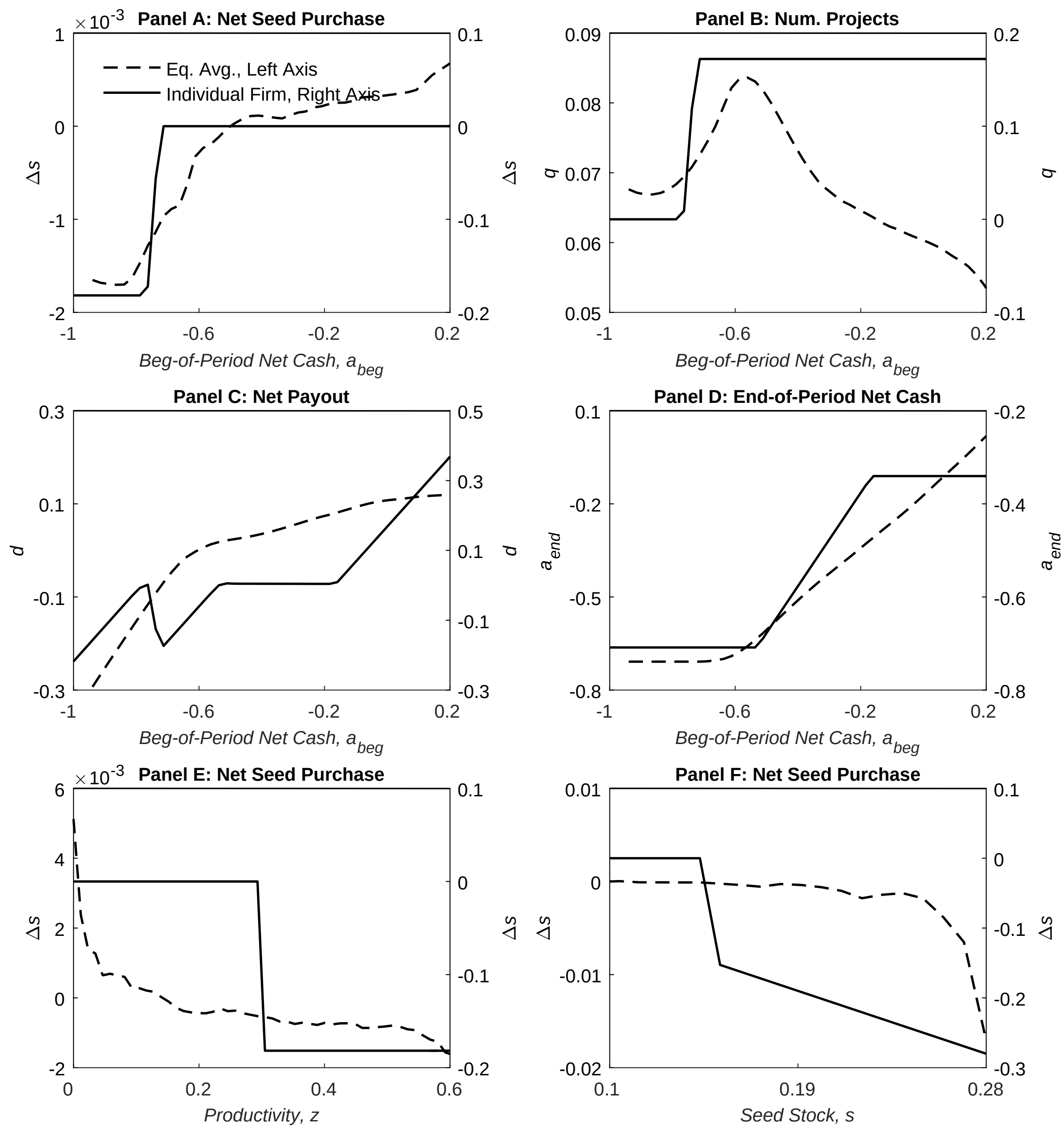


Figure 4: Comparative Statics

This figure presents several comparative statics. In each plot, one parameter is varied while the others are held fixed at their estimated values.

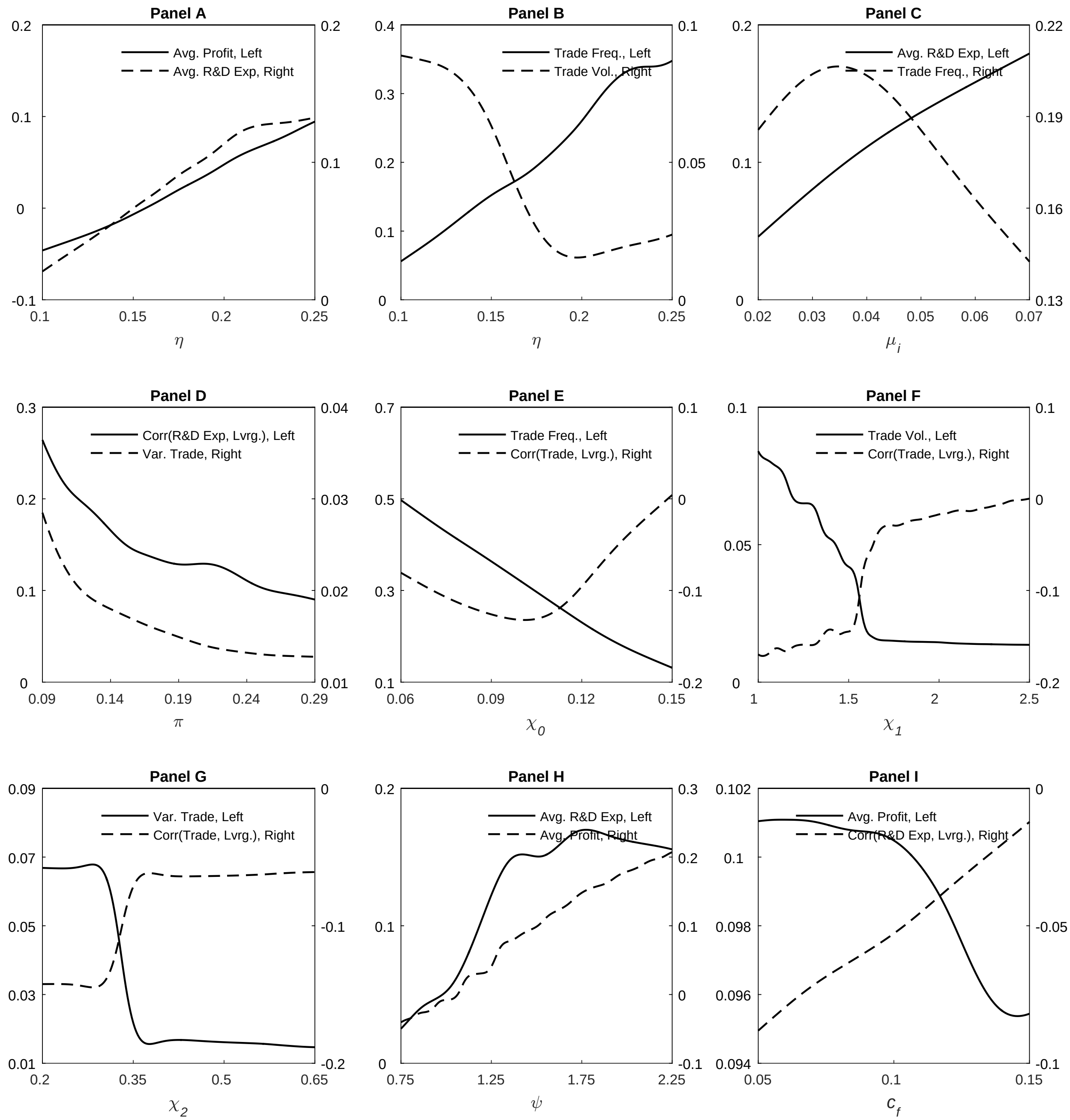


Figure 5: Firm Impulse Responses to Seed and Cash Shocks

This figure shows the firm's impulse responses to seed and cash shocks. Before time zero, the firm is fed with a long sequence of median seed and cash flow shocks, i and ϵ, respectively, and the productivity depreciation rate is at its average level, $\pi \times \delta$. At time zero, the firm becomes subject to large one-time shocks. In Panel A, the firm receives a large, positive seed inflow, while in Panel B, the firm experiences a large, positive seed inflow plus a large operating loss. Each panel shows how cash holdings, net payout, productivity, net seed purchase, and the number of developed projects evolve in response to the shocks.

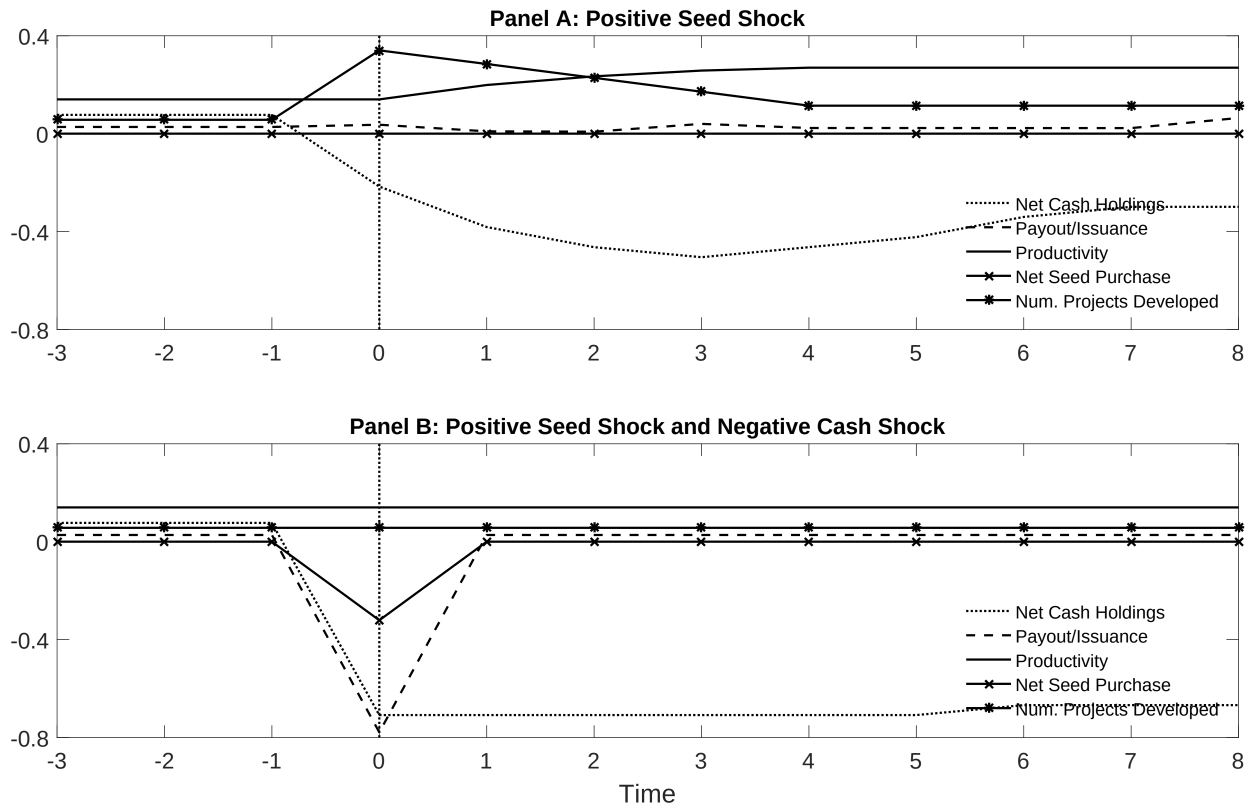


Figure 6: The Direct and Indirect Effects of Seed Trading

This figure shows the decomposition of IAT gains into direct and indirect effects for a range of trading costs. The x-axis is the number of multiples of trading costs. That is, $x = 1$ is the benchmark case where all parameters are estimated from the data; when moving along the x-axis, the trading cost parameters, χ_0, χ_1, and χ_2, vary but all other parameters are unchanged. The y-axis is the percentage changes in efficiency measures relative to the without-trade specification. Three efficiency measures are considered: the average number of planted seeds (Panel A), the average losses due to costly external financing (Panel B), and the average firm value (Panel C). The direct effects are plotted in dashed lines against the left scale, while the indirect effects are plotted as solid lines against the right scale. Reported in annotations are the local trading cost elasticities of the efficiency measures computed at the benchmark parameter levels.

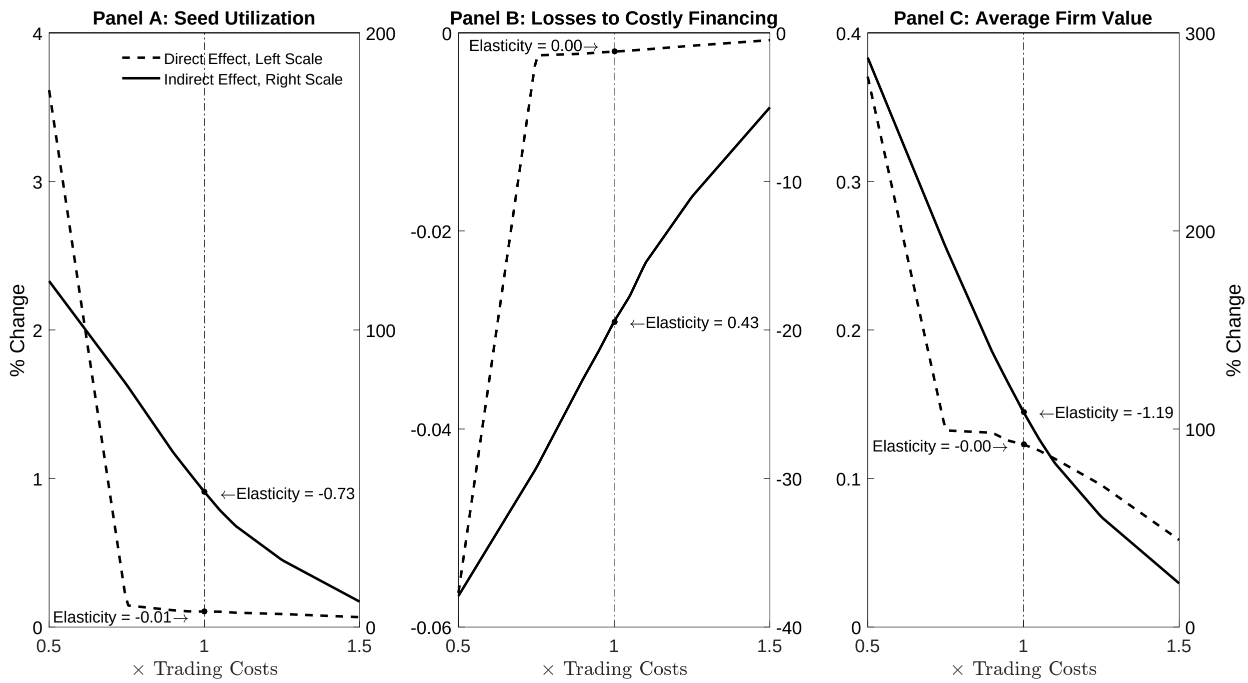


Figure 7: Costs of Seed Trading and the Efficiency Losses to Financial Frictions

This figure shows the issuance cost, λ, and trading cost, χ_j, $j = 0, 1, 2$, elasticity of three equilibrium efficiency measures, namely, the average firm value, $\mathbb{E}[v - a_{beg}]$, the average marginal value of net cash holdings, $\mathbb{E}[\frac{\partial v}{\partial a_{beg}}]$, and the value loss to seed misallocatio, L^s. L^s is defined as:

$$L^s = 1 - \frac{\int \left[v(a_{beg}, z, s) - a_{beg}\right] d\Gamma}{\int \left[v(a_{beg}, z, s^*) - a_{beg}\right] d\Gamma}, \tag{21}$$

where Γ is the equilibrium distribution of firm states (a_{beg}, z, s) and $s^* = s^*(a_{beg}, z)$ is the socially optimal seed stock, defined as:

$$s^*(a_{beg}, z) = \underset{\tilde{s} \text{ s.t. } \int \tilde{s} d\Gamma = \int s d\Gamma}{\arg\max} \int \left[v(a_{beg}, z, \tilde{s}) - a_{beg}\right] d\Gamma.$$

The solid lines show the dependences of the issuance cost elasticities on the trading costs, and the dashed lines show the dependence of the trading cost elasticities on the issuance cost. The x-axis corresponds to multiples of these costs' estimates. For instance, when the trading cost multiple is equal to 0.5, the values on the solid lines are the issuance cost elasticities if χ_0, χ_1, and χ_2 are half of their estimates.

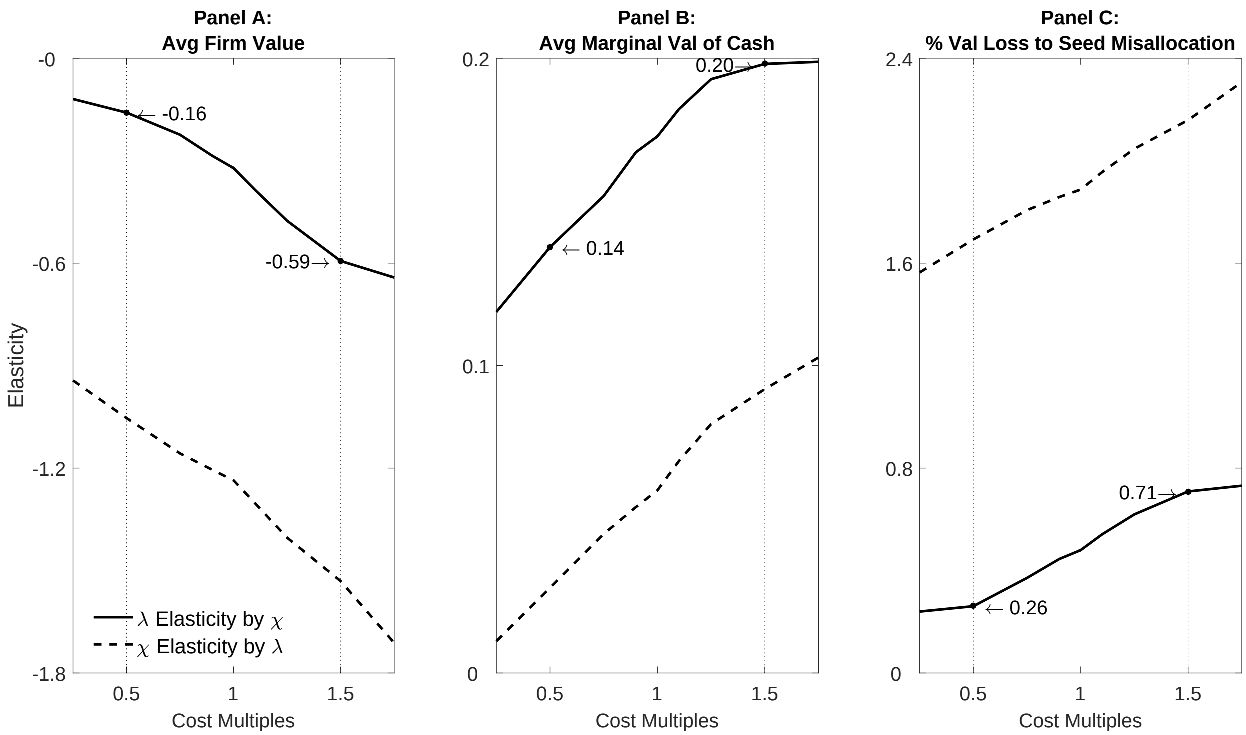


Figure 8: Timing of Patent Sales

This figure shows the timing of patent sales in terms of firms' cash holdings. Each firm's time series is sorted into five bins by lagged cash holdings. Panels A, B, C, and D show the average net patent sales in each bin. The solid lines are the mean values, and the dashed lines enclose the 95% confidence intervals. Small/large firms are firms with book assets below/above the sample median. Rated firms are those that ever receive a bond rating from Standard & Poor's during the sample period; the rest are grouped as unrated. Net patent sale, $n^s_{i,t}$, is defined as:

$$n^s_{i,t} = \Big[\sum_{j \in \mathbb{Q}^s_{i,t}} \frac{C_j}{\hat{\mathbb{E}}\big[C_k \big| Y_k = Y_j, T_k = T_j\big]} - \sum_{j \in \mathbb{Q}^b_{i,t}} \frac{C_j}{\hat{\mathbb{E}}\big[C_k \big| Y_k = Y_j, T_k = T_j\big]} \Big] / \bar{K}_i,$$

where $\bar{K}_i$ is firm i's average book assets, $\mathbb{Q}^b_{i,t}$ and $\mathbb{Q}^s_{i,t}$ are the sets of patents firm i buys and sells in quarter t, respectively, C_j is the number of citations received by patent j, and Y_j and T_j denote the grant year and technology class of patent j, respectively.

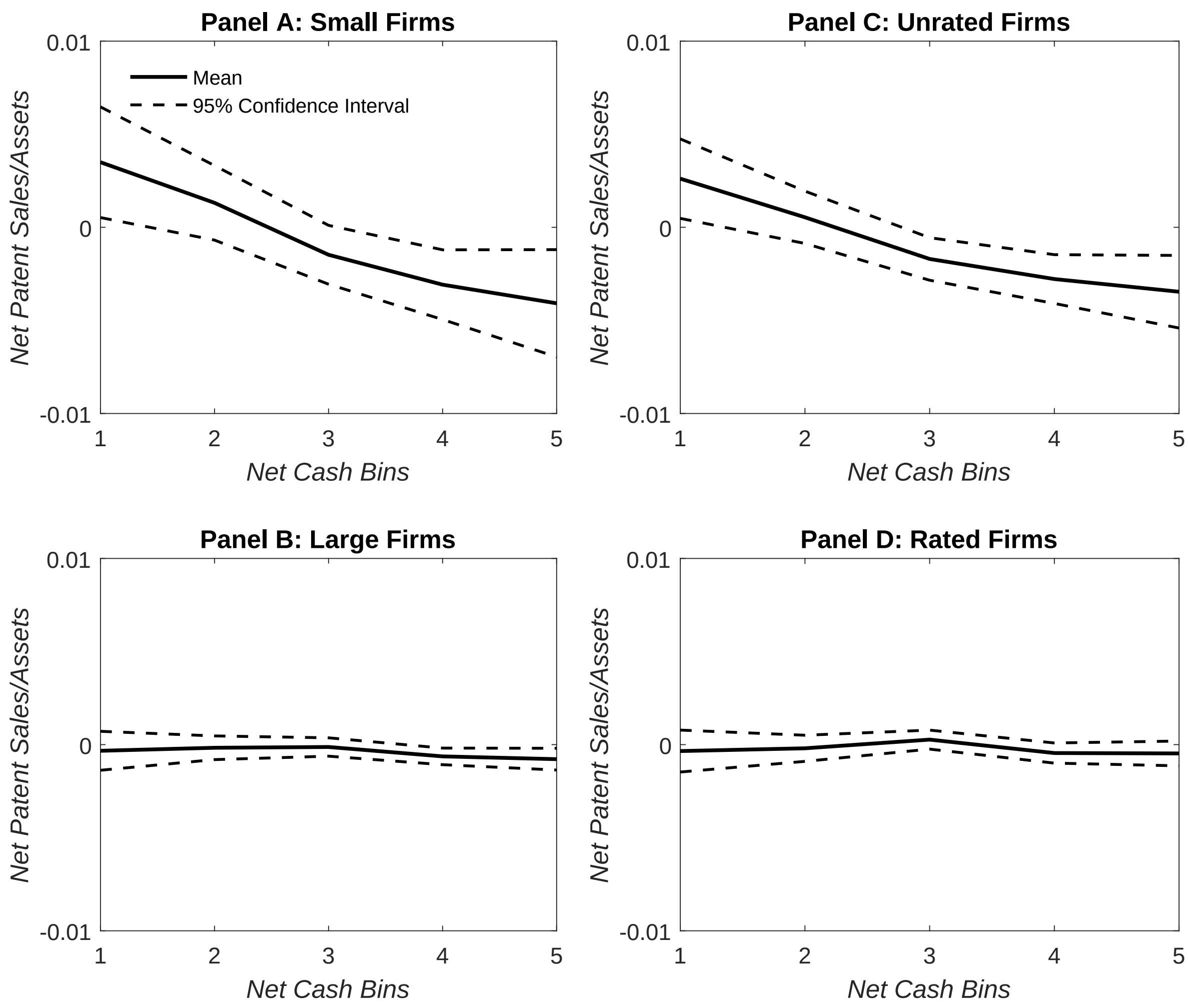


Figure 9: Firm R&D around Patent Sales

This figure shows firms' R&D expenses in two-year horizons before and after patent sales. Specifically, for each quarter t in which firm i sells patents, I define the demeaned R&D as:

$$rd_{i,h}^{\text{demeaned}} = \frac{RD_{i,t+h}}{K_{i,t-1}} - \frac{1}{17}\sum_{l=-8}^{8}\frac{RD_{i,t+l}}{K_{i,t-1}},\ h=-8,-7,...,8.$$

$RD_{i,t+h}$ is firm i's annualized R&D expense in quarter $t+h$, and $K_{i,t-1}$ is the firm's book assets in the quarter before patent sales. I compute the average of $rd_{i,h}^{\text{demeaned}}$ for each $h=-8,-7,...,8$, and I consider four subsamples—small, large, rated, and unrated firms. Small/large firms are firms with book assets below/above the median value of the quarter before the patent sales. Rated firms are those that ever receive a bond rating from S&P during the sample period; I group the rest as unrated. In the plots below, the solid lines are the means of $rd_{i,h}^{\text{demeaned}}$ and the dashed lines enclose its 95% confidence interval.

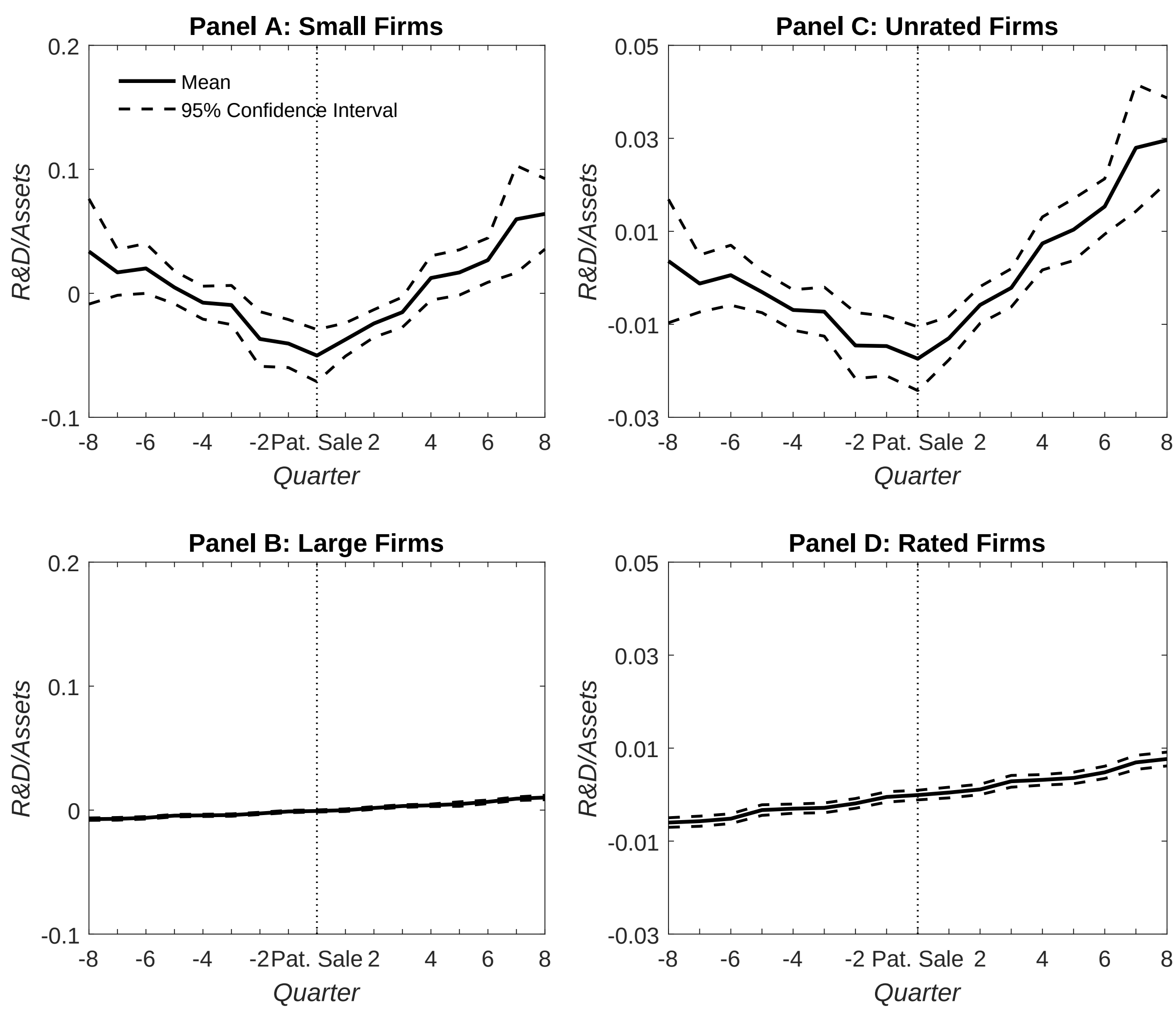


Figure 10: Timing of Equity Issuances

This figure shows the timing of equity issuances in terms of firms' cash holdings. I sort each firm's time series into five quintiles by cash holdings. I then pool together the firm-quarters in each quintile and compute the mean issuances. In the plots below, the solid lines are the mean values, and the dashed lines enclose the 95% confidence intervals. I consider four subsamples: small, large, rated, and unrated firms. Small/large firms are firms with book assets below/above the sample median. Rated firms are those that ever receive a bond rating from S&P during the sample period; I group the rest as unrated. Equity issuance is defined as total proceeds divided by the firm's book assets.

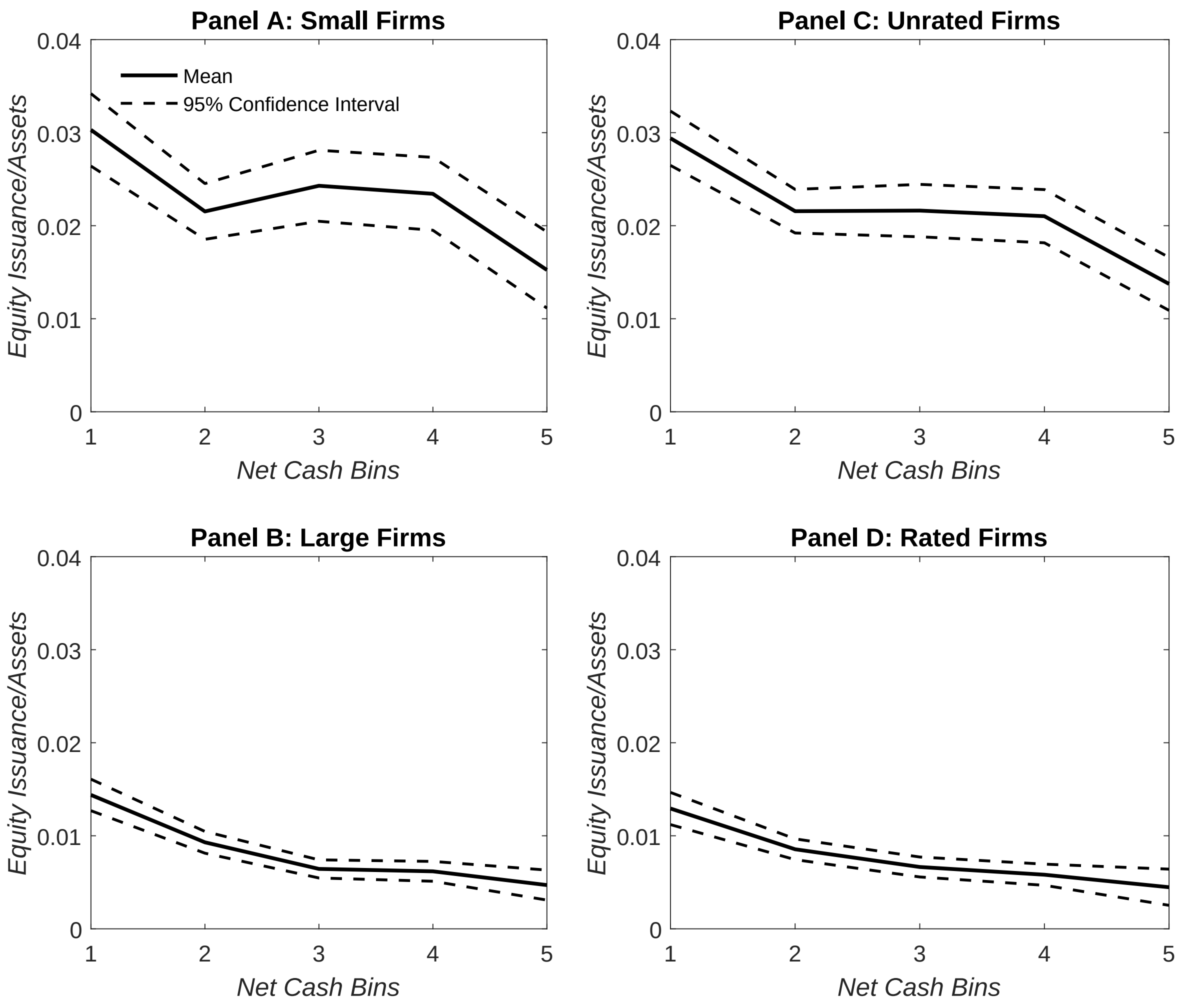


Figure 11: Firm R&D around Equity Issuances

This figure plots firm's R&D expenses in two-year horizons before and after equity issuances. Specifically, for each quarter t in which firm i issues equity, I define the demeaned R&D as:

$$rd_{i,h}^{\text{demeaned}} = \frac{RD_{i,t+h}}{K_{i,t-1}} - \frac{1}{17}\sum_{l=-8}^{8}\frac{RD_{i,t+l}}{K_{i,t-1}},\ h = -8, -7, ..., 8.$$

$RD_{i,t+h}$ is firm i's annualized R&D expense in quarter $t+h$, and $K_{i,t-1}$ is the firm's book assets in the quarter before the issuance. I compute the average of $rd_{i,h}^{\text{demeaned}}$ for each $h = -8, -7, ..., 8$, and I consider four subsamples—small, large, rated, and unrated firms. Small/large firms are firms with book assets below/above the median value of the quarter before the patent sales. Rated firms are those that ever receive a bond rating from S&P during the sample period; I group the rest as unrated. In the plots below, the solid lines are the means of $rd_{i,h}^{\text{demeaned}}$ and the dashed lines enclose the 95% confidence interval.

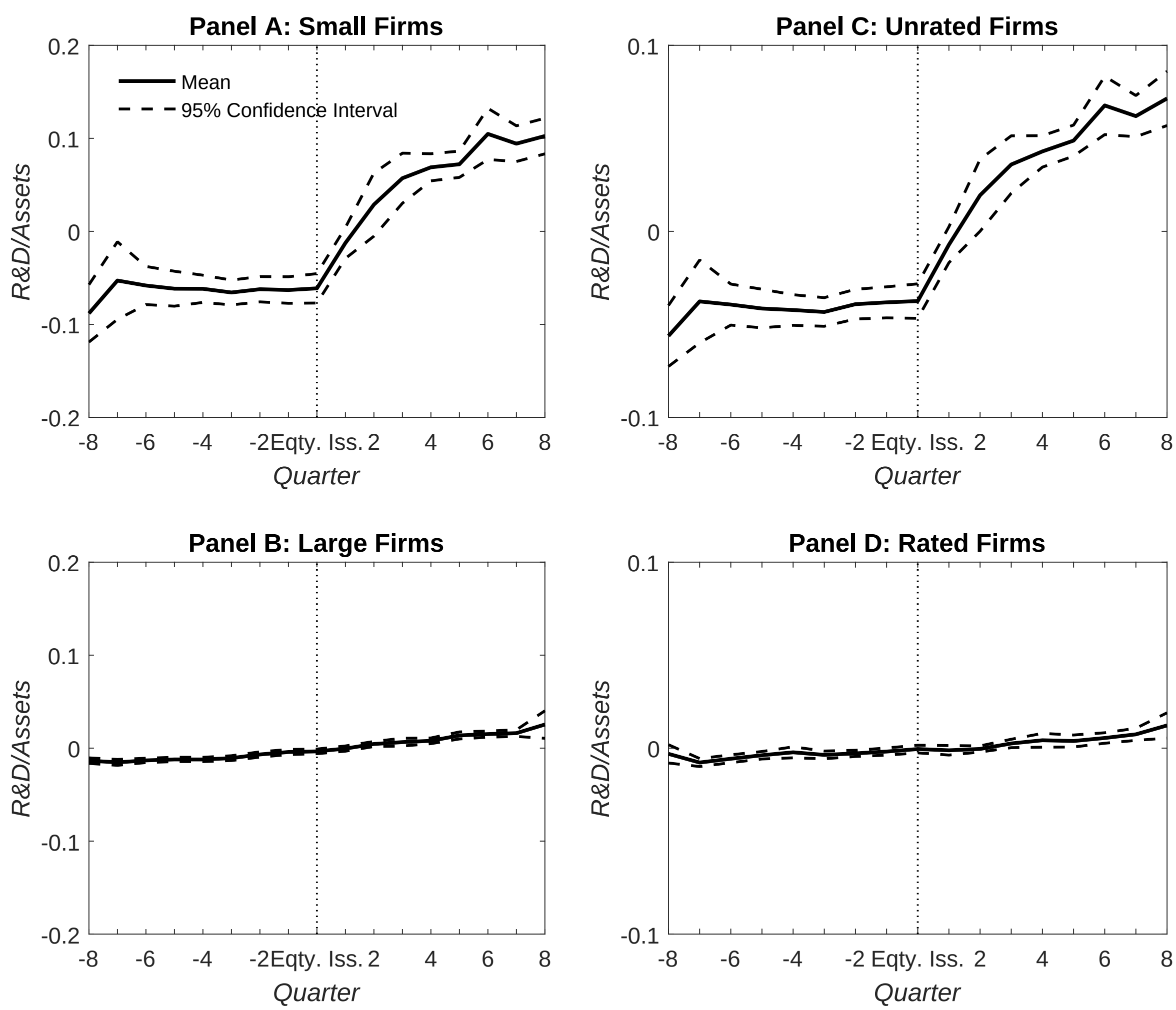


Figure 12: Technological Distance and Patent Sales

This figure shows firms' R&D expenses around sales of core and peripheral patents and the timing of these patent sales. Core (peripheral) patent trades are those that involve patents whose technological distance from the firms' patent portfolio is below (above) the sample median. Panels A and B show firms' R&D expenses around core and peripheral patent sales, where quarter 0 is the quarter with patent sales. R&D expenses, $rd_{i,h}^{\text{demeaned}}$, is defined as:

$$rd_{i,h}^{\text{demeaned}} = \frac{RD_{i,t+h}}{K_{i,t-1}} - \frac{1}{17}\sum_{l=-8}^{8}\frac{RD_{i,t+l}}{K_{i,t-1}},\ h = -8, -7, ..., 8.$$

In Panels C and D, each firm's time series is sorted into five quintiles based on its lagged net cash holdings. The panels show the firms' net patent sales in each bin. Net patent sale, $n_{i,t}^s$, is defined as:

$$n_{i,t}^s = \Big[\sum_{j\in\mathbb{Q}_{i,t}^s}\frac{C_j}{\hat{\mathbb{E}}\big[C_k\big|Y_k = Y_j, T_k = T_j\big]} - \sum_{j\in\mathbb{Q}_{i,t}^b}\frac{C_j}{\hat{\mathbb{E}}\big[C_k\big|Y_k = Y_j, T_k = T_j\big]}\Big]/\bar{K}_i,$$

where $\bar{K}_i$ is firm i's average book assets, $\mathbb{Q}_{i,t}^b$ and $\mathbb{Q}_{i,t}^s$ are the sets of patents firm i buys and sells in quarter t, respectively, C_j is the number of citations received by patent j, and Y_j and T_j denote the grant year and technology class of patent j, respectively. In all panels, the solid lines are the mean values and the dashed lines show the 95% confidence intervals.

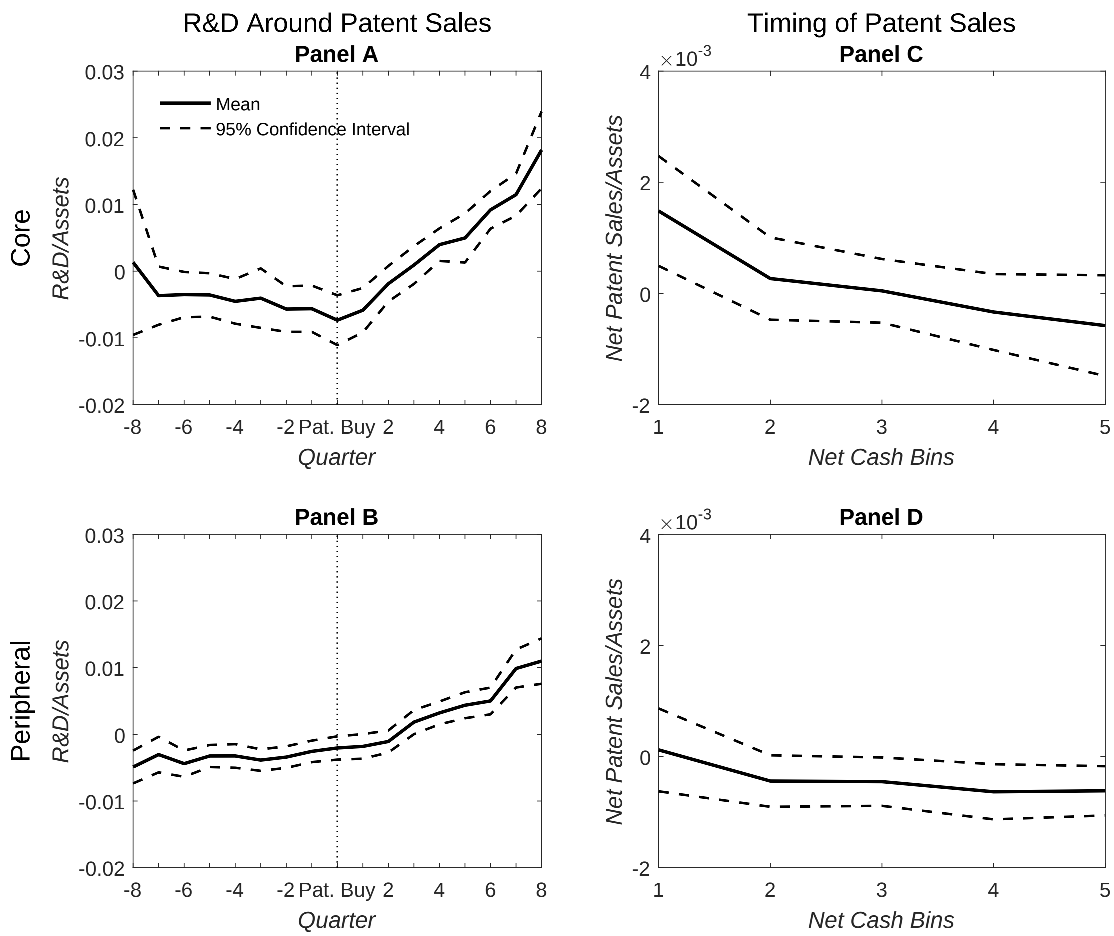


Figure 13: Patent Owners' Net Cash Holdings throughout Patent Lifetimes

This figure shows firms' (book-assets-scaled) net cash holdings from the time they buy or are issued a patent till the time they eventually sell the patent (quarter 0). Four subsamples are considered: large, small, rated, and unrated firms. The solid lines are the average net cash holdings and the dashed lines enclose its 95% confidence interval.

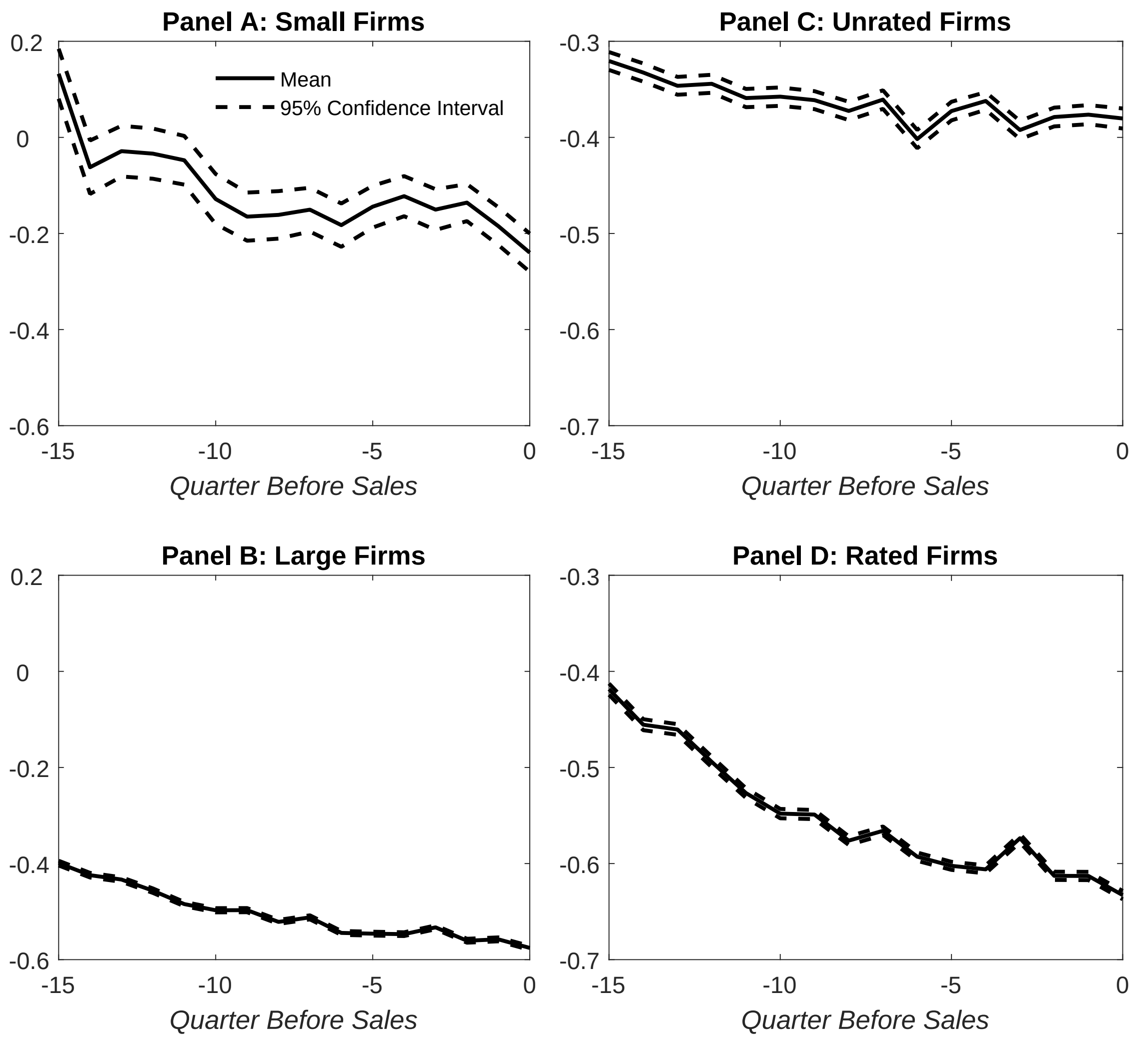
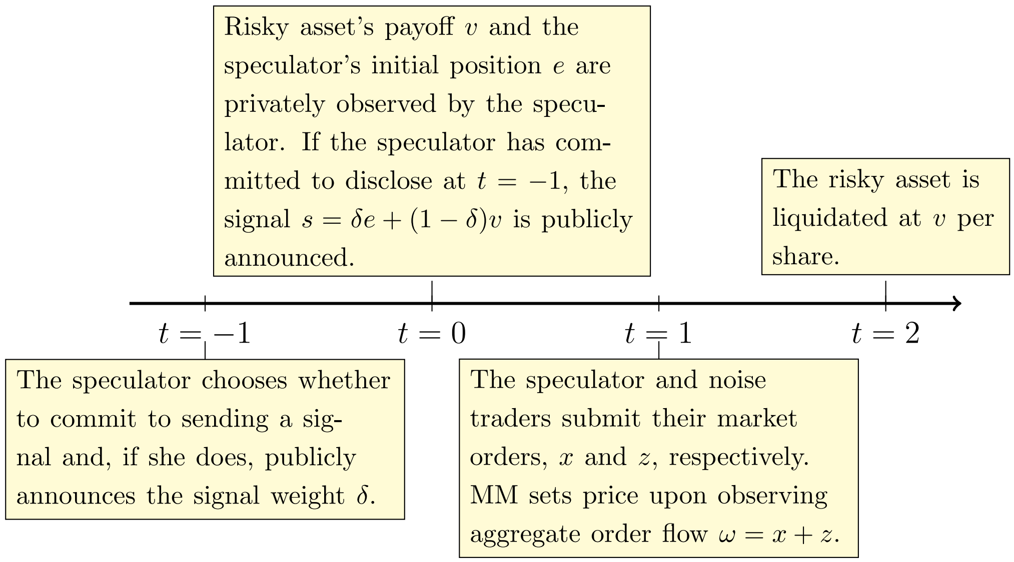
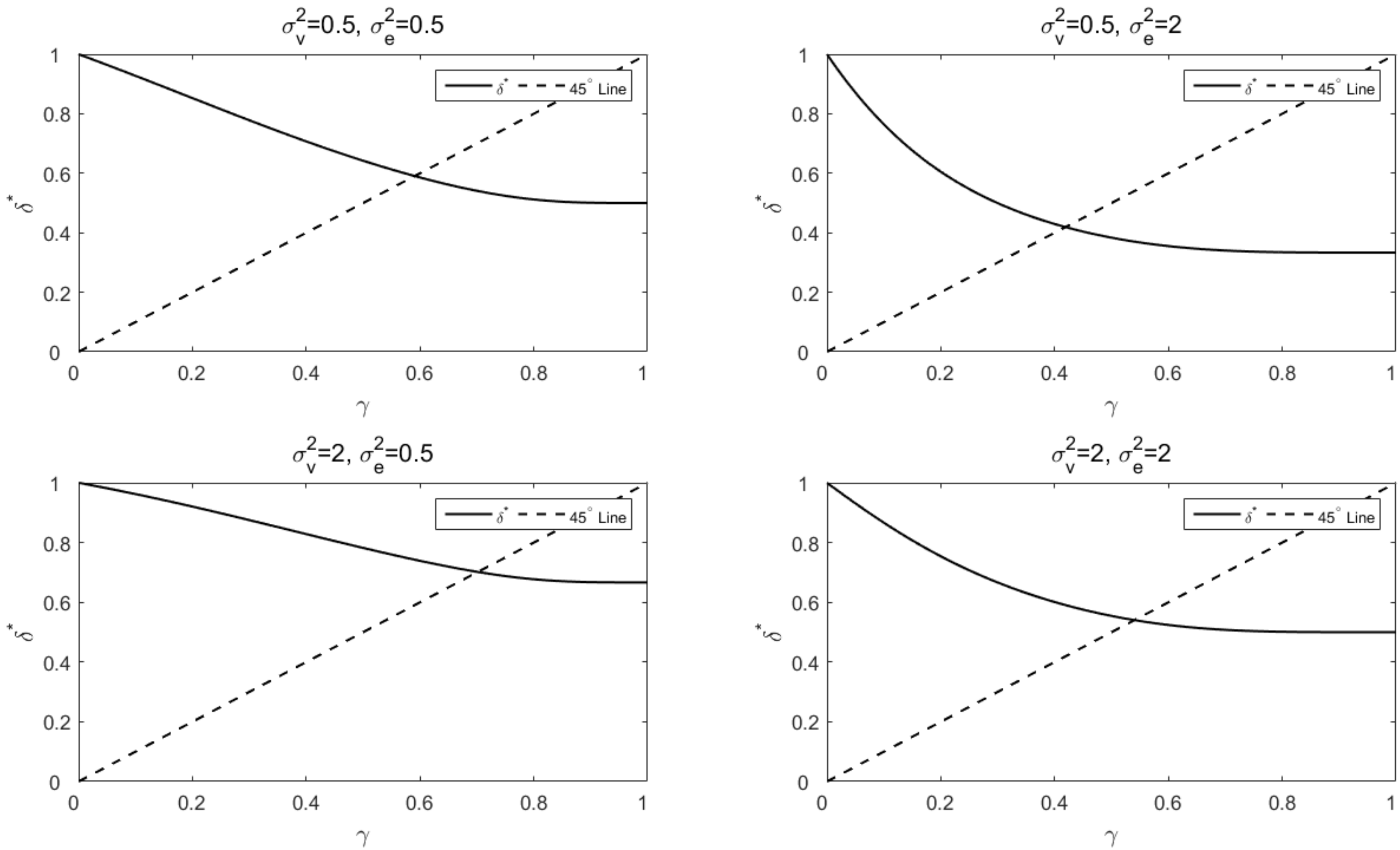


Figure 14: Time Line



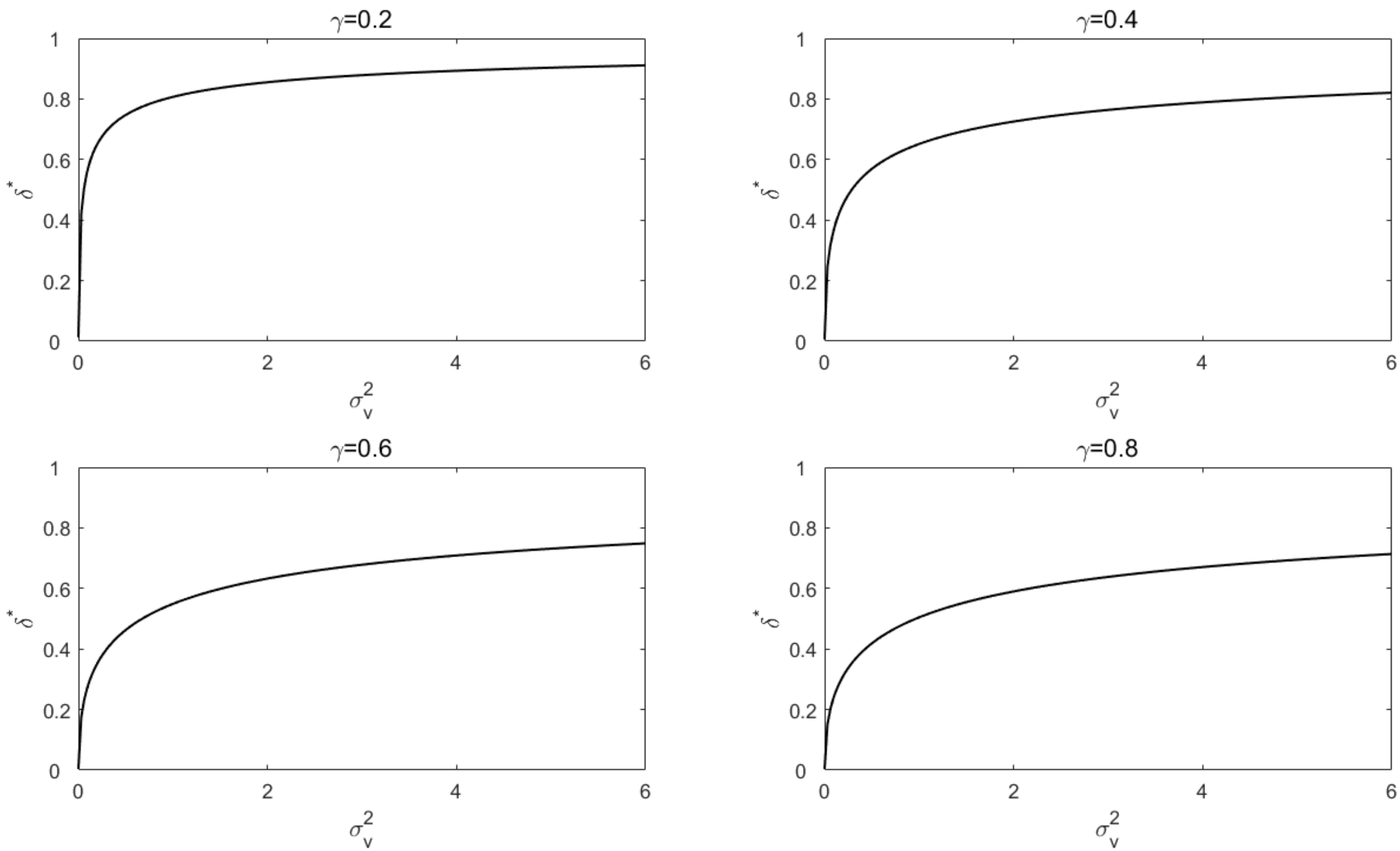
This figure depicts the time line of the baseline model (starting from date $t = 0$) and the signaling model (starting from date $t = -1$).

Figure 15: Optimal Signal Weight and Short-termism



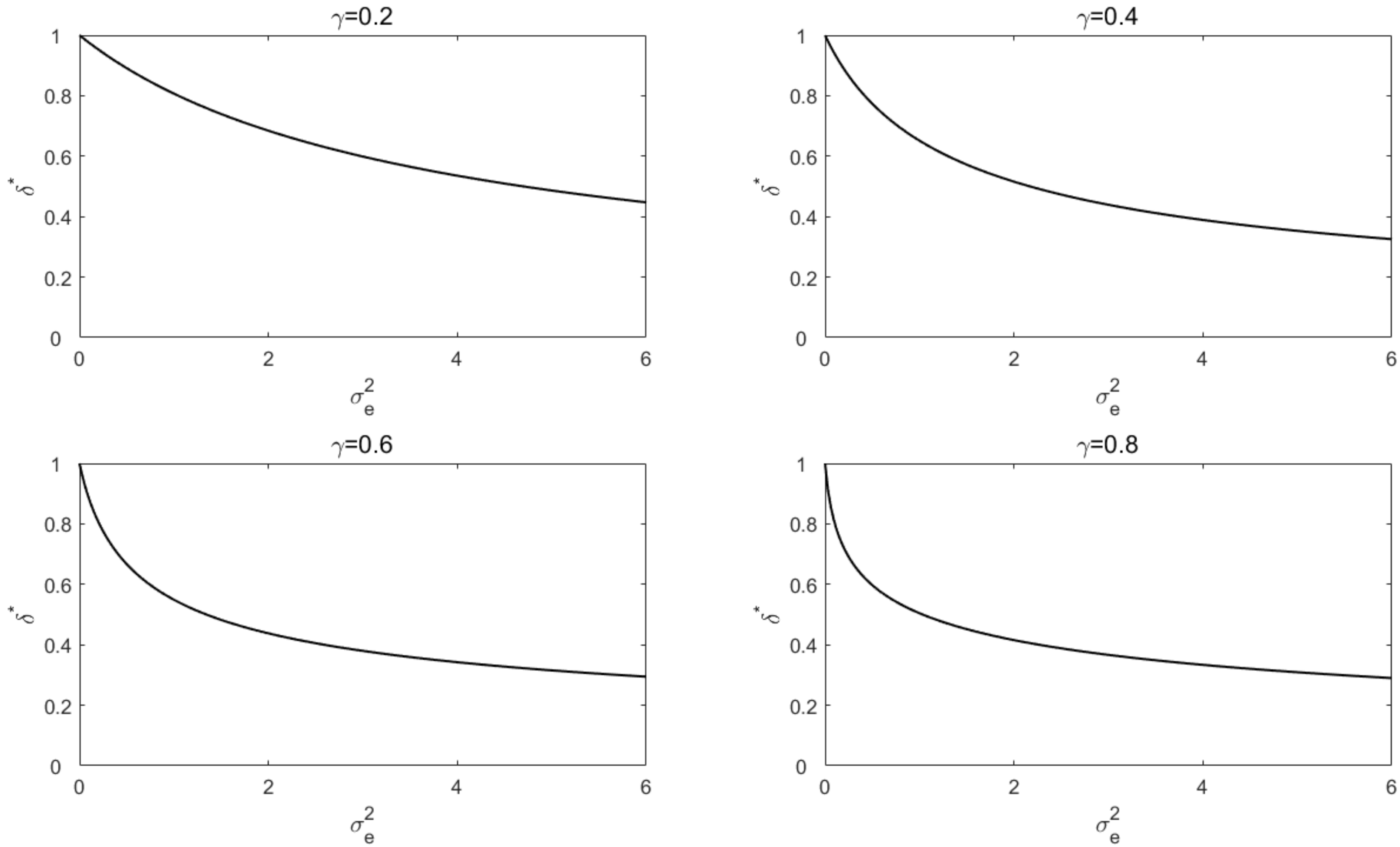
This figure plots, for four different combinations of σ_e^2 and σ_v^2, the optimal signal weight as a function of γ—the weight of short-term gain in the speculator's objective function, when $\sigma_z^2 = 1$. In each of the four graphs, the solid line represents $\delta^*(\gamma)$ and the dashed line is the 45° line.

Figure 16: Optimal Signal Weight and Fundamental Uncertainty



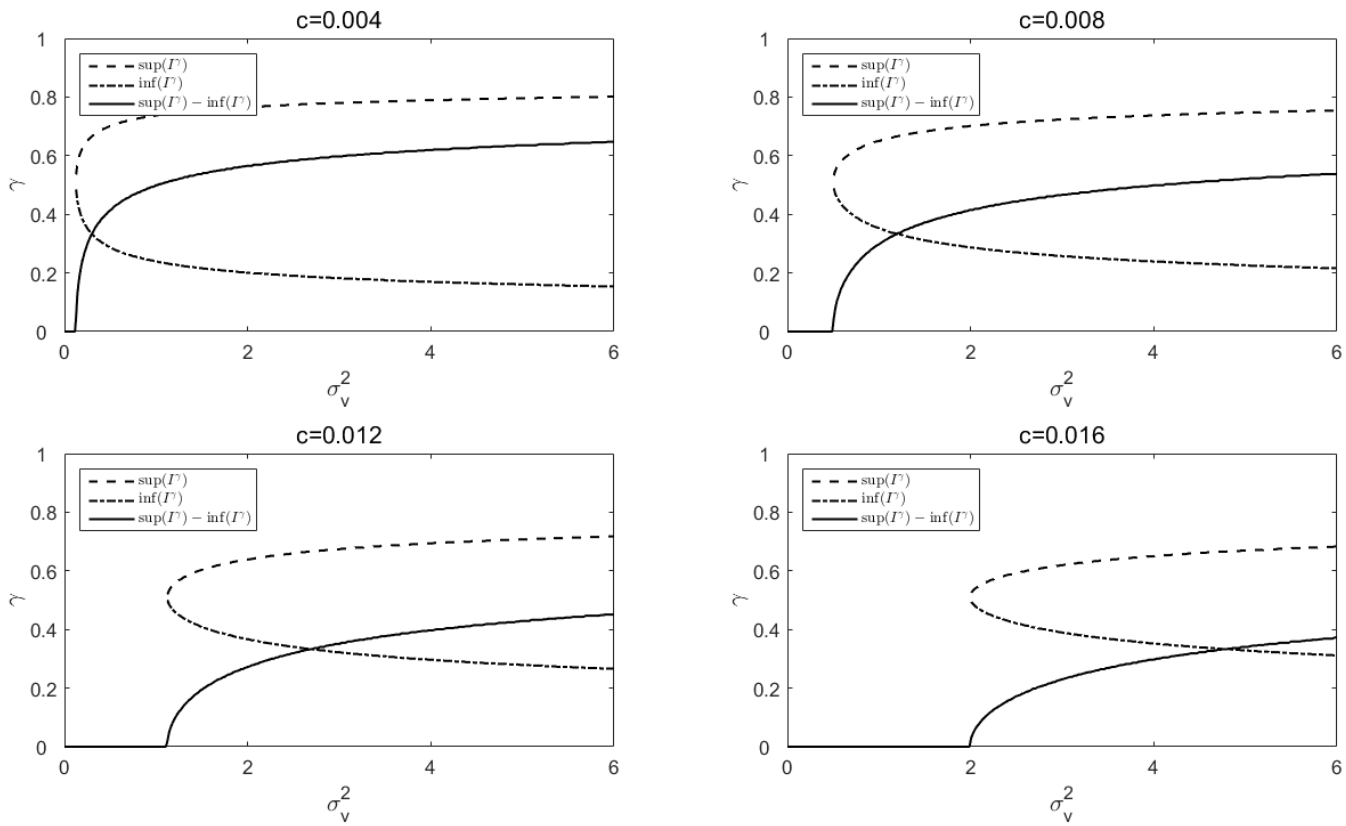
This figure plots, for four different γ's, the optimal signal weight as a function of σ_v^2—information asymmetry surrounding the fundamental, when $\sigma_e^2 = 1$ and $\sigma_z^2 = 1$.

Figure 17: Optimal Signal Weight and Endowment Uncertainty



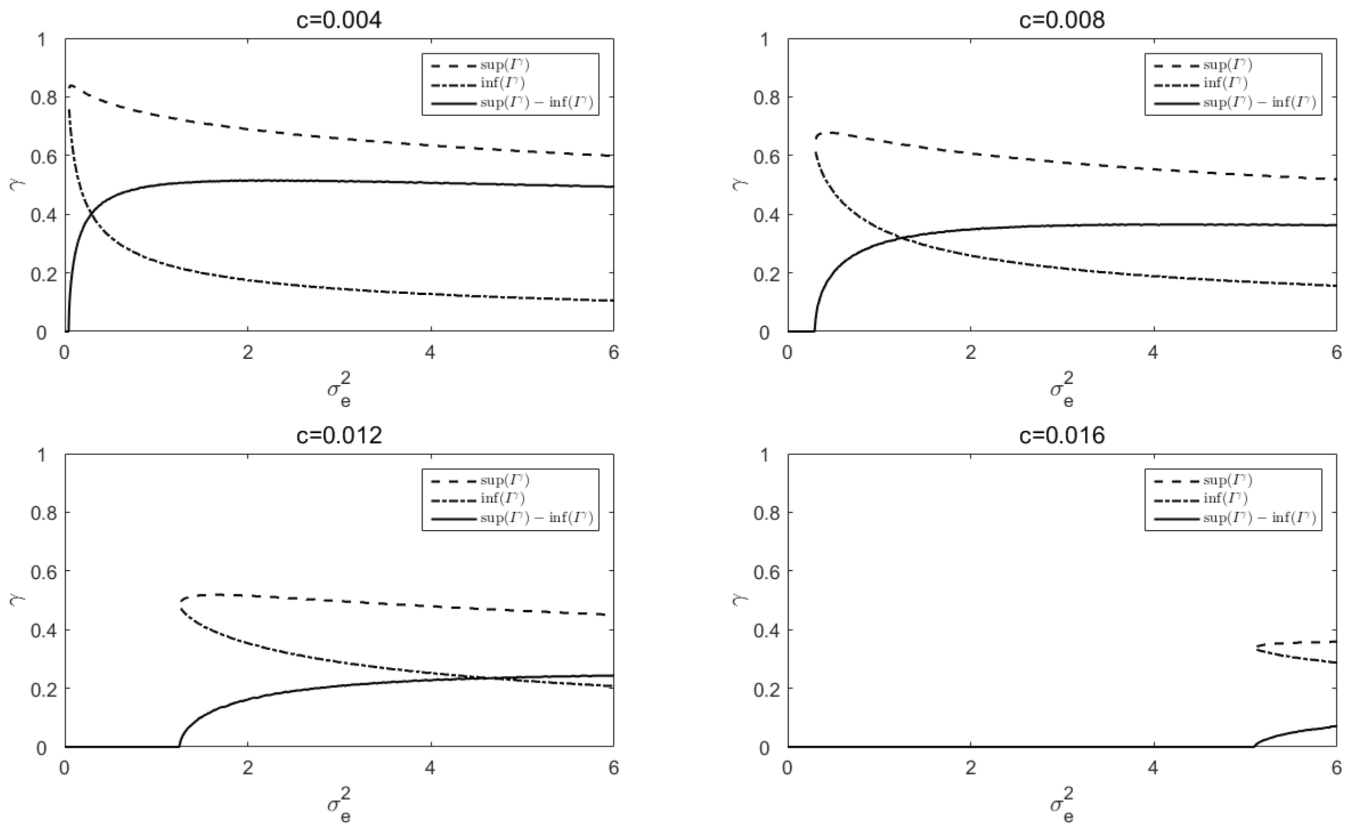
This figure plots, for four different γ's, the optimal signal weight as a function of σ_e^2—information asymmetry surrounding the speculator's initial position, when $\sigma_v^2 = 1$ and $\sigma_z^2 = 1$.

Figure 18: Cost of Disclosure and Fundamental Uncertainty



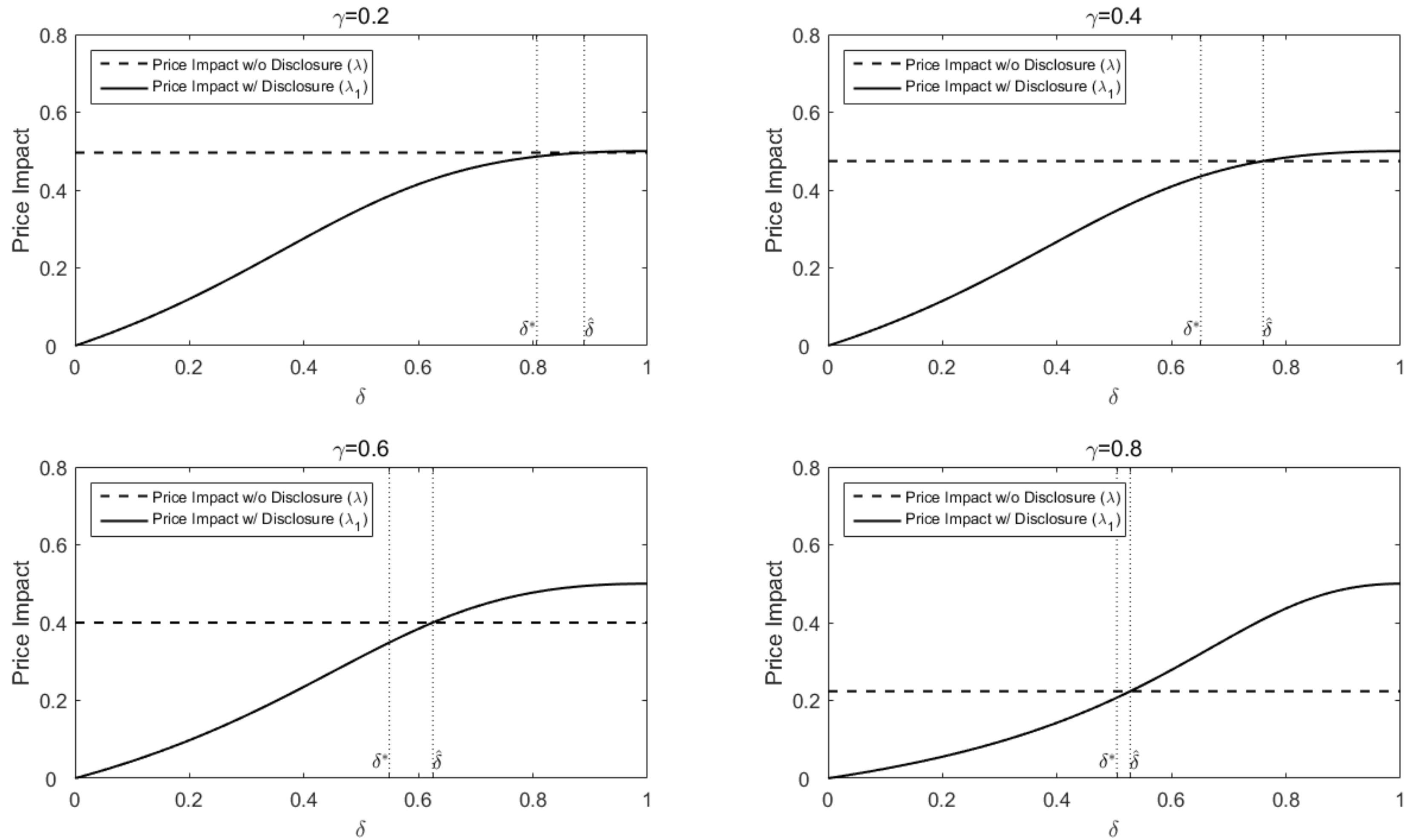
This figure plots, for four different values of a fixed disclosure cost c, the correspondence from σ_v^2 to I^γ, holding σ_e^2 and σ_z^2 fixed. $I^\gamma(c, \sigma_v^2, \sigma_e^2, \sigma_z^2)$ denotes the set of γ such that the speculator prefers disclosure (with an optimally chosen signal weight) to no disclosure. The two dashed lines represent upper and lower bounds for I^γ and the solid line represents the width of the interval $[\inf I^\gamma, \sup I^\gamma]$.

Figure 19: Cost of Disclosure and Endowment Uncertainty



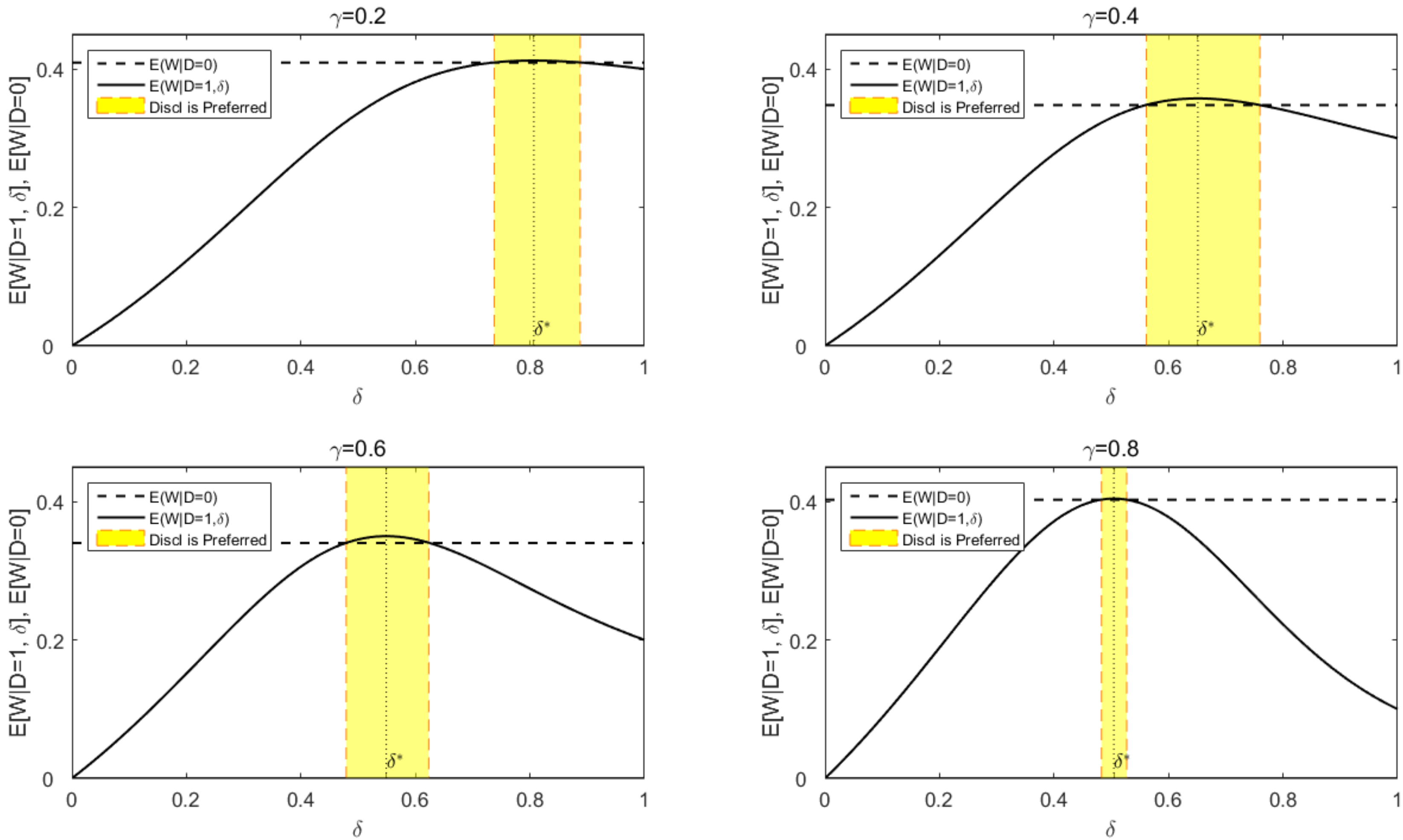
This figure plots, for four different values of a fixed disclosure cost c, the correspondence from σ_e^2 to I^γ, holding σ_v^2 and σ_z^2 fixed. $I^\gamma(c, \sigma_v^2, \sigma_e^2, \sigma_z^2)$ denotes the set of γ such that the speculator prefers disclosure (with an optimally chosen signal weight) to no disclosure. The two dashed lines represent upper and lower bounds for I^γ and the solid line represents the width of the interval $[\inf I^\gamma, \sup I^\gamma]$.

Figure 20: Signal Weight and Market Depth



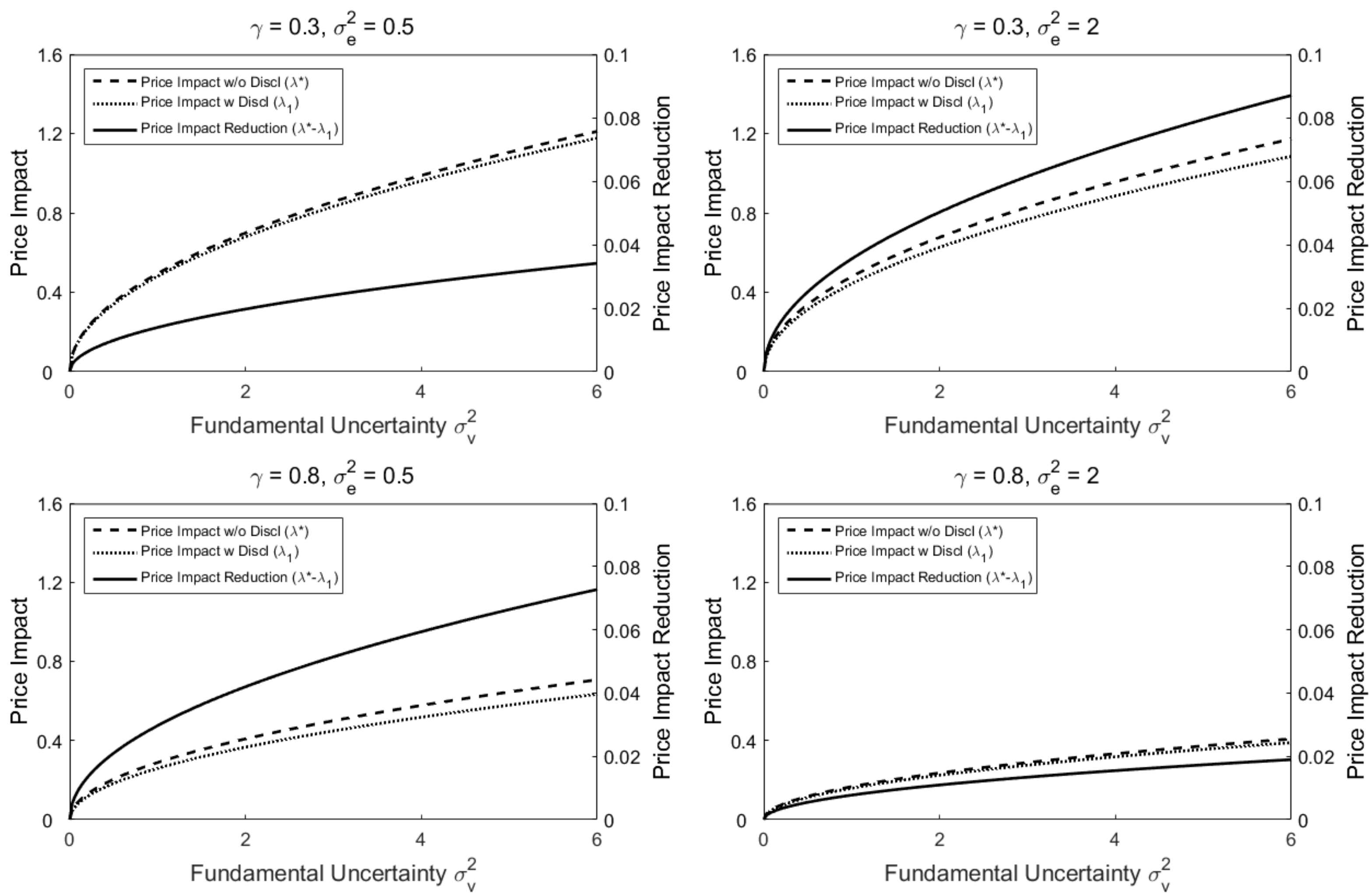
This figure plots, for different values of γ, equilibrium price impact as a function of signal weight δ, when $\sigma_v^2 = 1$, $\sigma_e^2 = 1$, and $\sigma_z^2 = 1$. Price impact is defined as how much the market clearing price changes in response to a unit increase in order flow. In each of the four graphs, the solid line represents price impact in the signaling equilibrium (λ_1), whereas the dashed line plots price impact in the non-signaling/baseline equilibrium (λ^*).

Figure 21: Gains from PBT and PBD



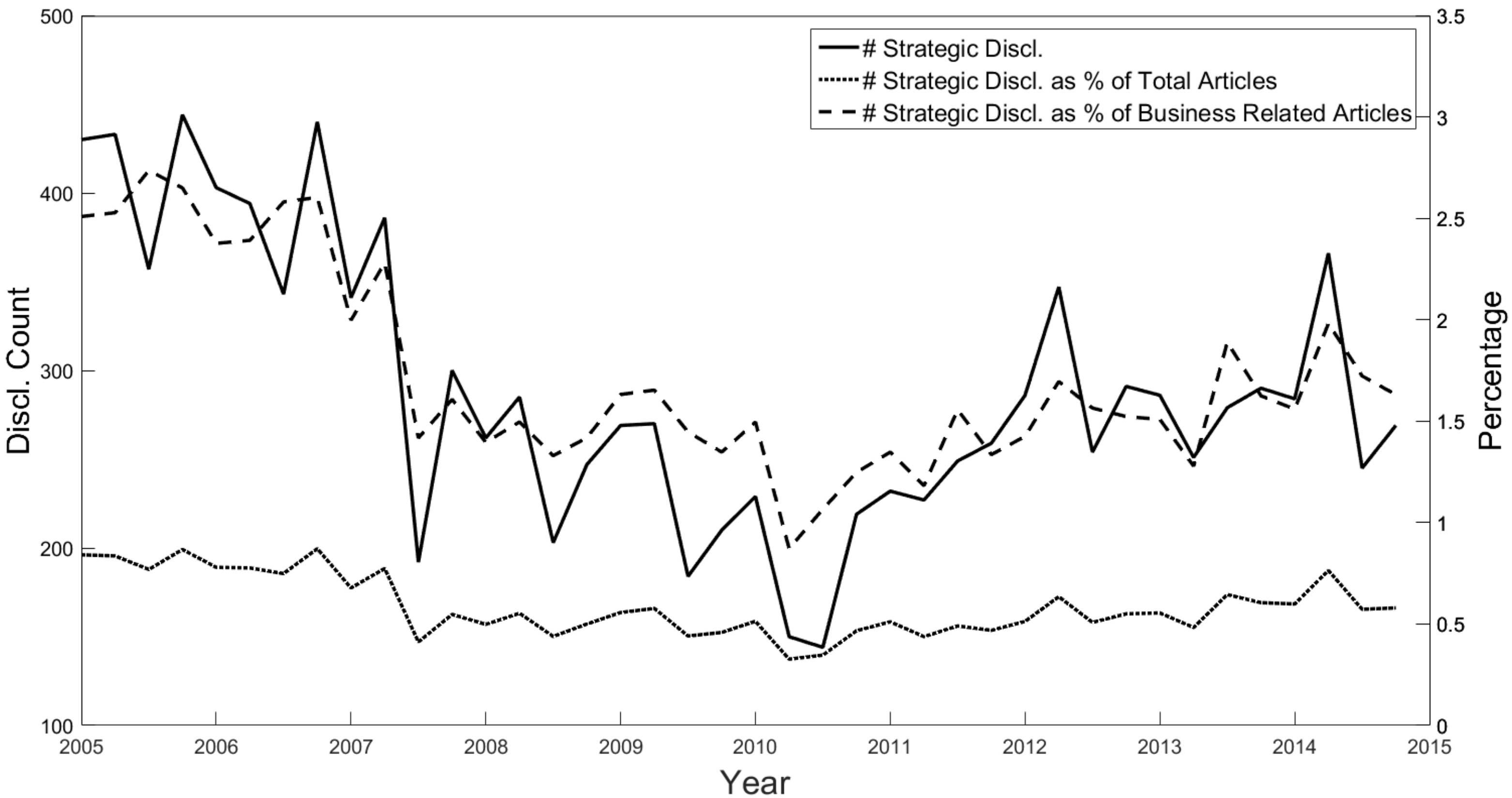
This figure plots, for four different values of γ, the speculator's *ex ante* expected value function as a function of the speculator's signal weight δ, when $\sigma_v^2 = 1$, $\sigma_e^2 = 1$, and $\sigma_z^2 = 1$. In each graph, the solid line and the horizontal dashed line represent the speculator's *ex ante* expected value function in the signaling equilibrium ($\mathrm{E}\left[W|D = 1, \delta\right]$) and baseline equilibrium ($\mathrm{E}\left[W|D = 0\right]$), respectively. The vertical dotted line marks the optimal signal weight δ^*, and the shaded area marks the range where disclosure is preferred to no disclosure.

Figure 22: Price Impact and Fundamental Uncertainty



This figure plots, for different combinations of γ and σ_e^2, the relation between equilibrium price impact and fundamental uncertainty σ_v^2. Plotted against the left scale, the dashed and dotted lines are the price impact in the baseline equilibrium (λ^*) and the signaling equilibrium (λ_1), respectively. The solid line, on the right scale, is the reduction in price impact from the baseline equilibrium to the signaling equilibrium in correspondence with optimal signal weight δ^*, i.e., $\lambda^* - \lambda_1$.

Figure 23: Number of "Potentially Strategic" Disclosures Over Time



This figure plots the total number of "potentially strategic" disclosures (as defined in Section II.3.1) about S&P 1500 non-financial firms (left axis, solid line), and as a fraction (right axis) of the total number of business (dashed line) or all articles (dotted line) printed in WSJ, FT and NYT, over each quarter of the sample period 2005–2014.

Figure 24: Monetary Policy Shocks and Bank Equity Returns

This figure provides the scatter plot of the bank industry excess returns against the daily change in two-year Treasury yield on FOMC days from 1994 to 2017. The excess return is defined as the different between bank industry index return and the market return. The sample of the upper panel is when the Federal Funds rate is above 2% and the sample of the lower panel is when the Federal Funds rate is below 2%. We exclude observations during the burst of dot-com bubble (2000-2001) and the subprime financial crisis (2007-2009) because the stock returns are extremely volatile. The bank industry stock returns are retrieved from Kenneth French's website and the two-year Treasury yield is retrieved from FRED database of the Federal Reserve Bank of St. Louis.

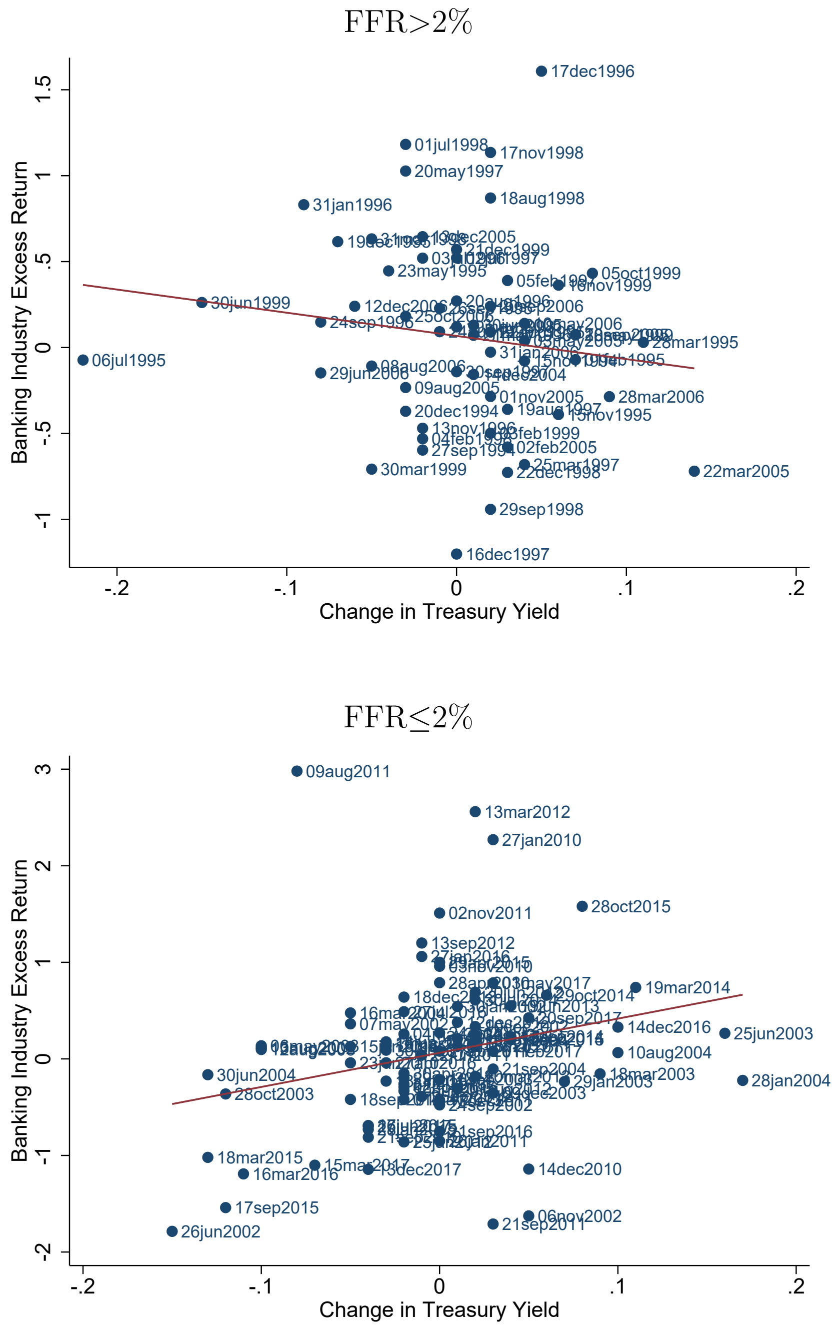


Figure 25: The Average Deposit Spread and the Fed Funds Rates

This figure plots the non-parametric relationship between the Fed Funds rate and the average deposit spread of U.S. banks. The sample is from 1985 to 2017. The data frequency is quarterly. The deposit spread is constructed using the Call report and the Fed Funds rate is retrieved from FRED database of the Federal Reserve Bank of St. Louis.

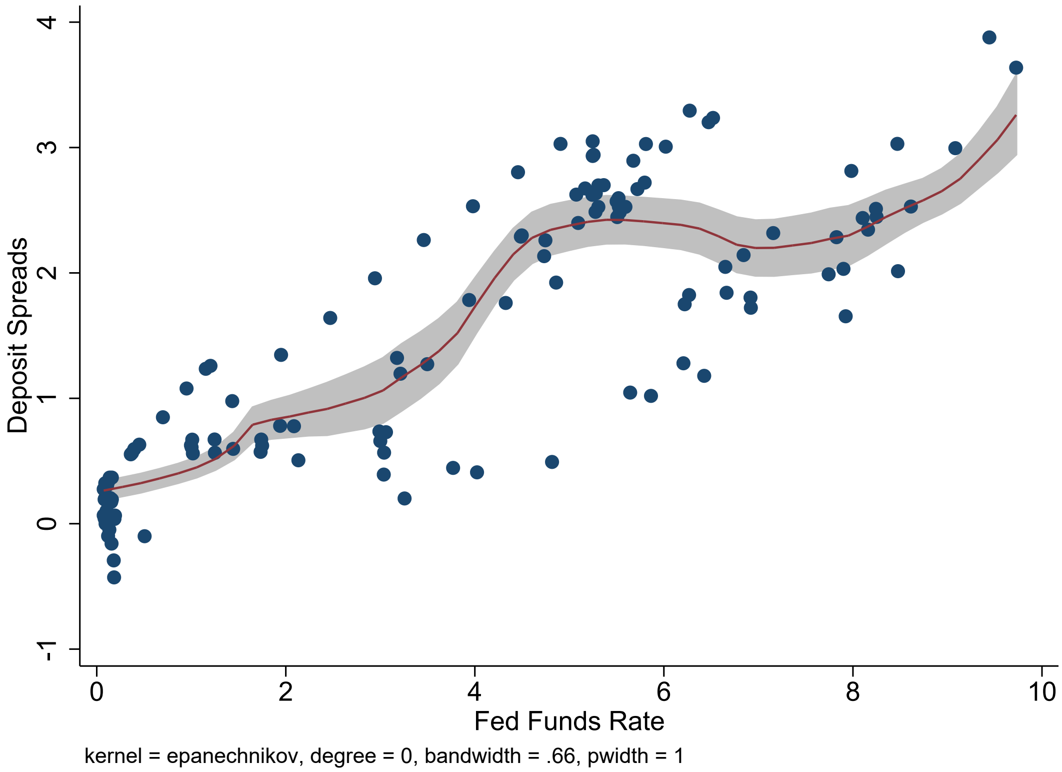


Figure 26: Loan-to-Deposit Ratios for U.S. Banks

This figure plots the loan-to-deposit ratio of U.S. banks after the start of five recessions from 1973 to 2017. The x-axis is the month since the start of recession and the y-axis the loan-to-deposit ratio. We normalize the ratio in month 0 to 1. We plot the path of the ratio until the ratio recovers to the pre-recession level. The data is retrieved from FRED database of the Federal Reserve Bank of St. Louis.

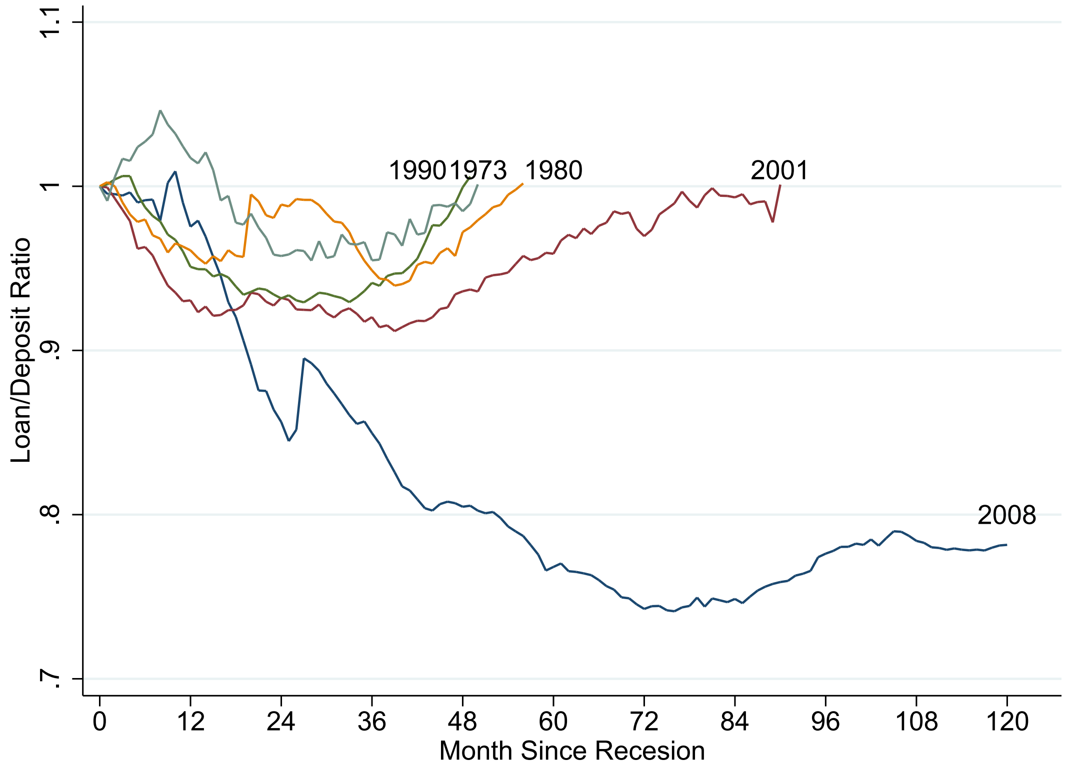


Figure 27: Timeline within a Period

This figure plots the loan-to-deposit ratio of U.S. banks after the start of five recessions from 1973 to 2017. The x-axis is the month since the start of recession and the y-axis the loan-to-deposit ratio. We normalize the ratio in month 0 to 1. We plot the path of the ratio until the ratio recovers to the pre-recession level. The data is retrieved from FRED database of the Federal Reserve Bank of St. Louis.

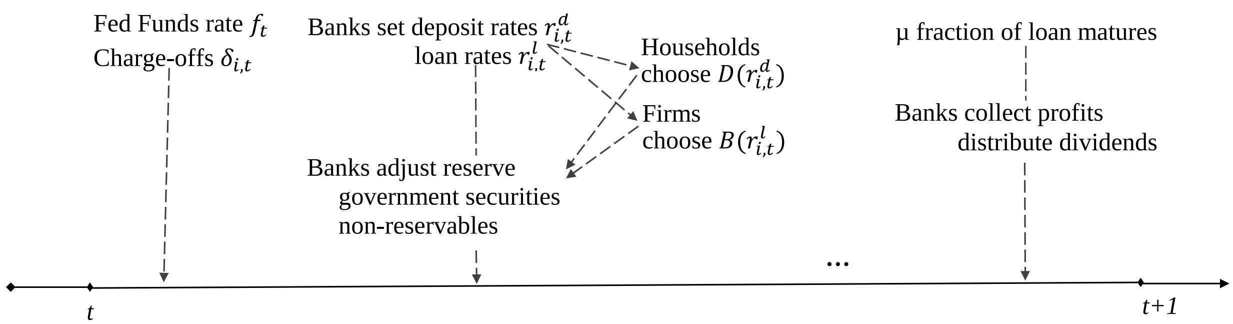


Figure 28: Fed Funds Rate and Bank Characteristics

This figure illustrates how bank capital and optimal lending vary with the Fed Funds rate. Banks' optimal lending is calculated under two alternative cases: the baseline line where banks are subject to the capital regulation and an alternative unconstrained case where the capital regulation is removed. The Fed Funds rate is on the x-axis; bank characteristics, scaled by their respective steady state values (when the Fed funds rate is 0.02), is on the y-axis.

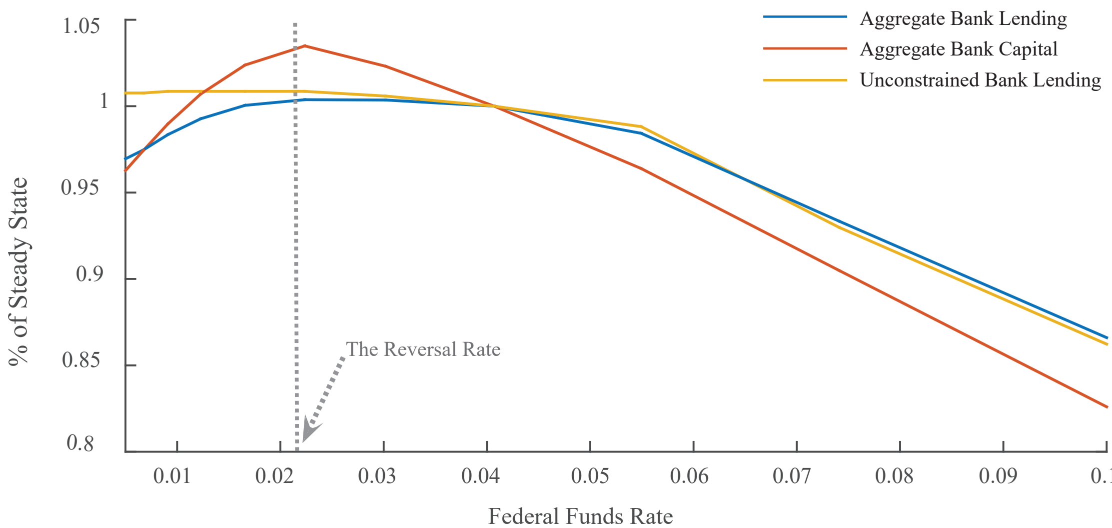
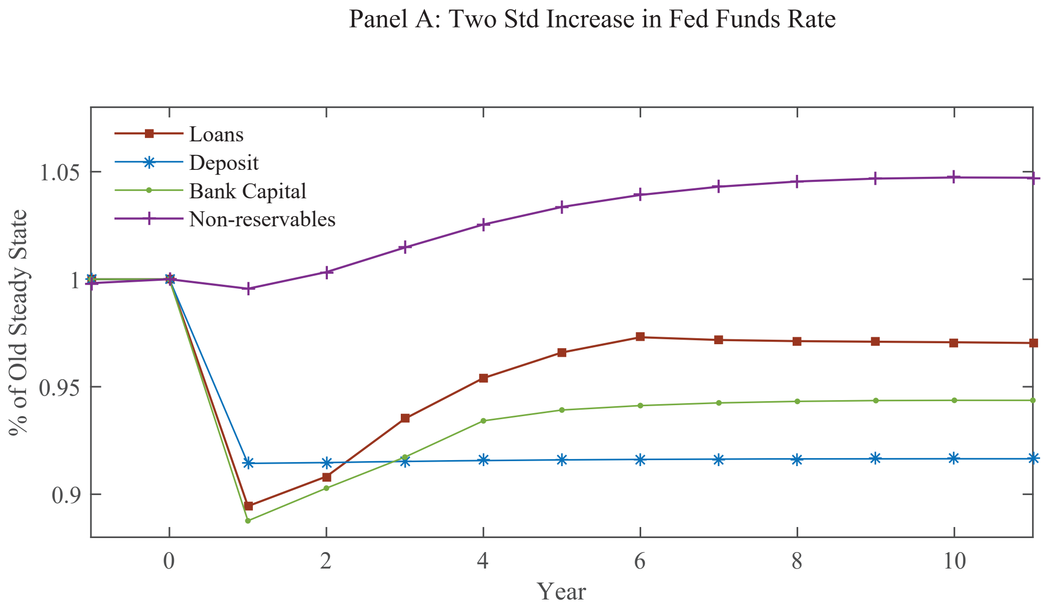
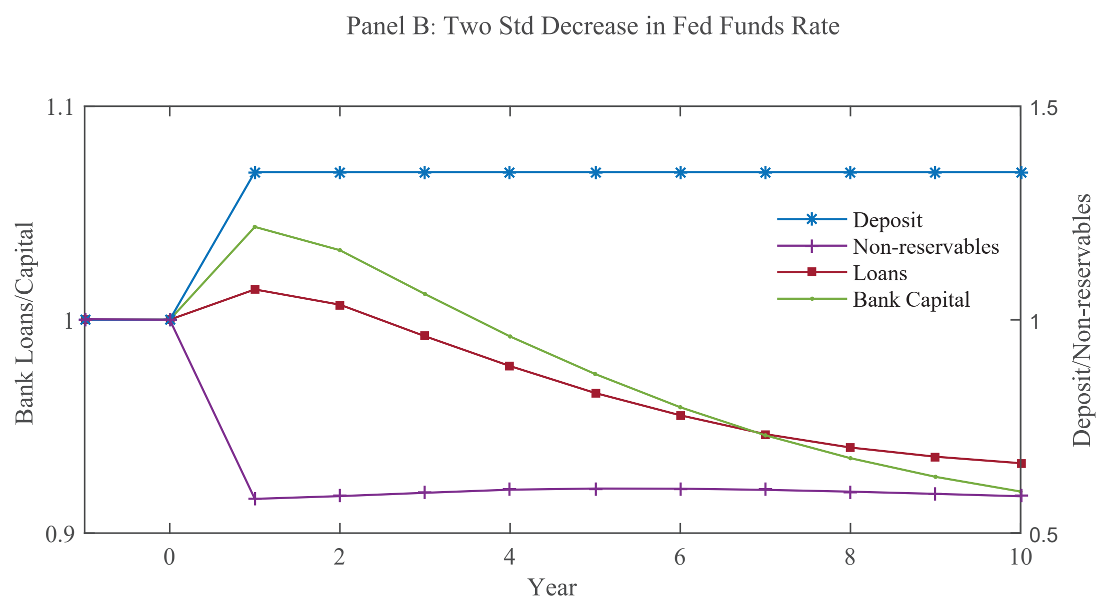


Figure 29: Impulse Response to Fed Funds Rate Shocks

This figure illustrates banks' impulse response to Fed fund rate shocks. The economy starts at Year 0 when it is in the old steady state with the FFR equal to 0.02; In Year 1, the FFR either increases or decreases by two standard deviations, and it stays at that level afterwards until the economy reaches the new steady state. Each variable in the graph is scaled by the level in the old steady state (when FFR = 0.02).





APPENDICES

Appendix A: Proofs of Propositions

Proof of Proposition 1

The outline of the proof is as follows. First, by applying Theorem 9.2 of Stokey and Lucas (1989), I show that the fixed point of the Bellman Equation (10) is the solution to the sequential problem where the firm's objective is to maximizes its discounted future cash flows. Next, I apply Blackwell's Theorem to show that the operator defined by equation (10) is a contraction mapping. Contraction mapping implies that the fixed point to equation (10) is unique, provided that the payoff function is bounded and the state space is compact, so the set of legitimate value functions forms a complete metric space. This proof proceeds in two steps. First, I consider a modified problem where I restrict the state variables to a compact space. Second, I show this restriction is without loss of generality.

Firm's Problem Confined to a Compact State Space

I define the operator T associated with the firm's problem as:

$$Tg(a_{beg}, z, s) = \max_{a_{end}, q, \Delta s} F(a_{beg}, z, s, a_{end}, q, \Delta s) + \frac{1}{1+r_f}\mathbb{E}g(a'_{beg}, z', s'), \tag{91}$$

where

$$F(a_{beg}, z, s, a_{end}, q, \Delta s) = d\big[1 + \lambda \mathbb{1}\{d < 0\}\big], \tag{92}$$

$$d = a_{beg} - a_{end} - q - p\Delta s - \chi(\Delta s), \tag{93}$$

$$0 \leq q \leq s + \Delta s, \tag{94}$$

$$a_{end} \geq \underline{a} \tag{95}$$

$$a'_{beg} = (1-\tau)\big[f(\epsilon', z') + a_{end} r_f\big] + a_{end}, \tag{96}$$

$$z' = (1 - \delta \times I_\delta)z + \psi\eta q \tag{97}$$

$$s' = (1-\eta)q + i'. \tag{98}$$

The operator $\mathbb{E}(\cdot)$ is taken over realizations of ϵ', i', and I'_δ. Since all three shocks are i.i.d., $\mathbb{E}(\cdot)$ satisfies the Feller property. I consider the value range of the firm's state and policy variables. Note that z and s have natural lower bounds of zero. Additionally, a_{beg} is bounded from below due to the borrowing constraint and the facts that z and ϵ' are bounded from below and that the function $F(\cdot)$ is continuous. For now, I impose the assumption that both a_{beg} and s are bounded from above. The upper bound on s then implies an upper bound on z. In addition, the fact that a_{beg}, z and s are bounded implies that the choice variables a_{end}, q and Δs are also bounded. Accordingly, let $\Omega \subset [\inf a_{beg}, \sup a_{beg}] \times [\inf z, \sup z] \times [\inf s, \sup s]$ be the compact state space, and let $\Phi(a_{beg}, z, s) \subset [\inf a_{end}, \sup a_{end}] \times [\inf q, \sup q] \times [\inf \Delta s, \sup \Delta s]$ be the compact choice set given state (a_{beg}, z, s). I partition the choice set as follows:

$$\Phi^1 = \Phi(a_{beg}, z, s) \cap \big\{|\Delta s| > 0\big\}, \tag{99}$$

and

$$\Phi^0 = \Phi(a_{beg}, z, s) \cap \big\{|\Delta s| = 0\big\}. \tag{100}$$

The operator T can thus be rewritten as:

$$Tg(a_{beg}, z, s) = \max \left\{ T^1 g(a_{beg}, z, s), T^0 g(a_{beg}, z, s) \right\}, \tag{101}$$

where:

$$T^j g(a_{beg}, z, s) = \max_{\{a_{end}, q, \Delta s\} \in \Phi^j} F(a_{beg}, z, s, a_{end}, q, \Delta s) + \frac{1}{1+r_f} \mathbb{E} g(a'_{beg}, z', s'), \quad j \in \{0, 1\}. \tag{102}$$

Because $F(.)$ is continuous in each subset $\Phi^j,\ j \in \{0,1\}$, $\Phi^j,\ j \in \{0,1\}$ is compact, and the operator $\mathbb{E}(\cdot)$ has the Feller property, for any continuous and bounded function g, $T^j,\ j \in \{0,1\}$ is continuous and bounded by the Theorem of the Maximum. It then follows from equation (101) that Tg is also continuous and bounded. Therefore, T maps continuous bounded functions to continuous bounded functions.

Next I apply Blackwell's Theorem for contraction mapping. Applying the Theorem requires establishing two conditions: the monotonicity condition and the discounting condition. Let $g_1 \leq g_2$ be two continuous bounded functions. Then:

$$\begin{aligned} Tg_1(a_{beg}, z, s) &= F(a_{beg}, z, s, a^*_{end}, q^*, \Delta s^*) + \mathbb{E} g_1(a'_{beg}, z', s') \\ &\leq F(a_{beg}, z, s, a^*_{end}, q^*, \Delta s^*) + \mathbb{E} g_2(a'_{beg}, z', s') \\ &\leq Tg_2(a_{beg}, z, s), \end{aligned}$$

where:

$$(a^*_{end}, q^*, \Delta s^*) = \arg \max_{a_{end}, q, \Delta s} F(a_{beg}, z, s, a_{end}, q, \Delta s) + \frac{1}{1+r_f} \mathbb{E} g_1(a'_{beg}, z', s'), \tag{103}$$

are the optimal policies under g_1. It then follows that $Tg_1 \leq Tg_2$. This establishes the monotonicity condition. Next, it is straight forward that for any $c > 0$, there is $T(g + c) = Tg + \frac{c}{1+r_f}$. This establishes the discounting condition. Therefore, Blackwell's Theorem implies T is a contraction mapping. It follows that there is a unique fixed point v to the operator T, which by Theorem 9.2 of Stokey and Lucas (1989) is also the solution to the firm's sequential problem.

To show that v as defined in equation (10) is monotonic in a_{beg}, z and s, let $g(a_{beg}, z, s)$ be any bounded continuous and weakly increasing function. Let $a_{\text{beg},2} \geq a_{\text{beg},1}$, $z_2 \geq z_1$, and $q_2 \geq q_1$ be two sets of state variables, and let $a^*_{\text{end},1}, s^*_1, \Delta s^*_1$ be the optimal policies for the state $(a_{\text{beg},1}, z_1, q_1)$. Then:

$$\begin{aligned} Tg(a_{\text{beg},1}, z_1, q_1) &= F(a_{\text{beg},1}, z_1, q_1, a^*_{\text{end},1}, q^*_1, \Delta s^*_1) + \frac{1}{1+r_f} \mathbb{E}\left[g \middle| z_1, a^*_{\text{end},1}, q^*_1, \Delta s^*_1\right] \\ &\leq F(a_{\text{beg},2}, z_2, q_2, a^*_{\text{end},1}, q^*_1, \Delta s^*_1) + \frac{1}{1+r_f} \mathbb{E}\left[g \middle| z_1, a^*_{\text{end},1}, q^*_1, \Delta s^*_1\right] \\ &\leq F(a_{\text{beg},2}, z_2, q_2, a^*_{\text{end},1}, q^*_1, \Delta s^*_1) + \frac{1}{1+r_f} \mathbb{E}\left[g \middle| z_2, a^*_{\text{end},1}, q^*_1, \Delta s^*_1\right] \\ &\leq Tg(a_{\text{beg},2}, z_2, q_2). \end{aligned}$$

The first inequality follows from the fact that F is increasing in its first three arguments and the fact that $\Phi(a_{\text{beg},1}, z_1, q_1) \subset \Phi(a_{\text{beg},2}, z_2, q_2)$, i.e., any feasible choice in the state $(a_{\text{beg},1}, z_1, q_1)$ is also feasible in the state $(a_{\text{beg},2}, z_2, q_2)$. The second inequality obtains because g is monotonically increasing, and therefore:

$$g(a'_{\text{beg},1}, z'_1, q'_1) \leq g(a'_{\text{beg},2}, z'_2, q'_2), \tag{104}$$

for any realization of ϵ', i' and I'_δ, where:

$$a'_{\text{beg},j} = (1-\tau)\big[f(\epsilon', z'_j) + a^*_{\text{end},1} r_f\big] + a^*_{\text{end},1},\; z'_j = (1-\delta \times I_\delta) z_j + \psi\eta q^*_1,\; s' = (1-\eta) q^*_1 + i',\; j \in \{1,2\}. \tag{105}$$

The last inequality holds by definition of a maximum. Therefore, T maps from the set of monotonic functions into itself. Because the space of weakly monotonic, bounded and continuous functions is a complete metric space, by Corollary 1 to Theorem 3.2 of Stokey and Lucas (1989), the fixed point of the operator T is monotonically increasing.

The Original Problem

To show that the problem restricted to a compact state space is equivalent to the original problem, it suffices to show that the firm's optimal choice of a_{end} and Δs are bounded, and therefore the arbitrary upper bounds for a_{beg} and s are slack. The proof proceeds as follows.

First, suppose all the fixed costs are turned off, that is, $\chi_0 = 0$. By applying Corollary 1 to Theorem 3.2 of Stokey and Lucas (1989), it can be shown that the fixed point of T is weakly concave. Denote this fixed point by $\bar{v}$. Second, it is straight forward to show that $v \le \bar{v}$. Since v is bounded above by a concave function, it is never optimal to choose arbitrarily large Δs. Finally, the firm would never choose arbitrarily large amount of savings (a_{end}) due to the corporate tax on cash holdings. ■

Proof of Proposition 2

Proof of Part 1

Without equity issuance cost, the operator T associated with the firm's problem is given by equation (91)–(98), with $\lambda = 0$. In particular,

$$F(a_{beg}, z, s, a_{end}, q, \Delta s) = a_{beg} - a_{end} - q - p\Delta s - \chi(\Delta s), \tag{106}$$

where the function $F(\cdot)$ is given by equation (92). Denote by $v_0(\cdot)$ the firm's value function in the absence of issuance cost. For any z, s and $a_{\text{beg},1} \ne a_{\text{beg},2}$, let $a^*_{\text{end},j}$, q^*_j and Δs^*_j be the firm's policy functions in the state $(a_{\text{beg},j}, z, s)$, $j = 1, 2$. There is:

$$\begin{aligned}
v_0(a_{\text{beg},1}, z, s) &= F(a_{\text{beg},1}, z, s, a^*_{\text{end},1}, q^*_1, \Delta s^*_1) + \frac{1}{1+r_f}\mathbb{E}v(a'_{\text{beg},1}, z'_1, q'_1) \\
&= a_{\text{beg},1} - a_{\text{beg},2} + F(a_{\text{beg},2}, z, s, a^*_{\text{end},1}, q^*_1, \Delta s^*_1) + \frac{1}{1+r_f}\mathbb{E}v(a'_{\text{beg},1}, z'_1, q'_1) \\
&\le a_{\text{beg},1} - a_{\text{beg},2} + F(a_{\text{beg},2}, z, s, a^*_{\text{end},2}, q^*_2, \Delta s^*_2) + \frac{1}{1+r_f}\mathbb{E}v(a'_{\text{beg},2}, z'_2, q'_2) \\
&= a_{\text{beg},1} - a_{\text{beg},2} + v_0(a_{\text{beg},2}, z, s),
\end{aligned} \tag{107}$$

where $a'_{\text{beg},j} = (1-\tau)\big[f(\epsilon', z'_j) + a^*_{\text{end},j} r_f\big] + a^*_{\text{end},j}$, $z'_j = (1 - I_\delta \times \delta) z + \psi\eta q^*_j$, and $q'_j = (1-\eta) q^*_j + i'$, $j = 1, 2$. The second line follows from the fact that $F(\cdot)$ is linear in a_{beg}, the third line follows from the fact that $a^*_{\text{end},2}$, q^*_2 and Δs^*_2 are the optimal policies in the state $(a_{\text{beg},2}, z, s)$, and the last line follows from the definition of an optimal policy. As the choices of $a_{\text{beg},1}$ and $a_{\text{beg},2}$ are arbitrary, there is also:

$$v_0(a_{\text{beg},2}, z, s) \le a_{\text{beg},2} - a_{\text{beg},1} + v_0(a_{\text{beg},1}, z, s). \tag{108}$$

equations (107) and (108) imply:

$$v_0(a_{\text{beg},1}, z, s) = (a_{\text{beg},1} - a_{\text{beg},2}) + v_0(a_{\text{beg},2}, z, s). \tag{109}$$

Because the choices of $a_{\text{beg},1}$, $a_{\text{beg},2}$, z, and s are arbitrary. There is:

$$v_0(a_{beg}, z, s) = a_{beg} + v_0(0, z, s) \equiv a_{beg} + u(z, s). \tag{110}$$

Since

$$\begin{aligned}(a^*_{end}, \Delta s^*, q^*) &= \arg \max_{a_{end},\Delta s,q} F(a_{beg}, z, s, a_{end}, q, \Delta s) + \frac{1}{1+r_f}\big[a_{end} + u(z', s')\big] \\ &= \arg \max_{a_{end},\Delta s,q} -q - p\Delta s - \chi(\Delta s) - \frac{r_f}{1+r_f} a_{end} + \frac{1}{1+r_f} u(z', s'),\end{aligned} \tag{111}$$

it follows immediately that $a^*_{end} = \underline{a}$, and Δs^* and q^* are independent of the state a_{beg}.

Proof of Part 2

Step 1: For any given choice q, define the lowest cost of obtaining q, via either in-house R&D, project trading or both, as:

$$c(q) = \min_{\Delta s} q + \chi(\Delta s) + p\Delta s, \tag{112}$$

such that

$$0 \le q \le s + \Delta s. \tag{113}$$

It is straight forward to show that:

$$\Delta s^*(q) = \begin{cases} \arg\max_{-s+q\le\Delta s<0} \big\{ -p\Delta s - \chi(\Delta s)\big\} & \text{if } q < s, \\ q - s & \text{if } q \ge s. \end{cases} \tag{114}$$

Define

$$\hat{\Delta s} = \arg\max_{\Delta s} \big\{ -p\Delta s - \chi^+(\Delta s)\big\}. \tag{115}$$

Given that $\chi(\Delta s) = \mathbb{1}\{\Delta s \ne 0\}\chi^+(|\Delta s|)$ and that $\chi^+(\cdot)$ is increasing and non-negative, $\hat{\Delta s}$ so defined is unique. Additionally, there is:

$$\arg \max_{-s+q\le\Delta s<0} \big\{ -p\Delta s - \chi(\Delta s)\big\} = \min\{\max\{\hat{\Delta s}, q - s\}, 0\}, \tag{116}$$

which monotonically increases with q. It then follows from equation (114) that $\Delta s^*(q)$ increases in q and is unique. Next, I show that $c(q)$ also increases in q. For any $q_1 < q_2$, let $\Delta s^*_1 = \Delta s^*(q_1)$ and $\Delta s^*_2 = \Delta s^*(q_2)$, then:

$$c(q_1) = q_1 + \chi(\Delta s^*_1) + p\Delta s^*_1 \le q_1 + \chi(\Delta s^*_2) + p\Delta s^*_2 < q_2 + \chi(\Delta s^*_2) + p\Delta s^*_2 = c(q_2), \tag{117}$$

where the first inequality follows from the definition of a minimum and the fact that $0 \le q_1 < q_2 \le s + \Delta s^*_2$.

Step 2: For any a_{end} and q, define the firm's end-of-period continuation value as:

$$u(a_{end}, z, q) = \frac{1}{1+r_f}\mathbb{E}v(a'_{beg}, z', s'), \tag{118}$$

where:

$$a'_{beg} = (1-\tau)\big[f(\epsilon', z') + a_{end}r_f\big] + a_{end}, \;\; z' = (1-\delta I_\delta)z + \psi\eta q, \;\; s' = (1-\eta)q + i'. \tag{119}$$

Step 3: Consider how a constrained firm's optimal project trading depends on its beginning-of-period net cash holdings. In particular, for any $a_{\text{beg},1} < a_{\text{beg},2}$, z, s such that the borrowing constraint binds (i.e., $a_{end} = \underline{a}$), let q_j^* and d_j^* be the firm's optimal policy in state $(a_{\text{beg},j}, z, s)$, $j = 1, 2$. Define the function $e(\cdot)$ as:

$$e(d) = (1 + \lambda \mathbb{1}\{d < 0\}) \times d. \tag{120}$$

Using $c(\cdot)$ as defined in equation (112), the firm's problem can be stated as:

$$v(a_{\text{beg},j}, z, s) = \max_q e\Big(a_{\text{beg},j} - \underline{a} - c(q)\Big) + u(\underline{a}, z, q),\ \ j = 1, 2. \tag{121}$$

Let the optimizers be q_1^* and q_2^* for $a_{\text{beg},1}$ and $a_{\text{beg},2}$, respectively. By definition of a maximum, there is:

$$e\Big(a_{\text{beg},1} - \underline{a} - c(q_1^*)\Big) + u(\underline{a}, z, q_1^*) > e\Big(a_{\text{beg},1} - \underline{a} - c(q_2^*)\Big) + u(\underline{a}, z, q_2^*), \tag{122}$$

and

$$e\Big(a_{\text{beg},2} - \underline{a} - c(q_2^*)\Big) + u(\underline{a}, z, q_2^*) > e\Big(a_{\text{beg},2} - \underline{a} - c(q_1^*)\Big) + u(\underline{a}, z, q_1^*). \tag{123}$$

Adding the two inequalities, there is:

$$e\Big[a_{\text{beg},1} - \underline{a} - c(q_1^*)\Big] - e\Big[a_{\text{beg},1} - \underline{a} - c(q_2^*)\Big] > e\Big[a_{\text{beg},2} - \underline{a} - c(q_1^*)\Big] - e\Big[a_{\text{beg},2} - \underline{a} - c(q_2^*)\Big]. \tag{124}$$

Because the function $e(\cdot)$ satisfy $\frac{\partial^2}{\partial d^2} e(d) \geq 0$, it must be that $q_2^* \geq q_1^*$. Hence q^* weakly increases in a_{beg}. It then follows from $\Delta s^*(q)$ being strictly increasing that the optimal net trading volume Δs^* is weakly increasing in the firm's beginning-of-period net cash holdings a_{beg}. ■

Proof of Proposition 3

Define the flow function as:

$$F^{\chi}(a_{beg}, z, s, a_{end}, q) = e\Big[a_{beg} - a_{end} - c(q)\Big], \tag{125}$$

where the functions $c(\cdot)$ and $e(\cdot)$ are defined by equations (112) and (120), respectively. The superscript χ denotes the transaction cost function $\chi(\Delta s)$. It is straight forward to show that for any $\chi_1 \leq \chi_2$, there is $F^{\chi_1}(a_{beg}, z, s, a_{end}, q) \geq F^{\chi_2}(a_{beg}, z, s, a_{end}, q)$. Let $v^{\chi}(a_{\text{beg},0}, z_0, q_0)$ be the firm's value function, where, again, I use the superscript χ to emphasize the dependence of the value function on the transaction cost function $\chi(\Delta s)$. There is:

$$v^{\chi}(a_{\text{beg},0}, z_0, q_0) = \mathbb{E}\Bigg[\sum_{t=0}^{\infty} \Big(\frac{1}{1 + r_f}\Big)^t F^{\chi}(a_{\text{beg},t}, z_t, q_t, a^{\chi}_{\text{end},t}, q^{\chi}_t)\Bigg]. \tag{126}$$

$a^{\chi}_{\text{end},t}$ and q^{χ}_t, $t = 0, 1, ...$ denote the firm's optimal policies under transaction cost specification χ.

It follows immediately that:

$$v^{\chi_2}(a_{\text{beg},0}, z_0, q_0) = \mathbb{E}\Big[\sum_{t=0}^{\infty}\Big(\frac{1}{1+r_f}\Big)^t F^{\chi_2}(a_{\text{beg},t}, z_t, q_t, a^{\chi_2}_{\text{end},t}, q^{\chi_2}_t)\Big] \tag{127}$$
$$\leq \mathbb{E}\Big[\sum_{t=0}^{\infty}\Big(\frac{1}{1+r_f}\Big)^t F^{\chi_1}(a_{\text{beg},t}, z_t, q_t, a^{\chi_2}_{\text{end},t}, q^{\chi_2}_t)\Big]$$
$$\leq \mathbb{E}\Big[\sum_{t=0}^{\infty}\Big(\frac{1}{1+r_f}\Big)^t F^{\chi_1}(a_{\text{beg},t}, z_t, q_t, a^{\chi_1}_{\text{end},t}, q^{\chi_1}_t)\Big] = v^{\chi_1}(a_{\text{beg},0}, z_0, q_0).$$

This proves that $v^{\chi}(\cdot)$ decreases with χ, for any state (a_{beg}, z, s). ■

Proof of Proposition 5

Conjecture that MM's pricing strategy takes the following form:

$$P_1 = P_0 + \lambda_1(\omega - \bar{\omega}) + \lambda_2(s - \bar{s}). \tag{128}$$

After observing v and e, the speculator's expected date $t = 1$ price is

$$\mathrm{E}\left[P_1 | v, e, D = 1, \delta\right] = P_0 + \lambda_1(x - \bar{x}) + \lambda_2(s - \bar{s}). \tag{129}$$

Plug this into her objective function:

$$\mathrm{E}\left[W | v, e, D = 1, \delta\right] = \gamma e[\lambda_1(x - \bar{x}) + \lambda_2(s - \bar{s})] + (1 - \gamma)[x(v - P_0 - \lambda_1(x - \bar{x}) - \lambda_2(s - \bar{s}))]. \tag{130}$$

This leads to the first order condition:

$$\frac{\partial}{\partial x}\mathrm{E}\left[W | v, e, D = 1, \delta\right] = \gamma e\lambda_1 + (1 - \gamma)[v - P_0 + \lambda_1\bar{x} - \lambda_2(s - \bar{s}) - 2\lambda_1 x] = 0. \tag{131}$$

Thus, defining $\beta = \frac{\gamma}{1-\gamma}$, there is

$$x^*(e, v) = \beta\bar{e} + \frac{\beta\lambda_1 - \delta\lambda_2}{2\lambda_1}(e - \bar{e}) + \frac{1 - (1 - \delta)\lambda_2}{2\lambda_1}(v - P_0). \tag{132}$$

The equilibrium is a fixed point: If the speculator optimizes with respect to the conjectured pricing rule (128) and MM makes inferences (according to the Bayesian rule) based on the speculator's optimization, then MM's expected liquidation value must be consistent with the conjectured pricing rule, i.e.,

$$P_1 = \mathrm{E}\left[v | s, \omega, D = 1, \delta\right]. \tag{133}$$

With normality, the conditional expectation can be expressed as

$$\mathrm{E}\left[v | s, \omega, D = 1, \delta\right] = P_0 + \sigma_v^2 \begin{bmatrix} 1 - \delta \\ 1 - (1 - \delta)\lambda_2 \end{bmatrix}' \times A^{-1} \times \begin{bmatrix} s - \bar{s} \\ 2\lambda_1(\omega - \bar{\omega}) \end{bmatrix}, \tag{134}$$

where $A =$

$$\begin{bmatrix} \delta^2\sigma_e^2 + (1-\delta)^2\sigma_v^2 & \delta(\beta\lambda_1 - \delta\lambda_2)\sigma_e^2 + (1-\delta)(1-(1-\delta)\lambda_2)\sigma_v^2 \\ \delta(\beta\lambda_1 - \delta\lambda_2)\sigma_e^2 + (1-\delta)(1-(1-\delta)\lambda_2)\sigma_v^2 & (\beta\lambda_1 - \delta\lambda_2)^2\sigma_e^2 + (1-(1-\delta)\lambda_2)^2\sigma_v^2 + 4\lambda_1^2\sigma_z^2 \end{bmatrix}. \tag{135}$$

Jointly solving Eq. (128) and Eq. (134) leads to

$$\lambda_1 = \frac{1}{\sqrt{\alpha^2\beta^2 + 4\frac{\sigma_z^2}{\sigma_v^2} + 4\alpha^2\frac{\sigma_z^2}{\sigma_e^2}}}, \tag{136}$$

and

$$\lambda_2 = -\frac{\lambda_1}{\delta}(\beta - \frac{4\lambda_1\sigma_z^2}{(\frac{1}{\alpha} - \beta\lambda_1)\sigma_e^2}). \tag{137}$$

■

Proof of Proposition 6

Proof of Part 1

In an equilibrium with disclosure, the speculator's *ex ante* expected value function is (e.g., Grossman and Stiglitz 1980; Vives 2008, Chapter 4)

$$\begin{aligned} &\mathrm{E}\left\{\mathrm{E}\left[W|v,e,D=1,\delta\right]\right\} = \mathrm{E}\left[W|D=1,\delta\right] \\ =&\gamma\,\mathrm{E}\left[(P_1-P_0)e|D=1,\delta\right] + (1-\gamma)\,\mathrm{E}\left[x^*(v-P_1)|D=1,\delta\right], \end{aligned} \tag{138}$$

by the law of iterated expectations. Substituting x^* and P_1 of Eqs. (30) and (31) into Eq. (138) and simplifying leads to

$$\mathrm{E}\left[W|D=1,\delta\right] = (1-\gamma)\lambda_1\sigma_z^2\frac{1+\alpha\beta\lambda_1}{1-\alpha\beta\lambda_1}, \tag{139}$$

where λ_1 is given by Eq. (32).

Proof of Part 2

In a baseline equilibrium, the speculator's *ex ante* expected value function is

$$\begin{aligned} &\mathrm{E}\left\{\mathrm{E}\left[W|v,e,D=0\right]\right\} = \mathrm{E}\left[W|D=0\right] \\ =&\gamma\,\mathrm{E}\left[(P_1-P_0)e|D=0\right] + (1-\gamma)\,\mathrm{E}\left[x^*(v-P_1)|D=0\right], \end{aligned} \tag{140}$$

by the law of iterated expectations. Substituting x^* and P_1 of Eqs. (25) and (26) into Eq. (140) and simplifying leads to

$$\mathrm{E}\left[W|D=0\right] = \frac{1-\gamma}{4\lambda^*}\left(\sigma_v^2 + \beta^2\lambda^{*2}\sigma_e^2\right), \tag{141}$$

where λ^* is given by Eq. (27).

Proof of Part 3

To establish weak inequality, it suffices to show that there exist a signal weight $\hat{\delta}$ such that

$$\mathrm{E}\left[W|D=1,\hat{\delta}\right] = \mathrm{E}\left[W|D=0\right]. \tag{142}$$

Consider the following candidate:

$$\hat{\delta} = \frac{1}{1+\hat{\alpha}}, \tag{143}$$

where

$$\hat{\alpha} = \lambda^* \beta \frac{\sigma_e^2}{\sigma_v^2} = \beta \sqrt{\frac{\sigma_v^2}{\beta^2 \sigma_e^2 + 4\sigma_z^2}} \frac{\sigma_e^2}{\sigma_v^2}. \tag{144}$$

Substituting the expression for $\hat{\alpha}$ into Eq. (35) and (36) establishes equality between the speculator's *ex ante* expected value function in the baseline and signaling equilibria.

To establish strict inequality, differentiate the speculator's *ex ante* expected value function in a signaling equilibrium with respect to the signal weight and evaluate the resulting derivative at $\hat{\delta}$. This gives

$$\left.\frac{\partial \,\mathrm{E}\left[W|D=1,\delta\right]}{\partial \delta}\right|_{\delta=\hat{\delta}} = -(1-\gamma)\sigma_z^2 \frac{\hat{\alpha}}{\hat{\delta}^2} \lambda_1^3 \frac{1+\alpha\beta\lambda_1}{1-\alpha\beta\lambda_1} (\beta^2 + 4\frac{\sigma_z^2}{\sigma_e^2}) \frac{2\sigma_z^2}{2\sigma_z^2 + \beta^2 \sigma_e^2} < 0. \tag{145}$$

Since the derivative is strictly less than zero, setting the signal weight to be slightly below the value $\hat{\delta}$ increases the speculator's *ex ante* expected value function to be strictly above that in the baseline equilibrium. ■

Proof of Proposition 7

For some realization (v, e, z), denote by $x^*(v, e, z)$ and $x^{**}(v, e, z)$ the speculator's trading strategies in the signaling equilibrium of the one-step game (SE) and the Perfect Bayesian Equilibrium of the two-step game (PBE), respectively. Additionally, denote by $P_1^*(v, e, z)$ and $P_1^{**}(v, e, z)$ MM's corresponding pricing rules. The two equilibria are equivalent if and only if (1) $x^*(v, e, z) = x^{**}(v, e, z)$ and (2) $P_1^*(v, e, z) = P_1^{**}(v, e, z)$.

Proof of Part 1

By construction, the speculator's trading strategy in PBE is the baseline trading strategy with MM's information set updated to reflect the information content of the signal. Thus Eq. (25) implies

$$x^{**} = \frac{\beta}{2}(e + \tilde{e}) + \frac{v - \tilde{v}}{2\tilde{\lambda}}, \tag{146}$$

where $\tilde{\lambda} = \sqrt{\frac{\tilde{\sigma}_v^2}{\beta^2 \tilde{\sigma}_e^2 + 4\sigma_z^2}}$ is the price impact derived from Eq. (27). By substituting Eq. (42) and (43) for $\tilde{\sigma}_v^2$ and $\tilde{\sigma}_e^2$ in Eq. (146), we get

$$\tilde{\lambda} = \lambda_1. \tag{147}$$

Intuitively, for SE and PBE to be equivalent, they must induce the same price impact.

Finally, in Eq. (146), replace $\tilde{v}$ and $\tilde{e}$ by the right hand sides of Eq. (40) and (41), respectively, and use the fact that $\tilde{\lambda} = \lambda_1$. There is

$$x^{**}(v, e, z) = \frac{v - P_0}{2\lambda_1} + \frac{\beta}{2}(e + \bar{e}) + \frac{1}{2\delta}[\beta - \frac{4\lambda_1}{\frac{1}{\alpha} - \lambda_1 \beta} \frac{\sigma_z^2}{\sigma_e^2}](s - \bar{s}) = x^*(v, e, z). \tag{148}$$

The last equality follows from Eq. (25) and the fact that $\frac{1}{2\delta}[\beta - \frac{4\lambda_1}{\frac{1}{\alpha} - \lambda_1\beta} \frac{\sigma_z^2}{\sigma_e^2}] = -\frac{\lambda_2}{2\lambda_1}$, as implied by Eq. (33).

Proof of Part 2

The equilibrium pricing rule in PBE is the baseline pricing rule, where MM's information set is updated to reflect the information content of the signal. By Eq. (26),

$$P_1^{**}(v,e,z) = \tilde{v} + \tilde{\lambda}(\omega - \tilde{\omega}), \tag{149}$$

where $\tilde{\omega} = \tilde{x} = \beta\tilde{e}$. Substituting Eq. (40) and (41) for $\tilde{v}$ and $\tilde{e}$, respectively, and using the fact that $\lambda_1 = \tilde{\lambda}$, there is

$$P_1^{**}(v,e,z) = P_0 + \lambda_1(\omega - \bar{\omega}) - \frac{\lambda_1}{\delta}[\beta - \frac{4\lambda_1}{\frac{1}{\alpha} - \lambda_1\beta}\frac{\sigma_z^2}{\sigma_e^2}](s - \bar{s}). \tag{150}$$

Lastly, substituting in Eq. (33) yields $P_1^{**}(v,e,z) = P_1^{*}(v,e,z)$. ■

Proof of Corollary 1

Proof of Part 1

Note that $\lambda_1 = \tilde{\lambda} = \frac{\tilde{\sigma}_v}{2\sqrt{\beta^2\tilde{\sigma}_e^2 + \sigma_z^2}}$. Thus Eq. (42) and (43), along with the facts that $\tilde{\sigma}_v^2$ increases with δ and that $\tilde{\sigma}_e^2$ decreases with δ imply that λ_1 is increasing in δ.

Proof of Part 2

If the speculator commits to the signal weight $\delta = \hat{\delta}$ (Eq. (143)), it is straight forward to show that the price impact in the signaling equilibrium equates the price impact in the baseline equilibrium—$\lambda_1 = \lambda^*$. It then follows immediately from Part 1 of Corollary (1) that Part 2 holds.

Proof of Part 3

We first consider a necessary condition for δ such that the speculator is better-off by committing to disclose a signal. Differentiating the speculator's *ex ante* expected value function $\mathrm{E}\left[W|D=1,\delta\right]$ with respect to δ, there is

$$\frac{\partial\,\mathrm{E}\left[W|D=1,\delta\right]}{\partial\delta} = (1-\gamma)\sigma_z^2\frac{2\alpha}{\delta^2}\lambda_1^3\frac{1+\alpha\beta\lambda_1}{1-\alpha\beta\lambda_1}\left[-\frac{4\beta}{\alpha}\frac{\sigma_z^2}{\sigma_v^2}\frac{\lambda_1}{1-\alpha^2\beta^2\lambda_1^2} + \frac{1}{2}(\beta^2 + 4\frac{\sigma_z^2}{\sigma_e^2})\right], \tag{151}$$

where $\alpha = \frac{1-\delta}{\delta}$ is given by Eq. (34). Since $(1-\gamma)\sigma_z^2\frac{2\alpha}{\delta^2}\lambda_1^3\frac{1+\alpha\beta\lambda_1}{1-\alpha\beta\lambda_1} > 0$, the sign of $\frac{\partial\,\mathrm{E}\left[W|D=1,\delta\right]}{\partial\delta}$ depends on the sign of the terms in the brackets on the right hand side of Eq. (151). These terms can be rewritten as

$$-\frac{4\beta}{\alpha}\frac{\sigma_z^2}{\sigma_v^2}\frac{\lambda_1}{1-\alpha^2\beta^2\lambda_1^2} + \frac{1}{2}(\beta^2 + 4\frac{\sigma_z^2}{\sigma_e^2}) = -4\beta\frac{\sigma_z^2}{\sigma_v^2}\frac{1}{\alpha\lambda_1[4\frac{\sigma_z^2}{\sigma_v^2} + 4\alpha^2\frac{\sigma_z^2}{\sigma_e^2}]} + \frac{1}{2}(\beta^2 + 4\frac{\sigma_z^2}{\sigma_e^2}). \tag{152}$$

It is straight forward to see that the expression (152) increases in α (both $\alpha\lambda_1$ and $4\frac{\sigma_u^2}{\sigma_v^2} + 4\alpha^2\frac{\sigma_u^2}{\sigma_z^2}$ increase in α) and thus decreases in δ. It then follows that the speculator's *ex ante* expected value function $\mathrm{E}\left[W|D=1,\delta\right]$ is either monotonic or first increasing and then decreasing in δ.

Note that, from the proof of Proposition 6, there is $\left.\frac{\partial\,\mathrm{E}\left[W|D=1,\delta\right]}{\partial\delta}\right|_{\delta=\hat{\delta}} < 0$. Additionally, letting $\check{\delta} = \frac{\sigma_v}{\sigma_v+\sigma_e} < \hat{\delta}$, it can be shown that, $\left.\frac{\partial\,\mathrm{E}\left[W|D=1,\delta\right]}{\partial\delta}\right|_{\delta=\check{\delta}} \geq 0$. It then follows that $\mathrm{E}\left[W|D=1,\delta\right]$ is first increasing and then decreasing in δ. Furthermore, because $\mathrm{E}\left[W|D=1,\hat{\delta}\right] = \mathrm{E}\left[W|D=0\right]$, a necessary condition for the speculator to be better-off with disclosure is that the signal weight satisfy $\delta \leq \hat{\delta}$. Because $\lambda_1 = \lambda^*$ when the speculator commits to disclose with signal weight $\delta = \hat{\delta}$,

$\lambda_1 < \lambda^*$ if and only if $\delta < \hat{\delta}$. Therefore, $\lambda_1 < \lambda^*$ whenever the signal weight δ is such that the speculator is better-off by disclosing a signal. ■

Proof of Corollary 2

Define ϕ as the fraction of the speculator's private information that gets impounded into the price:

$$\text{Var}\left(v|P_1\right) = (1-\phi^2)\sigma_v^2. \tag{153}$$

Relax the assumption that v and e are independent and let ρ be their correlation coefficient—$\rho = \text{Corr}\left(v, e\right)$. In a baseline equilibrium, there is

$$\text{Var}\left(v|P_1\right) = \frac{\left(\frac{1}{2\lambda}\sigma_v + \frac{\beta}{2}\rho\sigma_e\right)^2}{\frac{1}{4\lambda^2}\sigma_v^2 + \frac{\beta^2}{4}\sigma_e^2 + \frac{\beta}{2\lambda}\rho\sigma_v\sigma_e + \sigma_z^2}. \tag{154}$$

Proof of Part 1

In a baseline game with $\rho = 0$,

$$\phi^2 = \frac{\frac{1}{4\lambda^2}\sigma_v^2}{\frac{1}{4\lambda^2}\sigma_v^2 + \frac{\beta^2}{4}\sigma_e^2 + \sigma_z^2} = \frac{1}{2}. \tag{155}$$

The second equality follows from Eq. (27).

Proof of Part 2

After the revelation of a signal, define $\tilde{\rho}$ as the fraction of the speculator's remaining private fundamental information that gets impounded into the price, i.e.,

$$\text{Var}\left(v|P_1, s\right) = (1-\tilde{\phi}^2)\tilde{\sigma}_v^2. \tag{156}$$

An expression of $\tilde{\phi}$ can be obtained by replacing σ_v^2 and σ_e^2 by $\tilde{\sigma}_v^2$ and $\tilde{\sigma}_e^2$, respectively, in Eq. (155) and setting $\rho = -1$ (conditional on observing $s = \delta e + (1-\delta)v$, MM can back out either e or v from knowing the other, implying a perfect correlation between the two). Some simplification leads to

$$1 - \tilde{\phi}^2 = \frac{1}{\left(\sqrt{\frac{\beta^2}{4}\frac{\tilde{\sigma}_e^2}{\sigma_z^2} + 1} - \frac{\beta}{2}\frac{\tilde{\sigma}_e}{\sigma_z}\right)^2 + 1}. \tag{157}$$

Since

$$\sqrt{\frac{\beta^2}{4}\frac{\tilde{\sigma}_e^2}{\sigma_z^2} + 1} - \frac{\beta}{2}\frac{\tilde{\sigma}_e}{\sigma_z} = \frac{1}{\sqrt{\frac{\beta^2}{4}\frac{\tilde{\sigma}_e^2}{\sigma_z^2} + 1} + \frac{\beta}{2}\frac{\tilde{\sigma}_e}{\sigma_z}} < 1,$$

there is $1 - \tilde{\phi}^2 > \frac{1}{2}$—the equilibrium price only incorporates less than half of the speculator's remaining private fundamental information.

Proof of Part 3

From Eq. (156) and (157), there is

$$\mathrm{Var}\left(v|P_1,s\right)=\frac{\tilde{\sigma}_v^2}{\sqrt{\frac{\beta^2}{4}\frac{\tilde{\sigma}_e^2}{\sigma_z^2}+1}+\frac{\beta}{2}\frac{\tilde{\sigma}_e}{\sigma_z}}. \tag{158}$$

Since a larger δ increases $\tilde{\sigma}_v^2$ and decreases $\tilde{\sigma}_e^2$, $\mathrm{Var}\left(v|P_1,s\right)$ increases in δ.

Proof of Part 4
Evaluating Eq. (158) at $\delta=\hat{\delta}$ ($\hat{\delta}$ is defined by Eq. (143)) leads to

$$\mathrm{Var}\left(v|P_1,s\right)\big|_{\delta=\hat{\delta}}=\frac{1}{2}. \tag{159}$$

From the proof of Proposition 1, for the speculator to be better-off from disclosure, it must be that $\delta<\hat{\delta}$. Because $\mathrm{Var}\left(v|P_1,s\right)$ increases in δ, this implies $\mathrm{Var}\left(v|P_1,s\right)<\frac{1}{2}$ when the signal is voluntarily disclosed. ■

Appendix B: Patent Trading Sample Construction Details

In this section, I describe how I construct the sample, and, in particular, how I map patent transaction records to Compustat GVKEYs. Many steps of the mapping algorithm are analogous to those adopted by Hall et al. (2001), Bowen III (2016), Ma (2016), and Kogan et al. (2017).

The primary data used in the paper are from the Patent Assignment Dataset (PAD) managed by the U.S. Patent and Trademark Office (USPTO). PAD contains all assignments recorded with the USPTO from 1980 to present, totaling about 6 million records, pertaining to about 10 million patents.[1] For each record, the dataset contains the names of the assignors (the existing owners/sellers) and assignees (the recipients/buyers), patent numbers and application numbers for each of the assigned patents, and the execution date as well as the recording date of the assignment.

In addition to the PAD data, I also obtain patent grant information from the NBER Patent Data Project (henceforth the NBER data) and an extensive dataset (henceforth the KPSS data) prepared by Kogan et al. (2017). Both datasets provide patent citation information and identifiers of firms to which patents are initially granted. The NBER data covers patents issued between 1963 and 2006; the KPSS data has broader coverage, spanning 1926 to 2010. I also obtain patent inventor information from the coauthorship network dataset (henceforth the HBS data) established by Li et al. (2014).

Patent assignments acknowledge the transfer by a party of the rights, title, and interest in a patent or bundle of patents, but not all assignments are transactions. Other assignment types include licensing, patents pledged of or released from collaterals, mergers and employer assignments.[2] Thus the first step is to exclude non-transaction records. The conveyance type information provided by PAD allows me to drop some but not all of these records.[3] Importantly, the conveyance type cannot identify all employer assignments and licensing records. I follow Serrano (2010) to further eliminate likely employer assignments and licensing records. Specifically, I flag a record as employer assignment if (i) the assignment involves a single patent, a single assignor, and a single assignee, and (ii) the assignment record date precedes the patent grant date, the assignor name matches the inventor name (from the HBS data), or the assignee name matches the name to which the patent is granted (from NBER data). I flag a record as a license if the assignment description contains the word "license," "licensing," "lease," or "leasing." About 0.52 million transactions involving 1.24 million utility patents survive these steps.

Apart from names, PAD does not provide identifying information for assignors and assignees. To link these names to Compustat GVKEYs, I adopt a string matching algorithm, as outlined by the steps below:

[1]It is worth noting that recordings of patent assignment with the USPTO are not mandatory. However, according to Marco et al. (2015), failure to record an assignment renders it void against any subsequent purchaser or mortgagee. Theoretically, if an assignment goes unrecorded, the assignor may sell the patent to a subsequent purchaser, and the latter assignment, if recorded, will take priority in case of a litigation. This risk of double sales provides incentives for interest parties to register the patent reassignment with the USPTO.

[2]Employer assignments refer to the first within-firm transfer of a patent from inventing employees to their employers. They account for about 82% of PAD assignment records (Marco et al., 2015).

[3]Patent leasing/licensing may be considered as a form of patent transfer. I exclude licensing in this study as they are generally not publicly recorded. As discussed in Serrano (2018), only patent licenses of significant value and involving publicly traded firms are filed with the USPTO.

1. I clean assignor and assignee names for spelling errors. Because the same assigner/assignee tend to show up repeatedly in the vicinity of each other, I cross-check each name with its 100 closest neighbors in the data. Specifically, for each name A, if there exists another name B in its vicinity that is both close to A (in terms of the Levenshtein string distance) and has a greater number of occurrence in the neighborhood.[4] Then I replace A with B.

2. I standardize firm names using the STATA procedure made available by Wasi et al. (2015).

3. I link standardized assignor and assignee names to two firm name-identifier dictionaries. The first dictionary makes use of the employer assignment records previous discarded. Each employer assignment record contains a firm name as reported with the USPTO. Additionally, I know the identity of the firm because, by definition of employer assignment, this is the firm to which the patent is initially granted to. I, therefore, can obtain their identifiers from the two patent grant data (the NBER and KPSS data). The second dictionary is a list of firm names and name variants provided by the SEC. These names are identified by their CIK numbers, which can, in turn, be mapped to GVKEYs. I standardize names in both dictionaries as before. Finally, I match USPTO assignor and assignee names to names in the two dictionaries, I accept two types of matches. The first is exact and almost exact matches; these are name strings with a Levenshtein distance no greater than 10% of the average length of the two strings. The second is a fuzzy match, where I use the inverse-frequency match algorithm employed by the NBER data.[5]

Through these steps, I am able to match 95,410 buys and 49,148 sells, involving 7,612 firms and 450,838 utility patents. The number of buys exceeds sells because a larger proportion of patent sellers are individuals, and therefore are not picked up by the matching algorithms.

[4] The Levenshtein distance is the minimum number of single-character edits (insertions, deletions or substitutions) required to change one string into the other. Intuitively, it is a metric of dissimilarity between two strings sequences.

[5] The algorithm assigns scores to shared words in two strings based on their frequency of appearance in the NBER dataset. Less frequent words receive higher scores. For example, the word "Nike" gets a score of 2.04 while the word "American" only gets 0.03. The algorithm identifies a match when the matching score of two strings exceeds a certain threshold. Perl codes for the algorithm is made available by Jim Bessen at https://sites.google.com/site/patentdataproject/Home/posts/Name-matching-tool.

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