Essays in Financial Economics

by

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ABSTRACT

This dissertation consists of two essays. The essay "Is Capital Reallocation Really Procyclical?" studies the cyclicality of corporate asset reallocation and its implication for aggregate productivity efficiency. Empirically, aggregate reallocation is procyclical. This is puzzling given the documented evidence that the benefits of reallocation are countercyclical. I show that this procyclicality is driven entirely by the reallocation of bundled capital (e.g., business divisions), which is highly correlated with market valuations and is unrelated to measures of productivity dispersion. In contrast, reallocation of unbundled capital (e.g., specific machinery or equipment) is countercyclical and highly correlated with dispersion in productivity growth. To gauge the aggregate productivity impact of bundled transactions, I propose a heterogeneous agent model of investment featuring two distinct used-capital markets as well as a sentiment component. In equilibrium, unbundled capital is reallocated for productivity gains, whereas bundled capital is also reallocated for real, or perceived, synergies in the equity market. While equity overvaluation negatively affects aggregate productivity by encouraging excessive trading of capital, its adverse impact is largely offset by its positive externality on asset liquidity in the unbundled capital market. The second essay "The Profitability of Liquidity Provision" studies the profitability of liquidity provision in the US equity market. By tracking the cumulative inventory position of all passive liquidity providers and matching each aggregate position with its offsetting trade, I construct a measure of profits to liquidity provision (realized profitability) and assess how profitability varies with the average time to offset. Using a sample of all common stocks from 2017 to 2020, I show that there is substantial variation in the horizon at which trades are turned around even for the same stock. As a mark-to-market profit, the conventional realized spread—measured with a prespecified horizon—can deviate significantly from the realized profits to liquidity provision both in the cross-section and in the time series. I further show that, consistent with the risk-return tradeoff faced by liquidity providers as a whole, realized profitability is low for trades that are quickly turned around and high for trades that take longer to reverse.

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Chapter 1

IS CAPITAL REALLOCATION REALLY PROCYCLICAL?

1.1 Introduction

The empirical literature has documented a positive relationship between the aggregate amount of capital reallocated through asset sales across firms and total output. This procyclicality is puzzling because the benefits from reallocation (e.g., dispersion in productivity) are largely countercyclical (e.g., Eisfeldt and Rampini, 2006; Kehrig, 2015). This neoclassical view of reallocation, however, rests on the assumption that capital is a homogeneous factor of production whose productivity adjusts instantaneously. If capital instantaneously adapts to the production technology of its new owner, it should flow from less to more productive firms. Greater dispersion in productivity thus implies higher potential gains from reallocation and should spur more reallocation.

In reality, firms reallocate assets in two distinct used-capital markets, one for unbundled capital such as equipment and the other for bundled capital such as standalone business units. While the homogeneous capital assumption may hold reasonably well within the unbundled capital market, empirical evidence on the reallocation efficiency of bundled capital is at best inconclusive.[1] In addition, the documented features of acquisitions—occurring in times of high market valuations—cast further doubts on the motivation behind such transactions. When we draw inferences on the

[1] Using Census data for manufacturing industries, Maksimovic and Phillips (2001) recognize that evidence concerning the role of productivity in driving mergers and acquisitions is inconclusive at best. In their paper, mergers and acquisitions overall are followed by productivity losses, albeit insignificant.

economic efficiency of reallocation, it is important to take into account these differences. Suppose, for example, that unbundled reallocation is productivity-enhancing, whereas bundled reallocation is productivity neutral. Then inferences drawn from aggregate reallocation about productivity efficiency can be misleading.

I provide the first disaggregated evidence on the reallocation dynamics of both types of capital and document striking differences in their cyclicalities. This helps to explain why aggregate reallocation is procyclical and sheds light on the economic forces driving reallocation decisions in both markets. I then introduce a heterogeneous model of investment featuring segmented used-capital markets to study the productivity efficiency of procyclical reallocation in the aggregate.

A key part of the paper involves the categorization of capital transactions. The commonly employed database Compustat is not sufficient for this task. One of the issues with Compustat is that it does not distinguish between unbundled and bundled capital.[2] In addition, Compustat provides the transaction value, which is price times quantity, whereas economic theories are mainly concerned with quantities. This is particularly problematic because resale prices are known to be procyclical (Lanteri, 2018). To deal with these issues, I collect information on each capital transaction including the details of the assets being sold and the corresponding transaction prices. This information allows me to classify capital reallocation transactions into bundled or unbundled and disentangle prices from reallocation quantities.

Using these data, I document striking differences in both the resale prices and reallocation dynamics between the two markets. On average, both types of capital sell at a premium over their book value; however, this premium is much higher for bundled (37.5%) than for unbundled capital (1.5%), suggesting the existence of market

[2] Compustat does provide data on sales of property, plant, and equipment, however, it contains a lot of missing values and measurement errors, as I show in the Appendix.

segmentation. Consistent with the market segmentation argument, I show that the price of unbundled capital is highly sensitive to aggregate output shocks, suggesting a demand/supply-driven market responding to aggregate shocks. In contrast, the price of bundled capital is insensitive to such shocks.

I show that the existing evidence on procyclical reallocation is driven entirely by transactions in the bundled capital market. In the unbundled capital market, the fact that prices are procyclical makes it important to isolate the impact of price when analyzing the cyclicality of reallocation. Indeed, I find the value of reallocation in the unbundled market to be acyclical; however, once focusing on quantities, reallocation turns countercyclical. More importantly, unbundled reallocation is highly correlated with dispersion in total factor productivity growth. Thus, in line with neoclassical theory, there really is not a reallocation puzzle so long as we restrict our focus to this more homogeneous type of capital. On the other hand, bundled capital sales are procyclical, highly correlated with sentiment, and bear no consistent relation to productivity dispersion measures.

The evidence appears to suggest that bundled transactions are inefficient from the perspective of productivity. However, any inference on reallocation efficiency would be misleading if one were to disregard the fact that for a company, the decision to reallocate in the bundled market versus the unbundled market is closely interconnected through the relative price of assets. For example, firms will choose to sell assets in the bundled market if they expect to get a higher price there and sell in the unbundled market if otherwise. As a result of this interconnectedness, bundled reallocation can have indirect impact on aggregate productivity through its effect on unbundled transactions. To gauge the aggregate productivity impact of bundled transactions or procyclical reallocation overall, I construct a dynamic investment model that features two distinct used asset markets along with a sentiment component in the bundled market. By attributing the cyclicality of bundled transactions to irrational sentiment, the model aims to provide an upper bound to an estimate of the adverse impact that sentiment may have on aggregate reallocation efficiency.

Two features distinguish my model from a typical neoclassical model as in Yang (2008). First, I distinguish between two used-capital markets. To liquidate capital, firms can either disassemble the capital and then sell in the unbundled market, or directly post it for sale in the bundled market.[3] For the unbundled market, I use standard neoclassical assumptions, e.g., capital is homogeneous and traded at the market-clearing price. For the bundled market, I assume capital may potentially change the path of future productivity shocks of the buyer—bundled capital does not instantaneously adapt to new productivity levels. Second, I introduce sentiment by assuming that some investors irrationally perceive bundled transactions (e.g., acquisitions) by certain firms as overly beneficial (Shleifer and Vishny, 2003). This sentiment distorts transaction prices when the acquirer uses such a misvaluation strategically. As a result, the bundled capital price varies across transactions depending on the type of firms involved. In the model, variation in sentiment is captured by the percentage of firms affected by sentiment in the economy, which is assumed to increase following consecutive good aggregate shocks.

I show that, without the bundled market, reallocation is driven solely by shocks to productivity. It is optimal for firms to expand when productivity rises, and to downsize when productivity falls. The resale price of capital changes procyclically: it rises as good aggregate shocks improve productivity for all and vice versa. These patterns are similar to predictions from models in Lanteri (2018) and Yang (2008). With a bundled market, firms can now reallocate not only for productivity gains but also for synergy gains or financial benefits. For instance, as productivity falls, rather

[3] In the bundled market, deal completion is not guaranteed and occurs with some probability.

than passively waiting, certain firms may find it beneficial to acquire bundled assets for potential synergy; some may even be able to cash in gains by financing with overvalued equity.

Although the two markets are segmented, reallocation decisions between them are connected. Because bundled capital prices are directly affected by sentiment but not productivity shocks, the bundled market serves as a "cushion" for reallocation imbalances as certain firms switch to the bundled market when good (adverse) aggregate shocks raise (lower) the unbundled capital price above (below) certain levels.[4] Importantly, sentiment fueled reallocation distortions effectively improve asset liquidity in the unbundled market: e.g., as the unbundled capital price rises, firms previously overinvested in bundled capital become less willing to wait for an uncertain exit in the bundled market and more likely to sell unbundled, which in term lowers the price of unbundled capital. These cross-market interactions attenuate the response of the unbundled capital price to aggregate shocks, improving asset liquidity.

Sentiment in such an economy has two offsetting effects on aggregate productivity. On the one hand, it spurs excessive opportunistic trading in the bundled market featuring active overinvestment and divestment. These transactions can be counterproductive—e.g., when synergy fails to materialize and firms get stuck with unproductive capital for too long. On the other hand, equity overvaluation also introduces a positive externality on reallocation efficiency by improving asset liquidity in the unbundled market. In the model, the net impact relies crucially on the extent to which equity value distortion gets reflected in real asset prices.

I calibrate the model to match key moments on the levels and dynamics of both

[4]The "switchability" is imperfect here: e.g., for investing firms with high productivity, bundled capital is an inferior substitute for unbundled capital because it may cause deterioration in future productivity.

resale prices and reallocation quantities in both markets. The model helps explain who buys or sells capital, the corresponding reallocation efficiency, and the reallocation dynamics in both markets. In my calibration, buyers are more productive than sellers in 91.5% of the transactions in the unbundled market. In the bundled market, however, only 46.7% of the transactions involve a productive buyer.[5] Unlike Lanteri (2018), in which the price is so sensitive to aggregate shocks that it turns capital sales procyclical, unbundled reallocation is countercyclical in my model, mainly because the marginal benefit to reallocation during downturns exceeds the marginal cost of asset illiquidity. In addition, sales of bundled capital are procyclical and highly correlated with market valuation as more firms involve themselves in capital trading during these high-sentiment periods. This, however, does not imply that bundled transactions are purely financial plays. In the calibrated model, most firms still reallocate bundled capital for purely productivity reasons when it is cost-effective.[6] However, the model does predict higher reallocation efficiency during periods of low sentiment.

This paper provides an alternative to the financial constraint-based explanations for procyclical reallocation. Importantly, I argue it is "too much liquidity in booms" rather than "too little liquidity in busts" that has contributed to the procyclicality of aggregate reallocation. Consistent with the sentiment channel, I show that private firms appear to reallocate their assets more efficiently than their public counterparts. Specifically, both types of capital sales by private firms are highly correlated with productivity growth dispersion measures, regardless of the economic conditions. One possible reason is that, with limited access to the public equity market, private firms'

[5]Note that, despite exhibiting comparable or even lower TFP, bundled capital buyers still have greater marginal products than sellers overall.

[6]Less than 10% of firms are subject to the impact of market sentiment during normal periods; this number increases to around 38% during periods of high sentiment.

reallocation decisions are less affected by valuation distortions.[7]

Note that this paper does not imply that reallocation frictions (e.g., financial constraints, adverse selection, liquidity, etc.) are not important in driving the allocation of capital. In fact, I show in the model that reallocation will be rather constrained without the bundled market: firms reallocate much less and reallocation turns acyclical as a result of countercyclical asset illiquidity. However, the evidence does shed light on the important role sentiment plays in shaping the cyclical dynamics of aggregate reallocation through its impact on corporate asset prices.

Finally, to estimate the net impact of sentiment on aggregate TFP, I show in the model that moderate equity valuation distortions that do not affect real asset prices are beneficial: a 1% increase in equity overvaluation, ceteris paribus, increases aggregate TFP by 0.15%. In contrast, a 1% increase in real price distortion, ceteris paribus, reduces aggregate TFP by 0.16%. I show that the aggregate TFP in the calibrated economy is only 1.4% lower compared to the counterfactual economy with only the unbundled capital market.[8]

Section 1.2 discusses related papers, both theoretical and empirical, in the asset reallocation literature; Section 1.3 presents empirical test results and discussions; Section 1.4 describes the model and the calibration method; Section 1.5 presents simulation results and counterfactual exercises followed by interpretations; Section 1.6 concludes this chapter.

[7]Bundled sales by private firms are insignificantly and negatively correlated with investor sentiment.

[8]Using Compustat manufacturing firm data from 1985 to 2015, Eisfeldt and Shi (2018) roughly estimate the loss of output in recessions from depressed capital reallocation to be 9.08%.

1.2 Related Literature

This paper brings together two strands of related literature that appear to have evolved in isolation: the body of work that explores friction-based explanations of capital reallocation; and the merger wave literature. Using Compustat data, Eisfeldt and Rampini (2006) show that aggregate reallocation is procyclical and contrast it with countercyclical measures of benefits to reallocation. They conclude that there must exist a substantially countercyclical degree of friction that impedes efficient reallocation. Along those lines, many scholars demonstrate how procyclical reallocation can emerge as an equilibrium outcome in business cycle models where reallocation becomes endogenously more costly during downturns. For example, Eisfeldt and Rampini (2008) show that, under information asymmetry, reallocation is more costly for investors during bad times because managers are less willing to sell assets when outside options deteriorate. On the other hand, Li and Whited (2015) and Fuchs *et al.* (2016) show that adverse selection becomes more severe during recessions, leading to less reallocation. Chen and Song (2013) and Ai *et al.* (2019) show that financial constraint also plays an indispensable role in shaping the business cycle dynamics of reallocation.[9] A key implication of this literature is that capital is less efficiently deployed in economic downturns when reallocation is more costly.

In contrast, mergers tend to cluster in times that coincide with high equity valuation even if industry shocks do not. Nelson (1959), Shleifer and Vishny (2003), and Rhodes-Kropf and Viswanathan (2004) show theoretically how such clustering can result from managerial timing of equity overvaluations (sentiment). Supporting evidence is provided by Matthew Rhodes–Kropf and Viswanathan (2005), Dong *et al.* (2006), Bouwman *et al.* (2007), Savor and Lu (2009), and Baker *et al.* (2012). Val-

[9]For a comprehensive review of the literature, please refer to Eisfeldt and Shi (2018).

uation sentiment is known to be procyclical,[10] as are M&A waves. Thus the same observation—procyclical reallocation—has been interpreted as evidence of countercyclical frictions hindering efficient asset redeployment by the capital reallocation literature, and that of excessive capital trading in the absence of any synergies.

In this paper, I bridge the gap between the two strands by recognizing two types of capital transactions that have distinctly different motives: (1) Firms mostly adjust capital in the unbundled form in response to productivity shocks because unbundled capital serves as a homogeneous factor of production and is available at competitive market prices. (2) Although firms also reallocate bundled capital, the economic motivations are more complicated. One of the reasons is that bundled capital typically comes with its own production technology, which may or may not complement that of the buyer. Such uncertainty renders the asset an inferior substitute for unbundled capital for firms attempting to take advantage of good productivity shocks. Thus, compared to the unbundled market, transactions in the bundled market are less incentivized by productivity dispersion. In addition, without a competitive market, bundled capital is typically hard to value and prone to misvaluation. The latter opens the door to opportunistic trading. Consistent with existing evidence on M&As, I show that bundled capital sales are highly correlated with market valuation. I further show that, unlike the unbundled market where reallocation is countercyclical and highly correlated with productivity dispersion, the bundled market features procyclical capital sales that are unrelated to productivity dispersion measures. The evidence suggests that consistent with neoclassical theory, more capital is being efficiently reallocated when the benefit from redeployment is greatest. At the same time, it also makes clear the inadequacy of the same theory in reconciling the facts about bundled

[10]The empirical finance literature has documented that, over long horizons of 3 to 5 years, equity prices overreact to consistent patterns of news pointing in the same direction.

capital transactions documented in this paper, shedding light on the importance of the behavioral side of the financial market.

1.3 Empirical Evidence

In this section, I present new evidence on both the levels and dynamics of the resale prices and reallocation quantities from both used capital markets. Three main facts emerge: 1. The price of unbundled capital is highly sensitive to aggregate output shocks, whereas the price of bundled capital is not. 2. Reallocation of unbundled capital is countercyclical and highly correlated with dispersion in TFP growth. 3. Reallocation of bundled capital is procyclical, highly correlated with market sentiment, and bears no consistent relation to productivity dispersion measures. To alleviate concerns about external validity, I reconfirm some of the main results using data of private firms. Finally, I compare my results with the existing evidence on reallocation using Compustat data.

Data

To categorize capital transactions into either bundled or unbundled sales, I define unbundled capital as tangible fixed assets that are not readily operable by themselves as a business: e.g., equipment, property, building, land, etc. Bundled capital refers to assets that are organized to be operable as a business: e.g., subsidiary, division, product line, joint venture, etc. The goal of this classification is to distinguish capital that can easily take on the buyer's productivity characteristics from capital whose productivity is less flexible to adjust. The concept of capital homogeneity in this classification is narrower than what is typically perceived in the sense that it is relative—being able to adjust to the productivity level of the buyer. Unbundled capital is homogeneous in the sense that buyers of unbundled capital most likely employ the same capital for production. For example, it is more plausible for a farmer to acquire farming equipment than a manufacturing plant, whereas it is very common for firms to acquire businesses not directly related to their core operations.

Compustat lacks the details needed for capital classification and also contains a lot of missing values and measurement errors.[11] For example, Compustat reports proceeds from sales of property, plant, and equipment under the item "SPPE." However, SPPE contains not only the proceeds from sales of productive assets but also proceeds from sales and leaseback transactions. In addition, SPPE is always missing for companies that report asset sales under alternative names such as "proceeds from asset disposition." For example, McDonald's disposes of hundreds of millions in assets annually. However, SPPE shows zero sales for the 15 years ending 2015, during which the company reported under the item name "Sales of restaurant businesses and property."

To deal with these issues, I first electronically extract capital sales items from corporate cash flow tables. I then complement the items with explanatory information about the sales—the type of capital sold, the transaction proceeds, and the corresponding gains/losses—extracted from corporate 10K filings. For each firm-year in my sample, I manually classify capital sales as either bundled or unbundled; for each type, I then aggregate the transaction proceeds and the related gains or losses. Owing to data availability and quality constraints, I restrict my sample to large firms with a market capitalization above the NYSE medium size for the period 1995-2017. Not only do these firms have better 10K filing quality; they also have the most important economic effects due to the mere size of their operations.

[11] See Appendix A for sources of measurement errors and biases in asset sales data from Compustat.

Details on the collection procedure as well as summary statistics are provided in the Appendix. Private firm data are provided by S&P Capital IQ.

Resale Prices

Because of data limitations, evidence on used asset prices in the literature is scarce, and typically limited to either specific types of assets or specific types of sales. For instance, Lanteri (2018) documents that resale prices of aircraft are highly procyclical and much more volatile than prices of new capital.[12] Kermani and Ma (2020) find that the liquidation value of PP&E from non-financial firms is around 35%, which corresponds to an average resale price of 0.35.

In this section, I provide new evidence on the levels as well as the business cycle dynamics of resale prices for both types of capital. To study its cyclical dynamics, I first need to measure the price of capital. I compute the price as the ratio of the transaction value to the book value of the capital sold as in Equation (1.1). Typically when a firm sells an asset, it compares the proceeds from the sale with the carrying value of the asset sold;[13] any surplus is recorded as a gain and any deficit as a loss. Thus I can back out the book value of capital sold based on the proceeds and realized gain/loss from the sale.

$$P_s = \frac{\textit{Transaction value of capital sold}}{\textit{Book value of capital sold}} = \frac{\textit{Sales proceeds}}{\textit{Sales proceeds - Gain/+Loss}}. \tag{1.1}$$

This measure has several advantages over measures based on absolute market price. First, P_s is directly comparable across assets of different ages and wear-and-

[12]The price indices, however, only provide levels relative to a base period and thus do not allow for direct comparison between new and used capital.

[13]For fixed asset, the carrying value is the cost of the asset less accumulated depreciation; for a business unit, the carrying value also includes any goodwill attributable to that unit.

tear.[14] Second, P_s can be consistently calculated for different types of assets—be it a building or a business sector, allowing for the construction of an aggregate price measure using prices from different industries.

Panel A of Table 1 presents the averages as well as percentiles of the resale prices. Despite significant cross-sectional variations, unbundled capital on average sells at a price ranging from 1.015 using book-value-weighted average to 1.394 using transaction-value-weighted average, whereas bundled capital sells for a price ranging from 1.375 to 2.936. The fact that bundled capital on average sells for a much higher premium than unbundled may not appear surprising given the merger and acquisition literature;[15] however, it contradicts neoclassical models, which typically assume the existence of integrated used-capital markets with homogeneous capital. In such a setting, a higher price in one market will attract potential sellers from the other, forcing the two prices to converge.

In addition to the differences in price levels, the two also exhibit distinct dynamics, as shown in Panel B of Table 1. Specifically, while the unbundled capital price responds strongly to output shocks, as indicated by a correlation with log GDP growth at 0.594. The price of bundled capital is insensitive to such shocks (correlation at 0.092). Correlation with Hamilton filtered GDP is slightly smaller for the unbundled capital price (at 0.552); for bundled capital, however, the correlation increases to 0.155. To understand the bundled capital price dynamics, it is important to understand the features of different filters. There are three common filters one can use to stationalize GDP data before estimating cyclical correlations. First, the Hodrick–Prescott (HP) filter, originally designed for quarterly macroeconomic time

[14] Market prices of new and used capital are not directly comparable because used capital has already lost a portion of its value owing to, say, usage-related depreciation or damage-related impairment.

[15] A price premium could be from, say, synergies or misvaluation.

series, is the dominant choice in the literature on reallocation. However, the HP filter can produce spurious cyclical dynamics when applied on difference stationary data such as log annual GDP.[16] A s a result, in this article, I mainly use the Hamilton filter (Hamilton, 2018) and first-difference filter (computed as the difference between the economic variable and its own lag) for inferences. Of these two, first-difference has a clear economic interpretation, as it results simply in log GDP growth. Even though both filters stationalize GDP, they preserve different features of the data. Intuitively, for a difference stationary process, using first-difference preserves the original dynamics of the series—e.g., transitions of the economy into/out of a recession will have a large impact on the log GDP growth data. On the other hand, the Hamilton filter tends to smooth out large shocks, thus prolonging the impact of the shocks. The fact that the unbundled capital price reacts strongly to aggregate output shocks is consistent with predictions of neoclassical models with endogenized capital price, suggesting a supply/demand-driven market responding to aggregate productivity shocks. However, the dynamics of bundled capital prices are puzzling and worth further exploration.

In the data, the bundled capital price is less correlated with shocks to GDP than the Hamilton filtered GDP, which tends to prolong the shocks. This pattern resembles the phenomenon of long-term equity price overreaction to consecutive series of good news documented in the empirical finance literature. Barberis *et al.* (1998) have attributed this phenomenon to investor sentiment. I thus conjecture that sentiment could be an important factor affecting bundled capital price. To verify my conjecture, I first look at the correlation between the average price and the senti-

[16] See Hamilton (2018) or Hodrick (2020) for more details. In the Appendix, I also provide numerical examples in which the HP filter introduces biases in the estimation of correlation between two difference stationary time series.

ment index, as in column (6) of Panel A in Table 2. The correlation is insignificant (-0.16 using book-value-weighted price). However, considering the significant cross-sectional variations, the lack of correlation between the two may not be surprising if sentiment also affects the composition of sales in the market. For instance, a favorable capital environment may aid in the proliferation of superstar deals with excessive valuations; meanwhile, it may also attract a disproportionate number of bad sellers, most of whom end up with less desirable prices than those observed during normal times—when seller quality is higher. If such a composite effect exists, focusing on the average can conceal important dynamic relations.

To isolate such effects, I look at the correlations between sentiment and selected percentiles of the prices in the bundled market. As shown in columns (1)-(5) of Table 2, the price is positively correlated with sentiment among the top percentiles (correlation 0.41 at the 95th percentile); the estimate is more robust (0.43 with a t-stat of 2.07) after I control for the influence of aggregate economic conditions (Panel B). Additionally, sentiment is negatively correlated with prices at lower percentiles (consistent with my earlier conjecture that more deals are done at less favorable prices), resulting in an insignificant correlation between the average price and sentiment. By contrast, pricing in the unbundled market seems to be consistent across all transactions.

The evidence suggests segmentation of the corporate asset market between unbundled and bundled assets. Specifically, price dynamics in the unbundled market are consistent with a supply/demand-driven reallocation market responding to aggregate shocks. By contrast, price dynamics in the bundled market exhibit features distinct from those of a competitive market—e.g., transactions are done at different prices with distinct dynamics, reflecting the uniqueness of individual transactions; a small group of firms strikes extremely favorable prices that are highly sensitive to investor sentiment.

Reallocation Quantities

Existing evidence on capital reallocation is typically restricted to transaction values (price times quantity) as it relies on Compustat data. However, there are notable exceptions: Maksimovic and Phillips (2001) find that the share of plants changing ownership is procyclical in the manufacturing industries. Lanteri (2018), on the other hand, documents that the number of aircraft traded in the used capital market is also procyclical. Intriguing as these results are, their implications are restricted to specific industries. In this paper, I study capital reallocation using a representative sample excluding financials and utilities. More importantly, I can separately examine the cyclical dynamics of reallocation for two types of distinct capital: unbundled and bundled.

Since prices are procyclical, it is important to control for the impact of price when analyzing the cyclicality of reallocation. To do that, I construct a measure of capital reallocation free from the impact of resale price:

$$Reallocation\ Turnover_t^{Book} = \frac{Capital\ Sale_t^{Bval}}{Capital\ Stock_{t-1}^{Bval}}, \tag{1.2}$$

where $Capital\ Sale^{Bval}$ is the book value of capital sold, computed as

$$Capital\ Sale^{Bval} = Sales\ proceeds - Gain(+Loss), \tag{1.3}$$

and $Capital\ Stock^{Bval}$ uses the book value of net PP&E for unbundled capital and total assets for bundled capital. This ratio measures the relative quantity of reallocation that is not contaminated by current asset prices. For comparison with the existing literature, I also construct a similar ratio of reallocation value, which simply uses sales proceeds as the numerator in Equation (1.2).

I now turn to the results of my empirical investigation. Table 3 presents correlation estimates between output and reallocation turnovers for both types of capital. Two observations emerge: First, contrary to the common perception on aggregate reallocation, unbundled capital sales are highly countercyclical (cyclical correlation at -0.4). On the contrary, bundled capital sales are procyclical (cyclical correlation at 0.37); aggregate reallocation is procyclical as well, with a correlation at 0.13. This correlation is much smaller than the 0.54 documented in Eisfeldt and Rampini (2006), but theirs is based on reallocation value instead of quantity and using the Hodrick–Prescott filter on both series before the estimation of correlations. Using their approach to my data, I obtain a correlation of 0.44. These distinct patterns of reallocation between unbundled and bundled capital remain when we switch to first-difference as the GDP filter. Note that for unbundled capital, the correlations using reallocation value are insignificantly different from zero (0.021 under Hamilton and 0.026 under first-difference), which underlines the importance of isolating the impact of prices in studies of capital reallocation.

The emphasis the literature has placed on the cyclicality of reallocation has eclipsed a fundamentally more important question: Do firms reallocate more when the dispersion in productivity is greater? This question is important because, at the end of the day, what we care about is productivity gains, not simply cyclicality.

In panel A of Table 4, I compute the correlations between reallocation and measures of productivity dispersion. Productivity dispersion is measured in three different ways both within industry and across industries. First is the standard deviation (s.d.) of TFP growth as in column (1) for within-industry and column (4) for cross-industry. Second is the difference between the top and bottom quartiles (q3-q1), and last is the difference between the top and bottom percentiles (p90-p10). As we can see, reallocation of unbundled capital is highly correlated with dispersions in TFP growth, both within (from 0.29 using s.d. as a measure of dispersion to 0.42 using p90-p10) and across industries (from 0.38 to 0.57). On the other hand, such correlation is less clear-cut for bundled capital, being positive for some measures and negative for others.

In panel B, I also report the correlations of reallocation with dispersion measures in Tobin's Q, which has been interpreted by many as an alternative measure of productivity. Interestingly, reallocation of unbundled capital bears no relation to Q dispersions, whereas bundled capital sales are highly correlated with these measures. One potential reason could be that Tobin's Q, measured as the ratio of market value to book value of total assets, contains less information about productivity but more information about factors (e.g. valuation) that affect reallocation decisions in the bundled market but not in the unbundled market.[17]

Consistent with neoclassical theory, productivity dispersion appears to be a key driving factor of reallocation in the unbundled market. However, the relation is not clear-cut for the bundled market. What might cause this discrepancy in the reallocation dynamics between these two markets? To answer this question, it is helpful to think about the unique features of bundled capital. Unlike its unbundled counterpart, which typically has a market with relatively competitive prices, bundled capital, similar to the targets in the acquisition market, is typically hard to value and prone to misvaluation. For these complex assets, Shleifer and Vishny (2003) show that investor sentiment plays an important role in the related reallocation decisions. Similarly, I conjecture that sentiment may have a large impact on reallocation in the bundled market.

To test this conjecture, I compute the correlations between reallocation and sev-

[17]Time-series correlation between cross-sectional dispersion in Q and average Q ranges from 0.80 to 0.98 depending on how aggressively I winsorize the data.

eral proxies of sentiment, including the percentage of firms with Q above certain values, quartiles of Q, the average level of Q, and the sentiment index data from Professor Jeffrey Wurgler's website. The estimates are tabulated in Table 5. In line with my conjecture, bundled transactions are highly and significantly correlated with all sentiment proxies, which is not surprising as similar facts have been documented in the MA literature. However, what is new and interesting here is that, in the unbundled market, reallocation is unrelated to measures of sentiment. This evidence confirms that sentiment highly affects reallocation in the bundled market but not in the unbundled market.

To shed light on the potential factors driving reallocation in the two markets, I show in Table 6 that both firm-level productivity and aggregate productivity dispersion affect the probability of unbundled capital sales. Note that in the table, coefficients on proxies for financial constraints are all small and insignificant, alleviating the concern that firms sell unbundled assets due to financial distress. Moreover, consistent with the aggregate evidence, equity market valuation highly affects the probability of bundled capital sales, whereas productivity dispersion has no effect.

To wrap up, in this subsection, I document distinct patterns of reallocation between the two used capital markets. In the unbundled market where capital is closer to a homogeneous factor, reallocation is countercyclical and highly correlated with dispersion in productivity growth. Thus firms indeed reallocate more during times when benefits from reallocation are greater, regardless of the economic condition. In contrast, in the bundled market where capital is complex and hard to value, reallocation is procyclical, highly correlated with valuation sentiment, and bears no consistent relation to productivity dispersion measures.

Evidence from Private Firm Data

The data employed above are collected from 10Ks of public firms. To address concerns about the external validity, I present comparable results using private company data from S&P Capital IQ ("CIQ" thereafter).

Like Compustat, CIQ collects capital sales data from private companies' financial statements when available.[18] As a result, similar data limitations likely apply. For private firms, however, I argue that these issues are less severe. As a noisy measure of piece-wise capital sales, the Compustat item "sales of PP&E" may also include proceeds from other asset sales—these other assets may be a division, a subsidiary, or even investment securities. Because private firms are typically smaller than public firms—they are often single-segment firms that are less likely to hold miscellaneous assets, I argue that their "sales of PP&E" measure is more likely to be unbundled capital sales.

Compustat also lacks good quality price data for capital sales. The item "SPPIV" records gains and losses realized from sales of assets. However, similar to "sales of PPE", it often includes gains or losses from sales of miscellaneous assets, such as short-term equity investment. For private firms, Capital IQ provides a similar item, "gain/loss on sale of assets"; I argue that this item is cleaner for private firms, both because they do not invest as much in miscellaneous assets as large public firms do, and because Capital IQ has a separate item for equity sales, "gain/loss on sale of investments." Another advantage of these private firm data is that they contain two extra items that are not present in Compustat: "divestiture" and "cash acquisitions." Divestiture can be used as a proxy for bundled capital sales. More importantly, data on cash acquisitions provide me with potentially valuable information to distinguish

[18]E.g., some private firms voluntarily disclose their financial reports

the sentiment channel from neoclassical arguments.[19]

In this section, I examine the business-cycle dynamics of reallocation for private firms. Similar to the prior tests, two types of capital are studied: sales of PP&E and divestitures. I also look at the time-series dynamics of cash acquisitions. Three main observations emerge: (1) Reallocation of PP&E is countercyclical and highly correlated with TFP growth dispersion. (2) Reallocation in the form of divestitures is highly procyclical, and also positively correlated with dispersion in TFP growth. (3) Cash acquisitions are highly negatively correlated with market valuation measures constructed using Tobin's Q of public firms. All results are tabulated in Table 7.

Table 7 shows that the distinctive cyclical patterns of PP&E sales and divestitures resemble those of unbundled and bundled sales of capital by public firms. However, different from their public counterparts, both PP&E sales and divestitures by private firms correlate positively with productivity dispersion (although the positive correlation is weaker for divestitures), indicating that private firms overall reallocate their assets more efficiently than their public counterparts. This may not be surprising since private firms generally have limited access to the public equity market;[20] their capital reallocation decisions thus are less affected by equity valuation distortions. This may also help explain the overall insignificant or even negative correlation between divestitures and equity market valuation proxies in panel D. Interestingly, again in panel D, not only are divestitures negatively correlated with equity market valuation measures

[19]Neoclassical theory does not distinguish between cash and non-cash payments in asset acquisitions. Shleifer and Vishny (2003) construct a model of sentiment that reproduces the distinct patterns on the method of payments (cash versus non-cash) in M&As. One of the model's central predictions is that acquisitions are more likely to be non-cash when market valuations are high, and in cash when they are low.

[20]With the rising popularity of SPACs (special purpose acquisition companies), access to public equity funds by private entities has become easier over the years.

but so are sales of PP&E. Although almost none of these estimates are statistically significant, they are indicative of potential substitution between the public market and private market. Last, in line with Shleifer and Vishny (2003), cash acquisitions are significantly negatively correlated with market valuation, suggesting sentiment as an important factor in shaping firms' reallocation decisions in the bundled market.

1.4 An Investment Model with Valuation Sentiment

To gauge the aggregate productivity impact of procyclical bundled transactions and investor sentiment, I construct a dynamic investment model with two used asset markets and a sentiment component in the bundled market. The model assumes away typical factors (e.g., financial constraints, adverse selection, etc) other than sentiment that may have also affected the dynamics of bundled transactions. I make this simplifying choice to see how good the model can explain the data and also to provide us with a useful estimate of the upper bound impact of sentiment on aggregate reallocation efficiency.

The model has three distinguishing features: (1) There are two types of firms. Type I are firms whose equity price always reflects the efficient valuation of the company's operations. Type II are firms whose equity price is subject to sentiment-related distortions when they announce deals to acquire bundled capital as in Shleifer and Vishny (2003). Here I mainly focus on distortions around bundled acquisitions—for example, the combined value of two firms is perceived to be greater than the sum of individual values absent synergy.[21] This assumption is needed to generate the distinctive reallocation dynamics of both types of capital. (2) There exist two distinct used-capital markets. One for unbundled capital whose price is endogenously deter-

[21] Internet-related companies during the dot-com bubble are an intuitive example of companies affected by such distorted perceptions.

mined by the market clearing condition. The other for bundled capital whose price depends on the type of firms involved in the transaction. This assumption is needed to generate distinct price levels in both markets. (3) I allow for the possibility of structural changes in a firm's TFP following a successful acquisition of bundled capital. This assumption fundamentally distinguishes bundled capital from unbundled capital—acquisition of bundled capital comes with uncertainty, for example, because of synergy or "empire building" discount. These features enable me to rationalize the empirical regularities documented in the paper. The following sections introduce the model setup as well as the details of each feature above.

Firm Heterogeneity

For Type I firms, the managers' role of value optimization is equivalent to maximizing the present value of current and future cash flows from production and investment. Type II firms are those with valuations highly sensitive to broad waves of investor sentiment.[22] For these firms, absent agency frictions, the role of the manager is to maximize the current shareholder value, which comes from cash flows from production and investment as well as any gains realized from the equity market due to misvaluation.

Production Technology

Both types of firms share the same set of production technologies. Firms produce a common good using capital as the only input, they are fully equity financed, there is no cost of raising capital, and proceeds are paid out in each period. Each firm

[22] I do not explicitly model the source of such sentiment but rely on a growing literature on the circumstances under which equity prices can deviate from fundamentals.

employs capital k to produce goods $\pi = exp(z_a, z_i)k^{\alpha}$, where $0 < \alpha < 1$ (DRS) and (z_a, z_i) are productivity (or demand) shocks at the aggregate level and firm-specific level respectively.

In the model, business cycles are mainly driven by aggregate productivity shocks, which follow an AR(1) process with mean 0 and standard deviation of error term σ_a. The idiosyncratic shock follows a threshold AR(1) process with mean 0 and standard deviation of error term σ_i:

$$z_{a,t} = \rho_a z_{a,t-1} + \epsilon_a, \quad z_{i,t} = f(z^j_{i,t-1}) = \sum_{j \in \Omega} \rho^j_i z^j_{i,t-1} + \epsilon_i, \tag{1.4}$$

where Ω denotes the state space of aggregate shocks. Intuitively, it states that the persistence level of idiosyncratic shocks changes with the current state of aggregate shock (explained later).

At the beginning of each period, firms observe the realization of productivity shocks and determine whether to invest in new capital ($I_t >= 0$), to buy or sell used unbundled capital (U_t), or to propose acquisition or divestiture (B_t) in the bundled capital market. Acquisitions and divestitures can fail.[23] In case they fail, no assets will be reallocated; denote the final transaction quantity as $\bar{B}_t$, which is either 0 or B_t. Firms are allowed to invest in new capital while reallocating used capital at the same time, but participation in the two used-capital markets is mutually exclusive. Firms are not allowed to sell more capital than they already own. I assume there is a timing difference between new and used capital investment: new capital takes one period to be built for production, whereas used capital can be put into production in the current period.[24] This is intuitive—e.g., new office buildings take time to build

[23]Because I do not have the market-clearing condition in the bundled market, I need the failure rate to constrain the activity of Type II firms.

[24]The timing difference is to avoid the trivial scenario in which used capital price is bounded by new capital price.

but used buildings, once acquired, can be put to use immediately.

Segmented Used Capital Market

In the unbundled market, capital is a homogeneous factor of production whose price (p^u) competitively clears the market.

$$\sum_j U(k_{jt}, z_{ijt}, z_{at}, z_{at-1}, p_t^u) = 0, \tag{1.5}$$

where $k_j, z_{ij},$ and z_a denote the capital level, idiosyncratic productivity shock for firm j, and aggregate productivity shock, respectively. In equilibrium, p_t^u is determined by Equation (1.5), which requires information about capital decisions of all firms in the economy.

$$p_t^u = f(z_{a,t}, z_{a,t-1}, K_t, Z_{it}), \quad where\ K_t = (k_1, ..., k_n),\ Z_{it} = (z_{i1,t}, ...z_{in,t}). \tag{1.6}$$

By contrast, the market for bundled capital resembles the M&A market: firms can propose to buy or sell; deal completion, however, is not guaranteed and occurs with probability P_o. Unlike unbundled capital, which simply adapts to the TFP of its new owner, bundled capital, once acquired, can potentially change the productivity state of the acquirer ("structural change"). Specifically, following a successful acquisition, there is likelihood P_s that acquirer i will experience a change in its state variable from $z(z_a, z_i)$ to $\tilde{z}(z_a, \tilde{z}_i)$, which affects the transition probabilities to the next period (the next shock z' will be drawn from $F(z'|\tilde{z})$ instead of $F(z'|z)$).

In the data, capital in the bundled market is overpriced on average, and transactions occur with highly dispersed prices. In the model, for the sake of simplicity, the bundled capital price is assumed to have two levels, depending on whether the buyer or seller is a Type I or a Type II firm embraced by market sentiment. Specifically, p_n^b is the capital price faced by Type I firms, and p_s^b is the price for Type II firms in the bundled market.

Last, quadratic adjustment cost applies to new investment; for unbundled capital, both fixed cost and quadratic cost apply (typical assumption in the literature):

$$C_I(k, I) = \frac{\gamma}{2}(\frac{I}{k})^2 k, \quad C_U(k, U) = \frac{\gamma}{2}(\frac{U}{k})^2 k + f_U \cdot 1_{U \neq 0}. \tag{1.7}$$

Propositional cost of acquisition/divestiture in the bundled capital market:

$$\begin{aligned} C_B(k, B) &= \phi k \cdot 1_{\bar{B} \neq 0} \\ \bar{B} &= \begin{cases} B, & \text{deal completion with prob. } \mathsf{P}_o \\ 0, & \text{otherwise,} \end{cases} \end{aligned} \tag{1.8}$$

which captures forgone operating profit from processing bundled capital transactions.

Rationalizing the Price and Reallocation Dynamics in the Bundled Market

There are many reasons why the premiums paid for bundled capital are so high. It could be that the labor associated with such capital is more valuable to the acquirers—who lack the talents capable of managing the capital—than the original owner. However, such an explanation begs the question of why the acquirer did not search for other cheaper alternatives, especially during market booms when there are more business entries and labor mobility is higher. In addition, if the target is so unique that the buyer could not find other alternatives or could not find the talent to manage it, then most likely the target is in a business very different from that of the buyer. This uniqueness is exactly what makes these targets hard to value and prone to misvaluation. The fact that bundled transactions are highly procyclical is also inconsistent with the lack-of-talent argument because one would expect the talent constraint to be looser during market booms with higher labor mobility. Similarly, one could also argue that bundled acquisitions bring significant synergies. Although the empirical facts tell a different story—for example, using plant level data, Maksimovic and Phillips (2001) fail to find productivity gains at the combined business level following mergers and acquisitions. The evidence on both asset prices and reallocation dynamics lead me to pursue an alternative story similar in spirit to Shleifer and Vishny (2003). Specifically, I conjecture that some investors—with ample funds and desire for capital returns—hold irrational expectations about the benefits of certain bundled transactions. By focusing on the sentiment channel, the model yields an upper bound estimate of the impact of sentiment on aggregate reallocation efficiency.

Equity price distortions occur when some investors value acquisitions by certain firms as more beneficial than they are.[25] In practice, such an optimistic outlook could be induced by synergy or competition.[26] When the distortion is high enough, the firm manager has an incentive to acquire capital even when the acquisition may result in zero or even negative gain in production profit. This is because, by striking the deal, the manager can create value for the existing shareholders by financing the purchase with overvalued stocks. Intuitively, such an incentive can cause the manager to overpay for the target; p_s^b thus should be higher than p_n^b.[27] This mechanism

[25]For theoretical arguments on why influence of sentiment on stock prices would not be eliminated through arbitrage, see Morck *et al.* (1990b). On the empirical side, Matsusaka (1993) documents that buyers earned significantly positive announcement returns during the conglomerate merger wave (sentiment for diversification) when they made diversifying acquisitions; Morck *et al.* (1990a) also find that the stock price of buyers rose when they acquired firms catering to the concurrent sentiment toward specialization in the 1980s.

[26]An extreme example is SPACs, which are created specifically to pool funds to finance a merger or acquisition that has yet to be identified. Recent rallies in pre-merger SPAC prices see speculative investors betting on blank-check deals without valuation or an actual business.

[27]In a study on the performance of divestitures during the takeover wave in the '1980s, Kaplan and Weisbach (1992) report that for deals with comparable sale prices, targets are sold at 192% of their purchase price, which when adjusted for the contemporaneous increase in the SP 500 index, equals

resembles that of acquisition for stocks, a commonly used strategy in the M&A market that is particularly popular during periods of high market valuation.[28]

Sentiment in this model has two dimensions. One is the percentage of Type II firms (S_t) in the economy that are subject to a euphoric view of acquisitions. The other dimension captures the magnitude of the equity price distortion upon announcement of acquisitions; this distortion is defined in relation to the size of the target asset.

I make two additional assumptions about each of the above two dimensions. First, following consecutive good aggregate shocks, the percentage of Type II firms in the economy increases:

$$S_t(z_{at}, z_{at-1}) = S_o + \delta_s \cdot 1_{(z_{at}=H, z_{at-1}=H)}. \tag{1.9}$$

S_o is the percentage of Type II firms during normal periods and δ_s captures the spike in this number following consecutive good aggregate shocks ($z_a = H$). This assumption is important in generating the cyclicality in aggregate equity valuation and bundled reallocation. It is motivated by the documented phenomenon in the empirical finance literature: after consecutive good news, equities tend to receive extremely high valuations, which are later followed by reversions on average.[29]

Second, I assume certain investors value bundled acquisitions by Type II firms at b% over the book value of the target asset. For example, if the target asset contains one unit of capital, the assumption states that some investors are willing to give the firm $1+b$ in cash to acquire the asset. Note that these irrational views have little to do with the fundamentals of the specific firm. However, they do affect firms' reallocation decisions, for reasons explained below.

90% of their purchase price and 143% of their market value before the initial takeover announcement.

[28]Nelson (1959) find that acquisitions cluster during periods of high market valuation and the method of payment is generally equity. Shleifer and Vishny (2003) cite two other studies that also document a high correlation between market valuation and popularity of stock acquisitions.

[29]See Barberis *et al.* (1998) for a review of related literature.

The equity market does not play a role in typical neoclassical models because there is no value distortion, meaning the net present value (NPV) from equity financing is zero. In this model, the equity market can have a large impact on corporate reallocation. This is because, by financing acquisitions with overvalued equity, for each unit of capital acquired, existing shareholders benefit from the difference between the cash raised and the unit price paid.[30]

Valuation distortion serves as the lubricant facilitating capital buys and sales by Type II firms in the bundled market. The effect on the sell-side is obvious: the potential to sell at an extremely favorable price attracts otherwise non-movers into selling bundled. On the buy-side, supported by high valuation, potential buyers who would otherwise only buy at a price below x are now willing to enter the market at a much higher price threshold. Since I fix the bundled capital price at two levels, not all sales in the bundled market will be offset by buying orders. Firms as a whole may end up selling or buying more than they have bought or sold depending on the market condition and industry structure.[31]

Using a sentiment-based acquisition model, Shleifer and Vishny (2003) demonstrate that the proliferation of stock acquisition around periods of high market valuation is consistent with firms timing market inefficiencies by acquiring assets using overvalued stocks. The mechanism proposed in this model is very similar to the one in Shleifer and Vishny (2003), except that I assume (additionally) the existing share-

[30]For example, raising \$2 while issuing \$1 worth of equity results in an extra \$1 available as a dividend to existing shareholders. Here I frame it as a cash benefit for modeling convenience. One can think of it as any similar incentive on the existing shareholders' side: for example, extra utility from positive price responses to such acquisitions.

[31]In my sample, firms on average acquire more than they sell (e.g., from other public firms or private firms). Additionally, during high sentiment periods, the percentage of firms selling bundled assets increases by 11.2%, whereas the number drops by 10.9% for acquiring firms.

holders or managers of both acquirers and sellers can fully realize the gains from the misvaluation. As a result, in my model, both the buyer and seller benefit because the loss is borne entirely by the euphoric investors who pay for overvalued equity.[32]

Capital Reallocation Decisions

At the beginning of each period t, the firm manager optimally makes capital decisions (I_t, U_t, B_t) to maximize current shareholder value based on the firm's existing capital level, realized productivity shocks, capital prices (new capital price normalized to one; the price of bundled capital is p_n^b for Type I firms and p_s^b for Type II firms), and the potential financing benefit from a bundled acquisition (for Type II firms only). Investment in new capital takes one period to be ready for production, whereas used capital, once acquired, can be put into production immediately.

For Type I firms, in the event of successful completion (prob. P_o), the buyer(seller) pays(gets) a per-unit capital price of p_n^b. For Type II firms, in the event of successful completion, the buyer pays a unit capital price of p_s^b while at the same time pocketing a cash benefit from financing the deal with overvalued equity; the seller gets a unit capital price of p_s^b.

For both types of firms, with probability P_s, acquired bundled assets may alter the trajectory of the acquirers' future productivity shocks, as described in Section 1.4. Specifically, with two idiosyncratic productivity states, bundled acquisition exposes the productive firms to risks of technology disruption but provides the less productive ones potential benefits of synergy. Figure 1 illustrates the timeline of the whole process.

For both types of firms, the cash flow generated from operating and investing

[32]See Shleifer and Vishny (2003) for a discussion on scenarios under which both acquirers and targets benefit from an acquisition.

activities in period t, without entering the bundled capital market is:

$$\pi^u(k, z_i, z_a, z_{a,-1}, p^u) = e^{z_i+z_a}(k+U)^\alpha - (I + C_I) - (p^u U + C_U). \tag{1.10}$$

For Type I firms, the expected cash flow conditional on entering the bundled market ($B_t \neq 0$) is:

$$\begin{aligned}\pi_n^b(k, z_i, z_a, z_{a,-1}, p^u) &= \mathsf{P}_o\{e^{z_i+z_a}(k+U+B)^\alpha - p_n^b B - C_B\} \\ &\quad + (1-\mathsf{P}_o)\{e^{z_i+z_a}(k+U)^\alpha\} - (I + C_I) - (p^u U + C_U).\end{aligned} \tag{1.11}$$

For Type II firms, the cash flow also includes a potential financing benefit (bB_t):

$$\begin{aligned}\pi_s^b(k, z_i, z_a, z_{a,-1}, p^u) &= \mathsf{P}_o\{e^{z_i+z_a}(k+U+B)^\alpha - p_s^b B - C_B + bB\} \\ &\quad + (1-\mathsf{P}_o)\{e^{z_i+z_a}(k+U)^\alpha\} - (I + C_I) - (p^u U + C_U).\end{aligned} \tag{1.12}$$

I omit the subscripts "t" in Equation (1.10)-Equation (1.12) for simplicity.

The firm's optimization problem can be described using the following Bellman equations, which define the value of the firm as the discounted value of expected current and future cash flows. The value of firm i (of type $\zeta \in \{I, II\}$) without entering the bundled capital market is:

$$\begin{aligned}&V_{i\zeta}^u(k, z_i, z_a, z_{a,-1}, p^u) \\ &= \max_{\substack{I\geq 0,\, U\geq -k,\, B=0 \\ k'=(k+U)(1-\delta)+I}} \pi^u + \beta E(V_{i\zeta}(k', z_i', z_a', z_a, p^{u\prime} | z_a, z_i, p^u)).\end{aligned} \tag{1.13}$$

The value conditional on entering the bundled capital market is:

$$\begin{aligned}&V_{i\zeta}^b(k, z_i, z_a, z_{a,-1}, p^u)) \\ &= \max_{\substack{I\geq 0,\, U\geq -k,\, B\geq -k,\, U+B\geq -k \\ k_{nc}'=(k+U)(1-\delta)+I, \\ k_c'=(k+U+B)(1-\delta)+I}} \pi_i^b + \beta\Big\{(1-\mathsf{P}_o)E(V_{i\zeta}(k_{nc}', z_i', z_a', z_a, p^{u\prime}|z_a, z_i, p^u)) \\ &\qquad + \mathsf{P}_o\big\{1_{B>0}\big(\mathsf{P}_s E(V_{i\zeta}(k_c', z_i', z_a', z_a, p^{u\prime}|z_a, \tilde{z}_i, p^u)) \\ &\qquad + (1-\mathsf{P}_s)E(V_{i\zeta}(k_c', z_i', z_a', z_a, p^{u\prime}|z_a, z_i, p^u))\big) \\ &\qquad + 1_{B<0}E(V_{i\zeta}(k_c', z_i', z_a', z_a, p^{u\prime}|z_a, z_i, p^u))\big\}\end{aligned} \tag{1.14}$$

Optimization thus gives

$$V_{i\zeta}(k, z_i, z_a, z_{a,-1}, p^u) = max\{V_{i\zeta}^u, V_{i\zeta}^b\}, \quad \zeta \in \{I, II\}, \tag{1.15}$$

where $z_{a,-1}$ denotes aggregate shock one period before the optimization period. β is the discount factor; state variables with a prime indicate value of the state at the beginning of the next period.

Recursive Equilibrium

A recursive equilibrium exists in such an economy if the above-described dynamic programming problem has a fixed point. To describe the equilibrium, I first define the policy functions of the firm. Let $I(k, z_i, z_a, z_{a,-1}, p^u)$ be the firm's decision rule for new capital investment. Similarly, $U(k, z_i, z_a, z_{a,-1}, p^u)$ is the policy rule for unbundled capital investment/divestment and $B(k, z_i, z_a, z_{a,-1}, p^u)$ for bundled capital. In addition, let $L(K, Z_i)$ be the distribution of capital and idiosyncratic shocks across firms in the economy, which follows the law of motion $L_t = \Gamma(L_{t-1}, z_{at}, z_{at-1})$. L determines the equilibrium price of used unbundled capital as in Equation (1.5). Note that the policy functions differ for the two types of firms ($(I, U, B)^I$ and $(I, U, B)^{II}$). I omit the superscripts in the following for simplicity of notation.

A recursive equilibrium is a set of functions I, U, B, V, k', Γ, p^u that solve the firm's optimization problem and clear the market for unbundled used capital:

- Value function V satisfies Equation (1.15); policy functions $\{I, U, B; k'\}$ solve the optimization problems as in equations (1.13)-(1.14) given the pricing function p^u and law of motion Γ.

- $p^u(L, z_a, z_{a,-1})$ clears the unbundled capital market as in Equation (1.5).

- Γ describes the evolution of the distribution of capital as well as the productivity level across the industry consistent with k' and the Markov process of $\{z_a, z_i\}$.

Numerical Solutions

Owing to the high dimensionality of certain state variables $L = (Z_i, K)$, a numerical solution is computationally infeasible. I follow the methodology proposed by Krusell and Smith (1997) to tackle this issue. Specifically, I approximate the distribution of capital by its first moment, mean capital $\bar{K}$. Agents perceive the law of motion as:

$$log(\bar{K}') = \alpha_0+\beta_0 log(K)+(\alpha_1+\beta_1 log(K))1_{z_a^{hl}}+(\alpha_2+\beta_2 log(K))1_{z_a^{lh}}+(\alpha_3+\beta_3 log(K))1_{z_a^{ll}}, \tag{1.16}$$

where $1_{z_a^{hl}}, 1_{z_a^{lh}}, 1_{z_a^{ll}}$ are indicator functions for the pairs of current and previous aggregate shock realizations $(z_a, z_{a,-1})$: z_a^{hl} indicates a high aggregate productivity state following a previous low aggregate productivity state; similarly, z_a^{lh} indicates a low aggregate state after a previous high state and z_a^{ll} two consecutive low states. The pair of parameters (α_0, β_0) thus describes the LOM following two consecutive high productivity shocks (z_a^{hh}). The perceived pricing function is:

$$p^u = \gamma_0 + \phi_0 log(K) + (\gamma_1 + \phi_1 log(K))1_{z_a^{hl}} + (\gamma_2 + \phi_2 log(K))1_{z_a^{lh}} + (\gamma_3 + \phi_3 log(K))1_{z_a^{ll}}. \tag{1.17}$$

As in Krusell and Smith (1997), the two approximations achieve very high accuracy, with R^2 reaching 0.99 for Equation (1.16) and 0.98 for Equation (1.17).

Given these laws of motion (LOMs), I obtain firms' policy functions by value function iteration. I then simulate a panel of 3,000 firms for 600 periods using these decision rules. For each period, I solve the price of unbundled capital that clears the market and calculate the mean aggregate capital for the next period based on the decisions of all firms. Using these data, I update the LOMs for both the mean capital and the price along with each simulation until the parameters in equations (1.16)-(1.17) converge.

I calibrate the model using collected data on bundled and unbundled sales (from the Data section) and Compustat data on acquisitions. Table 8 presents standard parameter choices. Parameters β, δ correspond to an annual discount rate of 7.5% and a capital depreciation rate of 10%.[33] I set α to 0.592 in the production and ρ_a, σ_a to 0.75 and 0.05 as in Cooper and Haltiwanger (2006).

One deviation from the literature is the modeling of idiosyncratic shocks. The prior literature typically assumes independence between aggregate and idiosyncratic shocks. However, with independent shocks, cross-firm dispersion in productivity growth is counterfactually procyclical. In this model, I assume that idiosyncratic shocks follow a threshold AR1 process in which the persistence level varies depending on the aggregate productivity level. To match an average boom-bust ratio of productivity growth dispersion of 0.85 in the data,[34] I use a persistence level of 0.55 when aggregate productivity is high and 0.9 when aggregate productivity is low. (Estimating the persistence level of such a process without conditioning on aggregate states produces an AR1 coefficient of 0.77 in simulation, a value commonly used in

[33]Although the choice of δ is common in the literature, the discount rate is slightly higher than the common value around 5%. But I believe it's a reasonable approximation of the investor required rate of return in the U.S. This choice is also close to the 6.5% used in Gomes (2001).

[34]Using multifactor productivity data from the Bureau of Labor Statistics (BLS), I calculate productivity growth dispersion as the standard deviation of productivity(%chg) across all industries. I calculate the boom-bust ratio of this dispersion as the mean dispersion during the boom to that during the bust, where the boom is classified as periods with positive cyclical GDP and bust otherwise. The ratio is 0.8798 using dispersion across 3-digit SIC industries and 0.8255 using 4-digit industries.

the literature for idiosyncratic shocks.)

The calibration follows two steps. First, to get initial parameter values I estimate the model to match 11 distinguishing moments related to resale prices and reallocation using the simulated method of moments. These moments include the average levels of both types of capital sales ($E(U)$, $E(B^-)$) and acquisition ($E(B^+)$), their correlations with total output($\rho(U,Y)$, $\rho(B^-,Y)$, $\rho(B^+,Y)$), correlation of bundled sales with market valuation $\rho(Q_m,\ B^-)$, average levels of unbundled and bundled capital price ($E(p^u)$, $E(p^b)$[35]), and correlation of unbundled price with total output $\rho(p^u,Y)$ and with market valuation $\rho(Q_m,\ B^-)$. Once I have these estimates, I calibrate the model until the final convergence of the LOMs for both aggregate capital and unbundled capital prices. Details of the solution method are provided in the Appendix.

1.5 Results

This section presents the results of quantitative experiments using the calibrated model. As Table 9 shows, the model closely reproduces the empirical patterns observed in the data: (1) countercyclical sales of unbundled capital, which is highly correlated with dispersion in productivity changes among firms in the economy; (2) procyclical bundled sales (as well as acquisitions), which is highly correlated with the market valuation. The model also helps rationalize the distinct resale price levels in the two markets.

Aside from the main (matched) moments, the model also produces other interesting predictions. For example, in this economy, 91.46% of unbundled deals involve

[35] p^b is calculated as the book-value-weighted average price of bundled capital across all deals in each period.

a more productive buyer than seller, whereas only 46.68% of bundled transactions involve a productive buyer. Taken together, buyers are more productive than sellers (or at least equally productive) in 62.4% of all transactions (value-weighted). To put this number into perspective, Maksimovic and Phillips (2001) document that buyers' plants are more productive than the acquired plants in 57.2% to 59.6% of capital transactions in their sample.

The following sections present simulation results concerning the corporate asset reallocation markets: characteristics of the buyers and sellers, the corresponding reallocation efficiency, aggregate reallocation dynamics, and aggregate TFP in the economy.

Who Buys/Sells Capital?

This section examines the characteristics of buyers and sellers in both markets. Figure 2 shows the average TFP and Tobin's Q of buyers and sellers in the bundled market 5 years around the reallocation, using both simulated and empirical data. As can be seen from both the model and the data, despite having a higher valuation (Q), buyers overall have comparable or even lower productivity than sellers in the years leading up to the transaction; the gap in productivity is greater during normal periods than in high-sentiment periods, and it tends to die down in the following years. By contrast, Figure 3 shows that buyers in the unbundled market are much more productive than sellers and also have higher Tobin's Q in the two years leading up to the transaction.

These patterns may appear puzzling when interpreted under typical neoclassical frameworks with homogeneous capital. However, a simple deviation from that assumption as in this model goes a long way toward rationalizing these facts: bundled capital, once acquired, can potentially alter the current idiosyncratic state of the firm and thus its future path of idiosyncratic shocks. As a result of this deviation, ceteris paribus, bundled capital is an inferior substitute for unbundled capital for firms that plan to take advantage of positive productivity shocks. By contrast, it is an attractive alternative for unproductive firms that can benefit from potential TFP changes (e.g., synergy) following bundled acquisitions. This difference in capital preference is greater during economic downturns when the costs (benefits) of staying unproductive (productive) are higher, which is manifested by the greater gap in average productivity between the sellers and the buyers.

The fact that Tobin's Q and average TFP convey inconsistent signals relates to the second feature of the model: valuation sentiment can distort reallocation decisions and asset prices for Type II firms. For these firms, such distortions not only reduce capital adjustment frictions but also render capital trading lucrative, even when there are no productivity gains. They enjoy higher valuations than otherwise similar firms and are more likely to engage in productivity-diminishing transactions at the expense of external investors—e.g., overinvestment in unproductive business, early liquidation of productive assets, etc. As a result, buyers in the bundled market overall exhibit much higher valuations but average productivity that is comparable to or even lower than sellers'. These patterns of relative productivity and valuation are mostly consistent with empirical observations, as shown in the right panel of Figure 2.[36]

By contrast, in the unbundled market, buyers are significantly more productive than sellers and also have higher valuations prior to the transaction. This contrast is largely due to the selection of buyers across the two markets: the potential risk associated with acquisition renders the unbundled market more attractive for marginal buy-

[36] An interesting deviation relates to the persistent gap in Q between buyers and sellers for transactions that occurred during normal periods in the data. This could be due to growth options or other factors that the model fails to incorporate.

ers with good idiosyncratic shocks, whereas the potential benefits from acquisition-related synergy attract marginal buyers with low idiosyncratic productivity to the bundled market. This selection is more severe during downturns when costs (benefits) from structural changes are higher for productive (less productive) marginal buyers. Since most firms (especially the ones selected into the unbundled market) are not subject to valuation distortions,[37] reallocation in this market is mostly driven by dispersion in productivity.

In the bundled market, productivity shocks still play a role, but a less prominent one: prior to the deal, buyers on average experience improvement in productivity relative to sellers who typically experience productivity declines; but this relative improvement is much smaller than in the unbundled market. In addition to the weakened role of productivity, equity value distortions provide strong incentives for firms that are able to exploit this distortion by trading bundled assets. As a result, equity valuation turns out to be an important driving factor of reallocation in this market.

Dynamics of Resale Price and Aggregate Reallocation

I now describe the dynamics of aggregate reallocation in the calibrated economy and compare it with that in an economy without a bundled capital market (under the neoclassical framework). Figure 4 plots reallocation as well as price dynamics from both simulated data and real data.

Let me start with the characteristics of an economy from a neoclassical investment model (Alternative model) with homogeneous capital and endogenized price, as shown

[37] Based on the estimation, only 7.6% of firms have sentiment-sensitive equity valuation during normal times.

in the second panel of Figure 4. The capital resale price in such an economy is highly procyclical. Similar to the model in Lanteri (2018), such an adverse price impact from aggregate shocks renders divestment more costly during recessions, and uncertainty about future idiosyncratic shocks dampens marginal buyers' incentive to load up on capital, both of which depress reallocation needs in downturns.

Unlike the Alternative model, in which the adverse price impact is so great that unbundled sales turn procyclical, unbundled reallocation is countercyclical in my model because the marginal benefits from reallocation are greater than the marginal costs from the adverse price impact. There are two main reasons for this discrepancy; both relate to the cross-market interactions of reallocation between the unbundled and bundled market. First, the adverse price impact from aggregate shocks is less severe in my model than in the Alternative model. Second, benefits from reallocation are greater in my model than in the Alternative model. I explain both below.

Resale price is extremely sensitive to aggregate shocks in the Alternative model because firms only reallocate for productivity gains in response to shocks: good shocks induce most firms to buy, driving up asset prices and vice versa. The existence of a bundled market provides firms with new yet realistic alternatives—for example, when hit by good aggregate shocks, rather than all rushing to buy unbundled assets, firms can also acquire bundled assets for either real synergies or perceived synergies by euphoric investors, or both. With a price less sensitive to aggregate shocks, the bundled market serves as a "cushion" for large reallocation imbalances caused by aggregate productivity changes.[38] In addition, as I explain in Section 1.5, reallocation distortions in the bundled market create hidden capital liquidity that can be activated in the unbundled market during periods of large price swings. These cross-market inter-

[38]For example, following good aggregate shocks, certain firms may find it optimal to switch to the bundled market for capital needs as the price of unbundled capital continues to rise.

actions help alleviate the adverse impact of aggregate shocks on prices and thus on reallocation. As shown in Figure 5, prices shoot up by less following good aggregate shocks (10%, compared with 15.3% in the Alternative model). Similar patterns of alleviated price impact can be observed for bad shocks; the magnitude is much smaller, though, mainly because marginal sellers are less willing to wait for disposition in the bundled market due to higher costs of holding unproductive capital.[39]

In comparison with the Alternative model, benefits of reallocation are greater in my model as shown by the higher dispersion in marginal products upon adverse shocks in Figure 6. In the Alternative model, capital adjustment cost is the only cause of gaps in marginal products. In my model, by contrast, a major contributing factor to such gaps is distorted incentives from high valuations in the bundled market. Here is how: an extremely favorable financing environment attracts Type II firms to excessive capital investment at the expense of productivity. Such distortions can persist during booms because, rather than selling excess capital in the unbundled market, these firms are willing to delay disposition in the expectation of extremely favorable asset prices in the bundled market. Once the economy turns sour, they end up with large amounts of assets that are too costly for most firms to carry as sentiment cools down. The opposite holds for firms lured into excessive divestment during a boom: most find it optimal to acquire unbundled assets during downturns when the price is low. On top of that, with a weakened price impact of aggregate shocks (mentioned above), firms are less willing to wait for price improvement in the unbundled market as they would in the Alternative model. As a result, unbundled reallocation spikes following bad shocks, as shown in Figure 5.

In the bundled market, on the other hand, reallocation is procyclical. This is because, unlike its unbundled counterpart, bundled capital comes with its own tech-

[39]Idiosyncratic shocks are more persistent during bad times.

nology, which may or may not complement that of its new owner. Such uncertainty renders the asset an inferior substitute for unbundled capital for firms that want to take advantage of good productivity shocks. As a result, productivity dispersion is less of an incentive for reallocation in the bundled market. Following consecutive good aggregate shocks, more firms find themselves in a favorable capital environment to either expand—even excessively—or cash in a portion of their business, which results in a higher level of reallocation activity. Although profitable, these transactions are not necessarily efficient for productivity—e.g., participants in this market tend to be overly active in capital trading that features frequent overinvestment and divestment. In the model, excessive capital trading is fueled by high sentiment surrounding Type II firms.

The fact that valuation sentiment can lead to opportunistic trading, however, does not suggest that bundled reallocation is purely a financial game that creates no value. Most firms (92.4% during normal times and 62.4% when sentiment is high) still make acquisition/divestiture decisions purely for productivity reasons, as they do in the unbundled market.[40] In addition, as I show below, such sentiment also has its bright side in facilitating efficient reallocation in the unbundled market. However, the evidence does underline the importance of market sentiment in shaping the cyclical dynamics of bundled reallocation.

Reallocation Efficiency and Aggregate Productivity

So far I have focused primarily on firms' TFP. However, with decreasing returns to scale (DRS), reallocation efficiency is determined by the marginal product of capital

[40]E.g., Figure 8 compares marginal products of Type I and Type II buyers/sellers in both markets. As can be seen, for Type I firms, reallocation decisions in both markets are similar in the sense that firms with higher MPK expand till their marginal products approach the marginal cost of capital.

(MPK), rather than the TFP of firms. In a frictionless economy with DRS technology, firms with different TFP can coexist. Reallocation of capital from low-MPK to high-MPK firms improves aggregate productivity, which is optimized once the marginal products of all firms are equalized. With frictions (physical or financial), capital adjustment is not complete, and the gaps in MPK between marginal capital buyers and sellers reflect the magnitude of such frictions.

As Figure 7 shows, reallocation in the unbundled capital is efficient in the sense that firms with greater (smaller) MPK expand (downsize) until the gap between the two converges (incompletely). Reallocation in the bundled market, however, is not as efficient as a result of excessive capital trading by firms with distorted valuations. Backed by an extremely favorable capital environment, these firms tend to either overinvest or overdivest. Unlike buyers in the unbundled market who acquire capital until their marginal products approach the marginal cost, bundled capital buyers tend to "overshoot," which drives their marginal products below the marginal cost. Such a tendency toward excessive but inefficient reallocation during high-sentiment times has been well documented in the merger wave literature; for example, Porter (1989) and Kaplan and Weisbach (1992) report that 44% to 60% of unrelated acquisitions made during the conglomerate merger wave in the 1960s were subsequently divested. Additionally, Ravenscraft and Scherer (1987) find that the profitability of acquired firms did not improve, on average.

Valuation sentiment in such an economy has two offsetting effects on aggregate TFP: (1) spurring excessive opportunistic trading of capital in the bundled market; (2) easing frictions to reallocation, thus facilitating efficient reallocation in the unbundled market. The first effect is straightforward, and Figure 8 visualizes the tendency of Type II firms to engage in aggressive expansions or contractions. In practice, excessive capital trading is not unusual. As Kaplan and Weisbach (1992) put it, "acquirers often buy other companies only to sell them afterward"; they find that prices obtained in such divestitures are high enough to justify the acquisitions ex-ante.[41] The second effect comes from the interaction of reallocation across these two markets: the sentiment that motivated overinvestment or overdivestment in the bundled market helps enhance capital liquidity in the unbundled market. In an economy without the bundled market, capital resale price is so sensitive to aggregate shocks that firms would postpone dispositions in downturns until the economy recovers. In the calibrated economy, such an effect is less severe thanks to the hidden liquidity from firms that previously overinvested or overdivested in the bundled market. For instance, following good aggregate shocks, firms previously overinvested in the bundled market would be enticed to sell their extra capital in the unbundled market as the unbundled capital price continues to rise.[42] Such hidden liquidity helps counteract the adverse price impact of aggregate shocks, and thus facilitates efficient capital reallocation. Figure 5 visualizes this effect. Compared to an economy with only unbundled capital, the resale price responds less to aggregate shocks. In addition, rather than delaying asset dispositions, firms reallocate more during economic downturns.

In the model, two important variables help quantify these two offsetting effects: the magnitude of overvaluation B and the level of real asset price inflation p_s^b. B captures the extent to which (irrational) euphoric investors overvalue the benefits of certain acquisitions, as a percentage of the capital acquired. On the other hand, p_s^b captures the level of the bundled capital price supported by such market euphoria. In the extreme (unrealistic) case where the impact of equity misvaluation is

[41] For deals with comparable sale prices, they find that targets are sold at 143% of their market value before the initial takeover announcement.

[42] E.g, for Type II firms, although pricing in the bundled market is extremely attractive, some will still be willing to sell unbundled at relatively lower prices because bundled transactions only succeed with a certain probability.

confined to the financial market—it does not affect real asset prices, and acquirers pocket all financial gains, moderate overvaluation eases reallocation frictions without encouraging excessive trading, because the incentive to overinvest is dampened by the expected cost of unloading capital in the future. At the other extreme, where equity misvaluation is fully incorporated into real asset prices—e.g., targets pocket all gains, greater overvaluation encourages more inefficient reallocation because the optimal strategy for corporate managers is to trade their assets like securities—as brokerage firms would do. Figure 9 plots the marginal impact of B and p_s^b on the aggregate TFP in the calibrated economy.

In practice, the typical case would be somewhere in between. In the calibrated economy, 56.3% of the financial benefits from valuation distortions can be attributed to the acquirer, and the remaining 43.7% ($(p_s^b - p_n^b)/B$) to the target. In the net, the counterproductive effect of sentiment dominates, resulting in a moderate loss in TFP—aggregate TFP in the calibrated economy is 1.4% lower than in the economy under the Alternative model.

1.6 Conclusion

I show the existing evidence on procyclical reallocation is entirely driven by transactions in the bundled market. In the unbundled market where capital serves as a homogeneous factor of production, firms reallocate more when the benefits to reallocation are greater. In contrast, bundled capital transactions are highly affected by factors not necessarily related to productivity. These facts are hard to rationalize without a proper understanding of the nature of bundled capital. Unlike its unbundled counterpart, which can easily adapt to buyers' productivity, bundled capital typically comes with its own production technology, which may or may not complement that of its buyer. Such uncertainty discourages reallocation needs that are motivated by productivity gains. In addition, owing to its uniqueness, bundled capital is typically hard to value and prone to misvaluation. The latter opens the door to opportunistic trading, which manifests itself in the proliferation of capital transactions during periods of high market valuation.

I show that a heterogeneous agent model of investment with segmented used asset markets and a valuation sentiment component generates predictions largely consistent with the evidence from both markets. In the model, equity overvaluation encourages excessive capital tradings in the bundled capital market (e.g., overinvestment and overdivestment). On the bright side, it also improves asset liquidity in the unbundled capital market, facilitating efficient asset reallocation. Its net impact on aggregate TFP relies on the extent to which financial distortions are transmitted to real asset prices. In the counterfactual exercise, I show that the aggregate TFP of the calibrated economy is only 1.4% lower compared to the economy with only the unbundled market.

By treating capital as a homogeneous good, the existing literature views procyclical reallocation as indicative of considerable countercyclical frictions hindering efficient asset redeployment. Results in this paper indicate that inferences on reallocation efficiency could be greatly biased if one fails to recognize the nature of the different capital good markets. To make the point, I show that, even if we fully attribute the cyclicality of bundled transactions to irrational sentiment, procyclical reallocation would not be as harmful as the literature would suggest.

Chapter 2

THE PROFITABILITY OF LIQUIDITY PROVISION

2.1 Introduction

Continuous trading where investors can immediately execute buy or sell orders is made possible by the presence of counter-parties who stand ready to take on the opposite side of those trades. These collective counter-parties are said to provide liquidity to the markets by competitively supplying the quotes at which traders can buy or sell. Liquidity providers hope to buy low at the bid quotes to then exit the inventory position by selling at a higher ask price (and vice-versa), profiting from the spread between the two (Demsetz (1968)); on average liquidity providers do not realize the prevailing full quoted spread due to subsequent movements in the market quotes between trades (see, Kraus and Stoll, 1972; Hasbrouck, 1988; Stoll, 1989; Huang and Stoll, 1994). The provision of liquidity involves taking on risks associated with temporarily holding inventory such as adverse selection, price volatility, etc. In this paper, we measure the proceeds from the aggregate provision of liquidity and investigate the relationship between this aggregate realized profitability and the risk associated with providing said liquidity.

When measuring the realized profits from providing liquidity one has to match each inventory exacerbating trade to an off-setting trade where the inventory position is reversed, completing a "round-trip" trade. Absent the availability of trade-level data associated with individual liquidity providers, researchers have traditionally relied on proxies to gauge the returns to liquidity provision, the most important of which has been the realized spread. The realized spread rs corresponds to the signed difference between the transaction price P_t and the midpoint $M_{t+\tau}$ at some pre-specified horizon τ into the future.(Huang and Stoll, 1996; Bessembinder and Kaufman, 1997):

$$rs_{t,\tau} = \delta_t(P_t - M_{t+\tau}) \;\; ; \;\; \delta_t = \begin{cases} +1 & \text{if trade } t \text{ is buyer-initiated} \\ -1 & \text{if trade } t \text{ is seller-initiated.} \end{cases} \tag{2.1}$$

The realized-spread was originally intended as an estimate of mark-to-market profit, taking it as a literal measurement of the realized proceeds would assume that liquidity providers exit every trade-induced inventory position at the midpoint τ units of time into the future. The use of the realized spread measure has been so widespread that it was formally adopted by the SEC as a measure of market quality—Rule 11Ac1-5 (now Rule 605) requires market centers to disclose the volume-weighted realized spreads computed with a τ of 5 minutes. The reported Rule 605 data is often used by scholars seeking to understand the impact of market structure on trade execution quality.

The arbitrary choice of τ in the realized spread, which is left up to the researcher's discretion, represents a potential source of significant misspecification. The realized spread is a mark-to-market profit measured at a predetermined point in time and can substantially deviate from the realized proceeds if the price is different at the time of actual exit.[1] Furthermore, the amount of risk associated with each round-trip trade is directly related to the time it takes to complete the turnover. Longer waiting times increase the risk that the value of inventory held will decline, either due to random price changes or having been adversely selected by a better informed liquidity-demanding trader. In equilibrium, spreads would be competitively set by liq-

[1]The importance of choosing the horizon at which to measure realized spreads has long been recognized by Huang and Stoll (1996): *"... If the period is too short, the subsequent price may reflect not a reversal but another trade in a series of trades pursuant to the same order. If the period is too long, unnecessary variability will enter into the measure..."*

uidity providers to compensate for the risk of bearing an inventory position (Glosten and Milgrom, 1985). Employing a measure with a uniform τ for every trade can not, by construction, capture any of the variation in realized profitability due to heterogeneous inventory turn-around time. Even if a "sensible" choice of τ is used, if trades are reversed at various horizons the conventional measure of realized spread—using a fixed horizon for all trades—can deviate significantly from the true profits. Virtu, a prolific US market-maker, for example, reported negative average realized spreads (measured over a five-minute horizon under Rule 605) for 11 consecutive months during the calendar year 2019, despite their actual market-making profits being positive.

In contrast to the realized spread, we measure the realized profits to liquidity provision by directly tracking the round trips completed by passive liquidity providers in the aggregate. We take the view that each trade has a passive (liquidity providing) and an aggressive (liquidity demanding) side. Using existing technologies (Holden and Jacobsen, 2014) to identify the passive side of every trade, we track the aggregate inventory position as if a single "Aggregate Liquidity Provider" (ALP) supplied the liquidity to every trade. The ALP represents the aggregate provision of liquidity by the traders who take the opposite side of every liquidity-taking trade.[2] In effect, we are using limit orders as a proxy for liquidity provision. The realized profits of a round trip initiated at P_t and completed at $P_{t+\tau}$ is measured as:

$$rp_{t,\tau} = \delta_t(P_t - P_{t+\tau}) \quad ; \quad \delta_t = \begin{cases} +1 & \text{if trade } t \text{ is buyer-initiated} \\ -1 & \text{if trade } t \text{ is seller-initiated.} \end{cases} \tag{2.2}$$

In our formulation, we do not determine τ ourselves but rather every trade's τ is individually determined by an inventory tracking system and the presentation of the data. Our focus on the aggregate provision does not require the use of trader-labeled

[2]The ALP takes on a positive inventory position when investors are selling, and a negative position when there's a preponderance of buyer-initiated trades.

transaction data.

We track the ALP's inventory position because we do not have data on individual liquidity providers. This means our measure could be contaminated by the inclusion of trades resulting from passive limit orders submitted by long-term investors who intend to acquire or dispose of a position (Foucault *et al.*, 2005). Despite this imperfection, we show that our measure does a better job at matching market-making revenues as compared to the five-minute realized spreads reported under the SEC's Rule 605. To illustrate, Figure 10 plots the volume-weighted monthly averages of the realized spreads reported by Virtu under Rule 605, and our measure of realized profitability. The two measures are plotted against a backdrop of Virtu's market-making revenue (from their quarterly and annual SEC filings) from September 2018 to January 2021. In contrast to the self-reported 5-minute realized spreads, which bear little relation to the general trend of trading revenues, our realized profitability, despite applying to liquidity provision in aggregate, much better captures the broad pattern of market-making revenues of Virtu.

The key feature that distinguishes our realized profitability from the conventional realized spread measure is the determination of the trade turnaround time τ, which requires us to match each trade with a subsequent offsetting trade (to form a round trip). To match offsetting trades we adopt a LIFO (Last-in First-out) inventory tracking system under which offsetting trades are matched with the most recent positions of the ALP, consistent with the fact that liquidity providers prefer a quick turnaround.[3] Our reliance on a set inventory tracking system essentially allows the data to determine τ as opposed to the researchers' arbitrary choice. Note that under any inventory tracking system, not all trades will be matched with an offsetting coun-

[3]We report results and discuss the methodological differences of using alternative inventory systems such as FIFO (First-in First-out) in Appendix B.

terpart on the same day; we restrict our analysis to trades that are turned around within a day. This restriction is based on the rationale that liquidity providers very often do "go home flat" and that limit order executions not offset on the same day are more likely to be trades by longer-term investors (Easley *et al.*, 2011). Using a sample of all common stocks in the US equity market from 2017 to 2020, we are able to identify a total of 16.8 billion round trips.

Using this data, we document substantial variation in the horizon τ at which trades are turned around, and show that realized spreads, measured with a fixed τ for all trades, can deviate significantly from the realized profits to liquidity provision both in the cross-section and in the time series. To shed light on the causes and implications of these discrepancies, we first examine how realized profitability varies with the endogenous market-making horizon τ and compare that to the term structure of realized spreads documented in Conrad and Wahal (2020). We then show how the specification of common τ across all trades can cause systematic mismeasurement in the estimates of profits using realized spread and provide possible solutions.

Since longer inventory turnaround time typically implies a higher risk of market making—for example, higher probability of adverse information exposure and price volatility, the relation between τ and realized profits should reflect the risk-return trade-off faced by an average liquidity provider. We collect round trips into groups with similar turnaround times τ and compute the dollar-volume weighted average realized profitability for each group to construct a term structure of aggregate realized profitability similar to that in Conrad and Wahal (2020) to visualize the relationship between turn-around time and profitability. Conrad and Wahal (2020) measure realized spreads at varying prespecified horizons and document that the average realized spread decreases sharply with the time horizon τ used for the measurement. Contrary to the findings of both Conrad and Wahal (2020) and Hasbrouck and Sofianos

(1993),[4] we find aggregate realized profitability to be increasing in the market-making horizon. Specifically, it increases from 1.9 bps for quick turn-around round trips ($\tau < 1$ seconds), up to 6 bps for trips turned around between 9 and 10 minutes. This upward-sloping term structure is consistent with the risk-return trade-off faced by liquidity providers in a competitive market-making environment—when the expected turnaround time τ is large, the duration of inventory risk exposure is longer and, as a result, a higher return is required (by setting wider spreads).[5]

To be clear, what we do is calculate the average profitability only for those round-trip trades with a similar τ (for example, all trips with horizons between 9 and 10 seconds) and repeat for various values of τ to construct our term structure. We use the average value of the realized spread calculated using the same τ for every trade regardless as to whether or not the particular trades were actually turned around at that time when constructing the realized-spread term structure. To reconcile the differences in our results to those obtained in the prior literature we decomposed out realized profitability measure into a realized spread component measured with the endogenous τ and the effective spread at the exit $(t + \tau)$ of the round trip:

$$rp_{t,\tau} = rs_{t,\tau} + \delta_t(M_{t+\tau} - P_{t+\tau}), \tag{2.3}$$

where the τ is the horizon at which the inventory acquired at time t is turned around under our inventory tracking system. The differences with the constant τ realized spread term structure may come from heterogeneity in τ in the $rs_{t,\tau}$ component or from including the effective spread component $\delta_t(M_{t+\tau} - P_{t+\tau})$. We find that the average effective spreads, $\delta_t(M_{t+\tau} - P_{t+\tau})$, are relatively stable across horizons, so the

[4]Hasbrouck and Sofianos (1993) used spectral analysis on average mark-to-market proceeds of NYSE specialist inventory changes to infer a downward term structure in realized spread.

[5]The notion of being compensated for providing "immediacy" and then waiting to connect buyers and sellers extends back to Demsetz (1968).

differences in term structure primarily stem from the heterogeneity in τ across trades. In other words, the differences in term structure come from the selection of trades assigned to each τ rather than including every trade for every τ. We find that, once we use an inventory tracking system to determine the τ for each trade and only plot out the realized spread component the resulting term structure is still upward-sloping (rising from 0.2 bps for $\tau < 1$ seconds to 3.5 bps for $9 < \tau \leq 10$ minutes).

Next, we investigate how the average level and shape of the term structure in realized profitability differ for stocks that are expected to have a quick turnaround and stocks in which liquidity providers must hold on to their position for a relatively long time. This analysis serves two purposes, (1) it helps to understand how the τ-realized profitability trade-off in the cross-section (when variations in inventory turnaround time τ are well expected) differs from that in the time series (when variations in τ are less well expected); (2) it allows to study how the deviation of realized spread from realized profitability varies across stocks.

We sort stocks into quintile groups based on their average τ and construct the term structure for each quintile using the round trips of only those stocks in the group. We find that, in the cross-section, average realized profitability increases sharply across quintile groups: from 2.45 bps for stocks with the fastest turnaround (average $\tau = 56$ seconds) to 15.53 bps for stocks with the slowest turnaround (average $\tau = 213$ seconds). This is intuitive because market making in stocks with longer average inventory turnaround is expectedly riskier; when providing liquidity in a stock with a historically longer average turn-around time, competitive spreads should be set wider to compensate for the market-making risk. Consistent with this explanation, we find the cross-sectional difference is mainly driven by the effective spread component of the realized profitability in Equation (2.3), which increases from 1.39 bps to 14.36 bps. When looking at groups of stocks with similar turn-around times, the trade-off between inventory turnaround time and realized profitability is drastically different for different stocks. Specifically, the term structure of realized profitability is sharply increasing only for the fastest group: from 1.2 bps for τ below 1 second to 7 bps for τ around 10 minutes. As for the slowest group, the term structure exhibits a downward slope (decreasing from 17.5 bps to 15 bps).

The differences in the shape of the within-group term structures suggest that the relevant risks/considerations faced by liquidity providers are qualitatively distinct across different stocks. Liquidity providers in the fastest group face intense competition in market making at extremely short horizons, they compete for the orders which are quickly turned around by posting quotes at more and more attractive prices, narrowing spreads. Market making at these horizons is much less risky for stocks with fast turnaround—competitive forces drive down the profitability commensurate with the level of risk at the fast end of the term structure relative to the slow end, resulting in the upward-sloping shape. In contrast, in the "slow" markets, the chances of a quick turnaround are lower because trades are more sparse—more elapsed time typically implies more volatility—and more likely to be informed. The downward-sloping term structure for these stocks paints a picture where the spread is initially set wide because inventory is rationally *expected* to take a long time to be turned around; the longer inventory is held, ex-post, the more likely it is that the market maker fell victim to adverse selection; however, when offsetting orders arrive unexpectedly quickly (only if simply by chance), a larger portion of the initial spread is captured.[6] We interpret the downward sloping term structure as suggestive that adverse selection is a greater issue for the competitive outcome in stocks with a slow

[6]The "unexpectedness" is reflected by the fact that, for stocks with a slow average inventory turnaround, the dollar volume at the extremely short horizons is very small compared to the total dollar volume.

expected turnaround,[7] consistent with Easley *et al.* (1996).

In contrast to realized profitability, the term structures of the conventional realized spread are similarly downward sloping for all groups (though for the fastest two groups, the term structures seem to suggest some reversal for horizons above one minute). The difference between realized spread and realized profitability decreases monotonically both in level and in the term structure as we move towards stocks with a slower expected inventory turnaround. Specifically, for stocks with the fastest expected turnaround, average realized profitability is 382% larger than realized spread even for the shortest horizon (within one second); the difference increases with the horizon—realized profitability is sharply increasing in τ whereas realized spread is largely decreasing in τ (from 0.40 bps for trades turned around within one second to 0.165 bps for τ between half and one minute before reverting to 0.23 bps for τ between 8 and 10 minutes). As for the slowest group, the difference between realized profitability and realized spread is much smaller: average realized profitability is 84% larger than realized spread for the shortest horizon; the difference increases with τ at a much slower rate as both term structures are decreasing in τ.

Because trades are turned around at variously different horizons, the above results suggest that mismeasurement in the estimates of profits using realized spread (with a common τ for all trades) can be large and also time-varying, especially for stocks with fast turnaround, of which the profitability is highly sensitive to the inventory turnaround τ. Indeed, Figure 11 shows aggregate realized spread (measured with 10s) is significantly lower than the realized profitability throughout our sample period with the difference spiking during periods with high market volatility (when variations in

[7] Note that we are not taking a stand as to whether the profits are too low or too high for any stock at any horizon because we do not observe the full cost structure of market making across varying horizons.

time to exit are likely large). Compared to fast stocks, the realized spread for slow stocks captures the dynamics of realized profitability relatively better, potentially due to the lower sensitivity of the profitability to τ. The fact that the realized spreads of both fast and slow stocks are much smaller than their realized profitability counterpart is driven by the effective spread on the exit trade which is not captured by realized spread. We show that adding the effective spread to the conventional realized spread not only brings it closer to realized profitability in levels but also in dynamics: the correlation between the two increases from 0.29 to 0.79 for fast stocks and 0.49 to 0.66 for slow stocks. We find that a fixed τ realized spread is less correlated with the realized spread component of realized profitability (0.59) than the average effective spread is (0.68); this suggests that the effective spread itself, which does not require any determinations of τ does a better job at capturing the time-series dynamics of the realized profitability than a misspecified conventional realized spread measure.

2.2 Realized Spreads and Realized Profitability

The Passive Liquidity Provider

We measure the liquidity provision profitability by tracking the trading profits of a hypothetical trader we call the passive aggregate liquidity provider (ALP), who takes the passive side of every trade. Absent the simultaneous arrival of perfectly off-setting aggressive market orders, every trade must have an aggressive (liquidity-taking) and passive (liquidity-providing) side. In the modern electronic order book markets of today, liquidity providers serve the role of market making by submitting limit orders on both sides of the book. Indeed, any trader who submits a limit order is, for that moment, helping to make the market. Our concept of the ALP is made up of all actors who, however temporarily, contribute to the provision of liquidity.

The ALP takes the passive side to every liquidity-demanding trade and is such the collective market maker.[8] By focusing on the passive liquidity providers as a whole (the ALP), our study aims to shed light on the profitability of the liquidity provision business as a whole.

However, as pointed out by Foucault *et al.* (2005), passive orders are not the exclusive province of dedicated liquidity providers, traders often use limit orders to take on long-term positions,[9] we refer to these traders as unintentional liquidity providers (ULPs). ULPs contribute to the cumulative inventory of the collective ALP by passively taking on their positions. If we want to interpret the realized profitability as a measure of profitability for intraday liquidity providers who go home flat, then ULPs represent a source of noise in our measure of profits to liquidity provision. In Section 2.3 we show how the usage of LIFO and robust tests using alternative inventory systems can alleviate such concern.

Realized Spreads as a Profitability Measure

Equilibrium bid-ask spread—quoted spread, effective spread—reflects both the costs of providing immediate trading (e.g., inventory holding, order processing, adverse selection) and competition between liquidity providers (e.g., Glosten and Milgrom, 1985; Stoll, 1978; Ho and Stoll, 1981; Ho and Stoll, 1983; Kyle, 1989). The empirical literature on the relation between bid-ask spreads and trade execution costs typically features a breakdown of the effective spread into a permanently component—price impact, measured as the drift in quote midpoint following a trade—reflecting

[8] The SEC defines market makers as firms that stand ready to buy and sell stock on a regular and continuous basis at a publicly quoted price.

[9] By "long-term" we mean that the trader intends to hold onto their position for more than a day, longer than the intraday market-making horizons targeted by liquidity providers that we study here.

the informativeness of a trade, and a transitory component, realized spread, reflecting the reversal in transaction price associated with liquidity provision (e.g., Glosten and Harris, 1988; Hasbrouck, 1988). By and large, realized spreads have been calculated as the drift of midpoint away from the trade price at some prechosen fixed horizon $\bar{\tau}$ in the future:

$$rs_{t,\bar{\tau}} = \delta_t(P_t - M_{t+\bar{\tau}}); \quad \delta_t = \begin{cases} +1 & \text{if trade } t \text{ is buyer-initiated} \\ -1 & \text{if trade } t \text{ is seller-initiated.} \end{cases} \tag{2.4}$$

This measure is typically interpreted as the residual profits captured by the liquidity providers following the realization of price impact from trades (from the decomposition of effective spread).

$$\underbrace{\delta_t(P_t - M_{t+\bar{\tau}})}_{\text{Realized spread } (rs_{t,\bar{\tau}})} = \underbrace{\delta_t(P_t - M_t)}_{\text{Effective spread } (es_t)} - \underbrace{\delta_t(M_t - M_{t+\bar{\tau}})}_{\text{Price impact } (pi_{t,\bar{\tau}})}. \tag{2.5}$$

Under the implicit assumption that the midpoint proxies for the fundamental value, what this signed difference (between P_t and $M_{t+\bar{\tau}}$) captures is a mark-to-market profit. A mark-to-market profit measure at one point can be way off as a measure of round-trip profit if the price subsequently moves before the actual sale.

Realized Profitability

In this paper, we seek to measure the proceeds from the round-trip trades, as opposed to mark-to-market estimates. We track the prices and quantities at which the ALP enters and exits inventory positions and compute the realized return of each round trip—we call this return "realized profitability." A round trip is a pair of (partial) trades that comprise a reversal in the ALP's inventory position. For instance, the ALP buying 10 shares from a seller in the morning and later selling 5 of those shares to a buyer in the evening would make a round trip for 5 shares. The proceeds of a round trip initiated by a time t trade at a price P_t and completed by an offsetting time $t+\tau^*$ trade at $P_{t+\tau^*}$, where τ^* is the time horizon identified under LIFO, is defined as:

$$\text{RoundTripProceeds}_{t,t+\tau^*} = \delta_t \; |Q_{t,t+\tau^*}| \; (P_t - P_{t+\tau^*}), \tag{2.6}$$

where $\delta_t = 1$ if the initiating trade at time t was an aggressive buy and $\delta_t = -1$ if it's an aggressive sell and $|Q_{t,t+\tau^*}|$ is the number of shares reversed by the $t+\tau^*$ trade. The realized profitability $rp_{t,t+\tau^*}$ of the round trip is computed as the per-share return of the proceeds:

$$rp_{t,t+\tau^*} = \frac{\text{RoundTripProceeds}_{t,t+\tau^*}}{|Q_{t,t+\tau^*}|} = \delta_t(P_t - P_{t+\tau^*}). \tag{2.7}$$

In contrast to the realized spread (Equation (2.4)) which measures mark-to-market profits at a prespecified horizon $\bar{\tau}$, realized profitability measures the profits of a trader providing liquidity to both the initiating and reversing trades (using the τ^* at which trades are turned around).[10]

Similar to the interpretation of realized spread as a residual profit to liquidity providers in Equation (2.5), our realized profitability can also be interpreted as such a residual profit. Specifically, it is equal to the sum of the effective spreads at the initiation and termination of the round-trip trade less the price impact measured over the duration of the round trip as in Equation (2.8).

$$\underbrace{\delta_t(P_t - P_{t+\tau^*})}_{rp_{t,\tau^*}} = \underbrace{\delta_t(P_t - M_t)}_{es_t} + \underbrace{\delta_t(M_{t+\tau^*} - P_{t+\tau^*})}_{es_{t+\tau^*}} - \underbrace{\delta_t(M_{t+\tau^*} - M_t)}_{pi_{t,\tau^*}}. \tag{2.8}$$

Here the sum of the effective spreads at time t and $t+\tau^*$ reflect the full spread quoted by the liquidity provider for the round trip which is composed of both the entering and exiting trades.

[10] For example, if the ALP buys 1 share at the bid B_t and then sells that share later at the ask $A_{t+\tau^*}$ then the realized profitability would be $A_{t+\tau^*} - B_t$.

Substituting in the realized spread, $rs_{t,\tau^*} = \delta_t(P_t - M_t) - \delta_t(M_t - M_{t+\tau^*})$, into Equation 2.8 allows us to decompose the rp_{t,τ^*} into a realized spread component (with an endogenous τ^*) and the effective spread at the exit:

$$rp_{t,\tau^*} = rs_{t,\tau^*} - \delta_t(P_{t+\tau^*} - M_{t+\tau^*}) = rs_{t,\tau^*} + \delta_{t+\tau}(P_{t+\tau^*} - M_{t+\tau^*}) \tag{2.9}$$

Note that because the trade at time $t+\tau$ is an offset to the initial time t trade it's therefore the case that $\delta_{t+\tau} = -\delta_t$.

This decomposition helps illuminate any sources of differences between the realized profitability measure and the conventional realized spread on average. Starting with the simplified case where every LIFO determined turn-around horizon τ^* happens to be equal to the same constant $\bar{\tau}$, then the average realized profitability ($\sum_i(w_i \cdot rp_{t_i,\tau_i^*})$) would be equal to the average conventional realized spread with horizon $\bar{\tau}$ ($\sum_i(w_i \cdot rs_{t_i,\bar{\tau}})$) plus the average effective spread. After discounting the average effective spread (which is not effected by heterogeneity in τ^*), any difference between the realized profitability and fixed-τ realized spread in the averages would stem from heterogeneity in the LIFO determined τ^*s, $\sum_i(w_i \cdot (rs_{t_i,\tau_i^*} - rs_{t_i,\bar{\tau}}))$.

2.3 Methodology and Sample

Identify Round Trips

The main empirical challenge regarding the calculation of the realized profitability is how one decides which trades reverse one another to make a round trip. To construct round trips, we track the market-making inventory of the LP using trades of each stock. Specifically, for each stock, we record the LP's inventory entries starting from the first trade of a day: for example, a seller-initiated trade will count as the first positive inventory. Any following trades will be either recorded as a new inventory entry or used to offset the existing inventory entries depending on the sign of the trade as compared to that of the existing inventory.

We primarily rely on a “Last In, First Out” (LIFO) inventory tracking system to decide which pieces of existing inventory are reversed by the incoming trades for two reasons: one, LIFO is economically appealing because it tends to match offsetting trades that are temporally closer (more likely from market makers), and two, everything else equal, an alternative system such as FIFO (“First-In, First-Out”) introduces a mechanical bias in the estimates of realized profitability when there is large order imbalance.[11] However, for robustness, we also show that first, estimates of realized profitability are very similar under both LIFO and alternative tracking systems (FIFO and Weighted-Average-Cost) during days with small or no order imbalance, and second, for days with order imbalance, the general inferences from alternative tracking systems are the same as that from LIFO results when we properly control for the bias introduced by order imbalance.

Sample and Data Description

We use the daily Trade and Quote (TAQ) data from WRDS for the construction of round trips from January 5, 2017 to December 31, 2020. We use common filters on the CRSP universe for the selection of our sample stocks: all common shares (share codes 10 or 11) with exchange codes 1, 2, or 3. We also remove shares with a market capitalization below $100 million or a share price below $1 at the beginning of each year in our sample, to make sure micro-caps do not drive results. The CRSP sample is manually matched with the TAQ Masterfiles using the CUSIP code. We purposefully exclude trades that are likely to be missigned by the Lee and Ready algorithm, such as the opening prints (the first trades of the day) and trades reported late or out of

[11] The implementation of both inventory tracking systems, the comparison between the two, and the bias of the FIFO estimates during large order imbalance days are detailed in Appendix B.

sequence. We also drop block trades, orders designated with condition "B," or large trades with a size over the 95 percentile for trades for that stock, these kinds of trades are often prenegotiated and do not reflect the trades with which intraday liquidity providers typically interact with. Acquisition (A) and Cash Sale (C) designated trades are also dropped for similar concerns, even though such large trades are interesting by themselves, they are not the focus of this paper. For the trade signing, we use the quote and tick test from Lee and Ready (1991) following the implementation for daily TAQ data of Holden and Jacobsen (2014). A trader-initiated sell corresponds to an LP buy and a trader-initiated buy corresponds to an LP sale.

The Realized Profitability

Distribution of τ

We identified a total of 16.8 billion round trips. Figure 12 plots the distribution (histogram) of the turnaround time τ of all the round trips.

There is wide dispersion in τ across trades: although 79% of the volume has a turnaround time of fewer than 60 seconds; 8% has a turnaround time of more than 5 minutes. Importantly, when we decompose the dollar-weighted variance of τ into a cross-stock component and a within-stock component we find that nearly all of the variation, 97%, comes from the time series within each stock.

$$\underbrace{\sum_{i,t} w_{i,t}(\tau_{i,t}-\overline{\tau})^2}_{TotalVariation} = \underbrace{\sum_{i} w_{i}(\bar{\tau}_{i}-\overline{\tau})^2}_{Across\ Stock} + \underbrace{\sum_{i,t} w_{i,t}(\tau_{i,t}-\overline{\tau}_{i})^2}_{Within\ Stock} - 2\underbrace{\sum_{i,t} w_{i,t}(\tau_{i,t}-\overline{\tau}_{i})(\overline{\tau}-\overline{\tau}_{i})}_{Covariance}, \tag{2.10}$$

where $w_{i,t}$ is the dollar-volume weight for stock i's t^{th} trade. The fact that trades are turned around at variously different horizons even for the same stock suggests that, unless the profitability to liquidity provision is insensitive to the market-making horizon, selecting any fixed τ to approximate the profits with realized spread is unlikely to be accurate. For instance, a τ of 60 seconds may be too short for some trades (e.g., large trades or partial trades from a large order)—short in the sense that price has yet to recover from the transitory drift caused by temporary order imbalance—but too long for other trades.

The discrepancy with realized spreads measured using a fixed horizon can be large especially during days with an abnormal amount of large or correlated orders (typically comes with high volatility in prices). To show this, in Figure 13 we plot the time series of the aggregate realized profitability together with the aggregate realized spread (at both 10 seconds and 6 minutes) and compare both time series with the realized revenue from market making reported by Virtu in their quarterly report. As one can observe, the realized spreads measured with both 10 seconds and 6-minute horizons fall far short of matching the time-series variation in Virtu's market-making revenue, especially during the highly volatile period in early 2020.

Aggregate Term Structure

To examine how realized profitability varies with the endogenous market-making horizon, we first sort all round trips into groups based on their turnaround τ (e.g., the first group contains round trips with τ between 0 and 1 second, the second group contains round trips with τ between 1 and 2 second, etc) and then for each group, we calculate the dollar-volume-weighted realized profitability (rp_τ). Such a structure allows easy comparison with the conventional realized spread, which is only defined at pre-specified horizons. Figure 14 plots the term structure of aggregate realized profitability, along with the corresponding effective spreads and price impacts from Equation (2.8).

We observe a clearly upward-sloping term structure of realized profitability which stands in stark contrast to the sharply downward-sloping term structure of realized spread (Conrad and Wahal, 2020). The term structure not being flat along with a large amount of within-stock variation in τ means that any choice of a fixed τ in the calculation of realized spreads will lead to a misspecified estimate of realized profitability. We argue such an upward-sloping term structure is consistent with the risk-return trade-off faced by liquidity providers as a whole—slower inventory turnaround exposes liquidity providers to greater risk of, say, adverse information or large price swings; as compensation, they demand a higher return.

The accompanying term structure of effective spread reconfirms the above argument. As the turnaround time increases, effective spread also increases. This upward-sloping term structure of effective spread implies two things. First, market makers have rational expectations concerning the time it takes for a trade to be turned around. Second, they quote a higher spread for trades that they expect would take longer to offload—to compensate for the higher risk associated with holding the temporary inventory.

Sharpe Ratio Term Structure

The upward term structure of aggregate realized spreads provides a useful but imprecise depiction of the risk-return trade-off market makers face. To better visualize such a trade-off, we compute the Sharpe ratio (the ratio of dollar-volume-weighted average to the standard deviation of the realized spread) of all round trips in each τ group.[12] Figure 15 plots the term structure of Sharpe ratio.

In a perfect world absent frictions or costs, Sharpe ratios of liquidity provision

[12]For robustness, we also estimate the ratios in an alternative way: we first compute the Sharpe ratio of round trips in each τ group on a daily basis, and then compute a simple average of these daily estimates. The resulting Sharpe ratio estimates are almost the same using both methods.

across varying horizons should be equalized. In reality, however, frictions such as a high barrier to entry (e.g., high-frequency market making requires significant initial capital investment and operational costs) can limit competition thus causing deviation from equality. If we interpret the differences in Sharpe ratios across market-making horizons as reflecting such costs. The term structure in Figure 15 can also be viewed as the term structure of market-making cost. In Figure 15, market making at shorter horizons (within 1 second) exhibits a much higher Sharpe ratio at 7.3. This number declines sharply over the horizons up until 60 seconds and then slowly flattens out. Such a pattern is not surprising as marketing making at extremely short horizons is significantly more costly due to, say, data costs or server costs. At longer horizons above 5 minutes, we still observe an annualized Sharpe ratio as high as 2.8. By contrast, using the conventional measure of realized spread, the Sharpe ratio falls to almost zero after 1 minute. The evidence sheds light on the biases the conventional measure can generate, which we will discuss in more detail in the following section.

2.4 Dissecting the Term Structure

In this section, we break down the aggregate term structure and study both its cross-sectional and time-series components. To do that, we first compute the average τ for each stock using all round trips of that stock in our sample. We then sort firms into decile groups based on their average τ. With the grouping, we can separately study the time-series dimension of the term structure (within each group) and the cross-section dimension (across the groups).

Cross-sectional Variations in τ

The top panel of Figure 16 plots the distribution of stocks across varying τs. The y-axis denotes the percentage of stocks with average τ within the range marked by the edges of the bars along the x-axis. The colors denote the decile groupings—the group with the fastest inventory turnaround is marked dark green whereas the group with the slowest inventory turnaround is marked dark red. The bottom panel of Figure 16 shows the (simple) average τ of stocks from each decile group.

As in Figure 16, the average inventory turnaround time is less than 200 seconds for more than 80% of all stocks. This is not surprising as we know the cross-sectional variation constitutes close to 0% to the aggregate variation in τ. The bottom decile group of stocks (the active group with the fastest inventory turnaround) has an average τ of 56 seconds. Whereas the average τ for the top decile group (the inactive group with the slowest turnaround) is 212 seconds.

Trade-off between τ and Realized Profitability in the Cross-section

Table 10 shows the dollar-volume-weighted average realized profitability for each decile group using all round trips of the stocks in that group. Realized profitability is strictly increasing in the average inventory turnaround time of a stock. The average realized profitability is 2.45 basis points for the stocks with the fastest turnaround time and increases to 15.53 for the stocks with the slowest inventory turnaround. Similarly, the term structure of exiting effective spread is also sharply upward sloping—increasing from 1.39 basis points to 14.36 basis points. The slope of this cross-sectional term structure is much steeper as compared to the aggregate term structure (raising from 3.2 to 4.6 for the same range in τ), reflecting a sharper risk-return trade-off in the cross-section: because the daily average turn-around time τ is relatively stable within a stock, liquidity providers should have a relatively good idea about the risk of market making in each stock and sets their quotes according to this perceived level of risk (increasing in τ). From Table 10 we see that the ALP is relatively good at pricing liquidity (setting the entering spread) in the cross-section and gets compensated accordingly. This is consistent with Comerton-Forde *et al.* (2010) who find that market makers widen spreads as trading risks increase.

In terms of other characteristics of the stocks, Panel B of Table 10 shows that stocks with short turnaround times tend to be larger than those with longer turnaround times. They also have higher valuations (lower book-to-market ratios) as compared to slow stocks. This leads to the natural concern that the apparent relationship between τ and realized profitability is not driven by τ but rather other stock-level characteristics that just happen to be correlated with τ. To this end, we report in Table 11 the dollar-volume-weighted average rp for stock subsets sorted first by size and then average τ and also for stock subsets sorted first by book-to-market and then average τ. The initial sort serves as a rough means of controlling for size. The positive relationship between τ and rp remains intact for both small and large stocks. We repeat the same exercise with book-to-market and find the τ, rp trade-off to be similarly robust.

Trade-off between τ and Realized Profitability in the Time Series (within stock)

In this section, we investigate how the term structure of realized profitability differs for stocks whose trades are expected to be turned around quickly and stocks in which liquidity providers must hold on to their position for relatively longer. To do that, we construct the within term structure of realized profitability for each quintile group by estimating the dollar-volume-weighted average realized profitability at varying horizons using round trips of all stocks in that group. These within-term structures primarily reflect the τ-realized profitability trade-off in the time series. For those concerned with the cross-section variation within each group, we show that using an alternative estimation—compute the term structure for each stock (using dollar volume weights) and then aggregate all term structures by simple averaging across all stocks within each group—yields almost the same results.

In Figure 17 we plot out, for all groups, the realized profitability term structure as well as the term structure of its components (the alternative realized spread and the effective spread at the exit). In contrast to the comparison of average realized profitability across the groups themselves, the relation between realized profitability and τ appears more complicated within each quintile group. Specifically, realized profitability is sharply increasing in τ only for those securities with the fastest inventory turnaround. The majority of trading, 83% (by dollar-volume), occurs in securities classified as "fast"; this causes the aggregate term structure to be upward-sloping. As we move towards the stocks with a slower turnaround time, the term structure begins to take on a downward slope (e.g., for the slowest two groups). This transformation from upward to downward sloping is even more pronounced when looking at the term structure of the realized spread component of the realized profitability. Similar variation in the term structure across securities does not emerge when looking at realized spreads. This is evidence of our realized profitability measure capturing aspects of the different markets which are missed by the conventional measure.

Figure 18 plots out the term structure of the realized spread, by using the same fixed τ for every trade, across the different groups of fast/slow stocks. We see a consistent downward-sloping term structure across the different groups with the only visible variation being in the gradient of the decline. The most important takeaway is that the fundamental trade-off between holding time τ and profitability is reversed for fast stocks. There are other implications as well. First, Huang and Stoll (1996) set forth the intuition that if the choice of τ is too short when computing realized spreads the observed price may not have reverted back to fundamental value, and if chosen too long it would be contaminated by the effects of other trades. By this logic, it should be the case that after a certain τ, the mean realized spreads should level out as the additional noise is averaged out. We do not see this, for each group, we see realized spreads continue to decline even past the average turnaround time for each group; in fact, we see a (partial) reversal beginning to manifest in the two fastest groups (which together make up 95% of the whole market).

Figure 19 plots the average entering and exiting effective spread for the round trips at different turnaround times for the fast/slow groupings. In the graph, effective spreads are largely increasing in τ across groups, suggesting that the ALP quoted higher spreads for trades that took longer to turn around. If we take the (realized) time-to-exit as a reasonable proxy for the (expected) market-making risk, we can see the effective spreads increase with the expected risk of market making. We interpret that as evidence of the ALP's overall capability to evaluate the riskiness of trades in the time series, quoting a wider spread when trades take longer to turn around.

In terms of realized profitability, we attribute the differences in the term structures to the varying level of competition intensity across the groups. Specifically, for the group with the fastest inventory turnaround, market making at extremely short horizons is relatively less risky. This temptation of "risk-free" profits attracts intensive competition from market makers with speed advantages, driving down the profitability at these extremely short horizons. As we move towards stocks with a slower inventory turnaround time, the prospect of "risk-free" return gets slimmer as trades are sparser and more likely to be informative. For these stocks, concerns about information asymmetry and adverse selection discourage competition on quotes from high-speed market markers. As a result, the realized profitability is larger at the extremely short horizons and the remaining term structure is mostly dominated by price impact from adverse selection.

Term Structure Steepness and Volatility

Our interpretation of the term structure for both fast and slow stocks centers on a risk-return trade-off. One way to check this intuition is to see whether or not these trade-offs are more or less pronounced during periods of elevated price risk. Simply put, the rp term structure for fast securities should have a steeper upward slope when volatility is high and the rp for slow securities should be more downward sloping if during these times adverse selection risks are elevated. To measure the slope of the term structure we run monthly regressions of round trip realized profitability rp on the turn-around time τ and use the coefficient on τ as our measure of the slope. For fast stocks, this coefficient is positive indicating that the longer hold-times are associated with higher returns to the ALP on average, for slow stocks it is the reverse. We proxy for the level of risk by computing the realized variation of transaction prices calculated following the methodology laid out by Zhang *et al.* (2005). Figure 20 plots the slope of the term structures against the RV for both groups of stocks. We found that whenever the RV increases, the slope of the fast term structure becomes more positive while that of the slow group becomes more negative.

Deviation of Realized Spread From Realized Profitability

The previous section suggests that conventional realized spread measures can deviate significantly from our realized profitability. The difference between the two, however, is monotonically decreasing both in level and in term structure as we move towards stocks with a slower expected inventory turnaround. Specifically, for stocks with the fastest expected turnaround, the average realized profitability spread is 382% larger than realized spread even for the shortest horizon (within one second); the difference increases with the horizon—realized profitability is sharply increasing in τ

whereas realized spread is largely decreasing in τ (from 0.40 bps for trades turned around within one second to 0.165 bps for τ between half and one minute before reverting to 0.23 bps for τ between 8 and 10 minutes). As for the slowest group, the difference between realized profitability and realized spread is much smaller: average realized profitability is 84% larger than realized spread for the shortest horizon; the difference increases with τ by a much slower rate as both term structures are decreasing in τ.

Because trades are turned around at variously different horizons, the above results suggest that the biases in the estimates of profits using realized spread with a common τ for all trades can be large and also time-varying, especially for fast turnaround stocks of which the realized profitability is highly sensitive to the τ. Indeed, Figure 21 shows aggregate realized spreads (measured at both 10 seconds and 6 minutes) are significantly lower than the realized profitability throughout our sample period with the difference spiking during periods with high market volatility (when variations in time to exit are likely large). Compared to fast stocks, realized spreads for slow stocks capture the dynamics of realized profitability much better, potentially due to the lower sensitivity of the profitability to τ. After detrending both time series by first differencing, the contemporary correlations between realized profitability and realized spreads for fast stocks lie at below 0.3 regardless of the horizon chosen for the estimation. For slow stocks, the correlations are much higher, hovering around 0.5. Still, these numbers suggest there is significant variation in realized profitability in the time series not captured by the conventional realized spread measure, even for the slow stocks.

2.5 Robustness: Alternative Inventory Tracking

When using FIFO, the aggregate term structure for the realized profitability is downward sloping. The issue is that, as we previously discussed, the downward slope may be a mechanical artifact of the interaction of the FIFO system with order imbalance. In Figure 22 we plot out the empirical term structure under FIFO for different stock-day trade imbalance deciles. Consistent with our result from Section B we observe a downward-sloping term structure that gets more dramatic as the level of order imbalance increases. Interestingly is that when restricting ourselves to low-imbalance stock days, when the influence of the mechanical bias is lower, the term structure is upward-sloping, consistent with our results using LIFO.

In Figure 23 we perform the slow-fast τ sorts using all stock days (top) and the 25% stock days with the lowest imbalance (bottom). The main difference in the term structure under FIFO when including high imbalance days seems to be one of level as they are all downward sloping. Restricting ourselves to low imbalance days, we get patterns broadly consistent with the LIFO results.

The shape of the LIFO term structure is stable across stock days with low or high order imbalances whereas the FIFO term structure is not. At first glance, this raises the concern that FIFO is capturing something LIFO is not on high-imbalance stock days. This behavior in the FIFO term structure is however perfectly in line with the mechanical relationship between the FIFO term structure and order imbalance examined in Section B. In other words, we believe that the drastic change in the FIFO term structure is due to a statistical artifact inherent to the method itself. Any alternative explanation would have to argue for the existence of an economically significant factor affecting liquidity provider inventories on high imbalance stock days that: (1) reverses the risk-return trade-off observed in low imbalance days, (2) is distinct from the FIFO mechanical bias, and (3) is sensitive to measurement methodology, showing up in FIFO but not LIFO.

2.6 Conclusion

The conventional realized spread estimates a mark-to-market profit at a prespecified (exogenous) market-making horizon; this profit can deviate significantly from the profits to liquidity provision if the price subsequently moves at the time of the exit. By tracking the cumulative inventory positions of all passive liquidity providers in the US equity market and matching each position with its offsetting trade, we construct a measure of profits to liquidity provision (realized profitability) that matches the dynamics of Virtu's market-making revenue much better than realized spread (at any reasonably prespecified horizon).

To make sense of the difference between our realized profitability and conventional realized spread, we assess how realized profitability varies with the endogenous market-making horizon τ and compare that to the term structure of realized spread in Conrad and Wahal (2020). We find, unlike the conventional realized spread, which is sharply decreasing in τ, our realized profitability is strictly increasing in τ. Since longer inventory turnaround typically implies a higher risk of market making, we interpret our result as consistent with the risk-return trade-off faced by an average liquidity provider in the competitive market-making business. By decomposing our realized profitability into an alternative realized spread component (measured with endogenized τ for each trade) and the effective spread at the exit trade, we show the bias in the conventional realized spread as a proxy for market-making profit is mainly caused by the specification of common τ across all trades.

Figure 1: Timeline

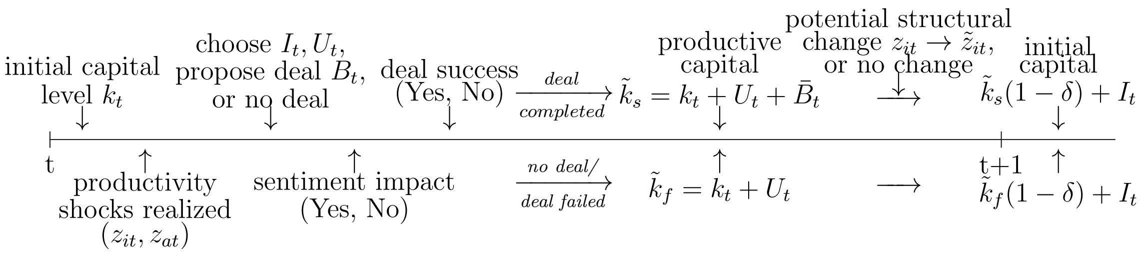
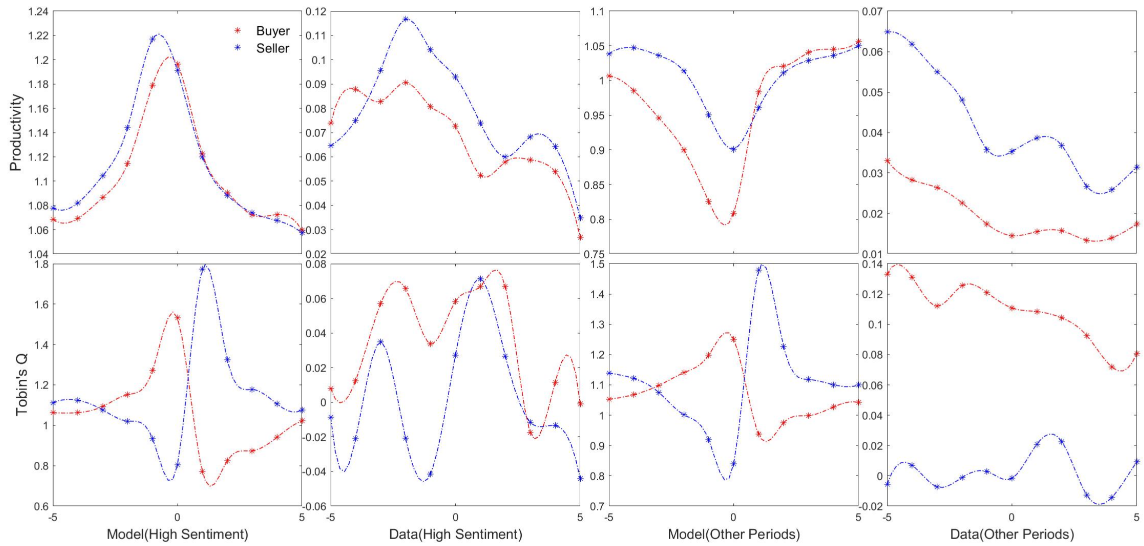
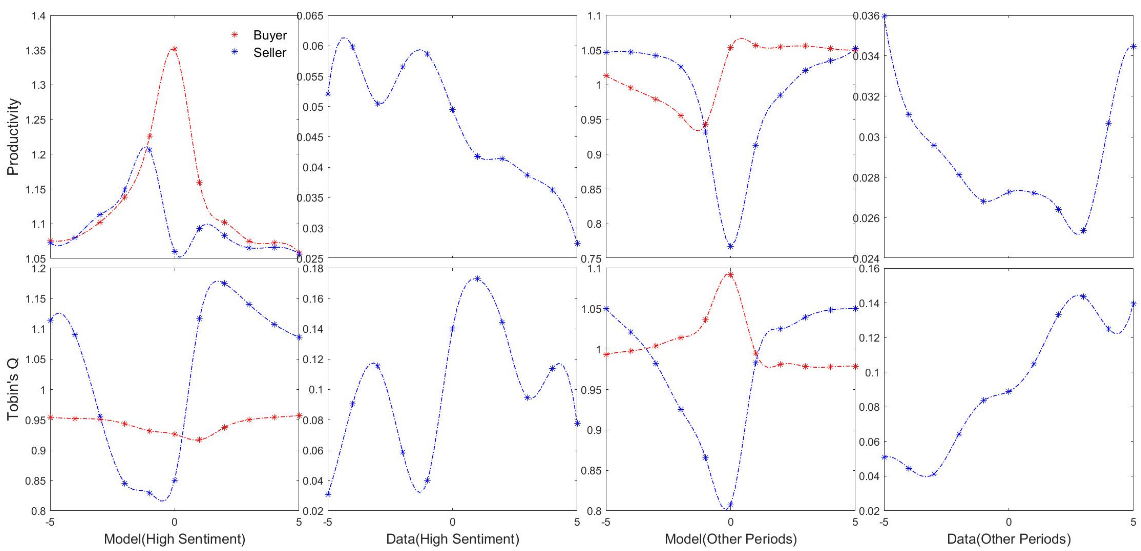


Figure 2: Characteristics of Buyers and Sellers in the Bundled Capital Market



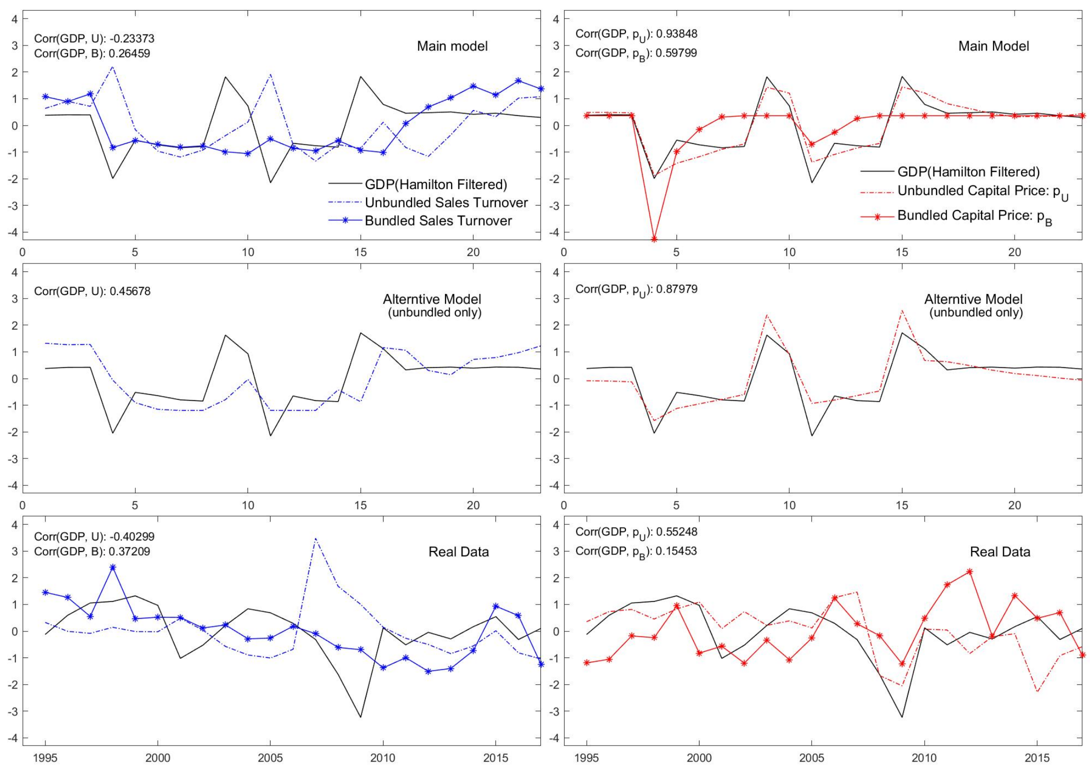
The top (bottom) panel plots average productivity and Tobin's Q of both the buyers and sellers 5 years before and after the transaction. Capital productivity is proxied by the gross profitability of the firm. Gross profitability is defined as the ratio of value added (SALE-COGS-XSGA) to the book equity of the firm. Results using alternative measures of productivity are shown in the Online Appendix. Transactions are grouped into two categories based on whether the transaction occurred during periods of high valuation sentiment or not. The left two columns use model generated data, whereas right two columns use data on bundled capital sales and Compustat data on acquisitions and accounting performances. All empirical measures are industry demeaned at 2 digit sic level. High sentiment periods are defined as years following consecutive good aggregate productivity shocks for model implied data and years with a sentiment index half a standard deviation above historical mean (alternative definition using consecutive GDP growth half a standard deviation above historical mean results in similar but noisier patterns).

Figure 3: Characteristics of Buyers and Sellers in the Unbundled Capital Market



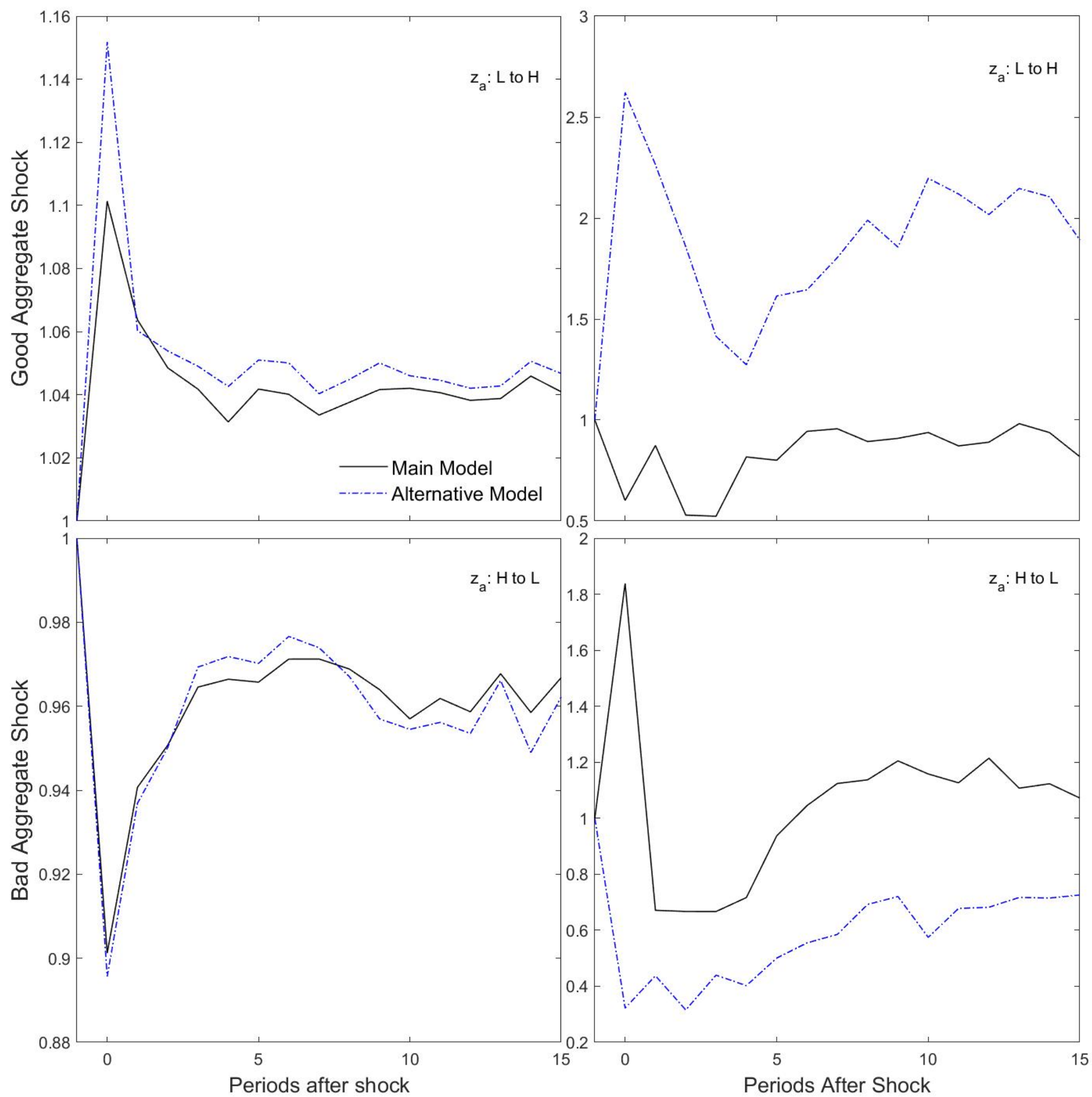
Definitions of the series follows Figure 2. The right two columns only demonstrate accounting measures on unbundled capital sellers (data on buyers not available).

Figure 4: Aggregate Reallocation and Asset Prices across Business Cycles



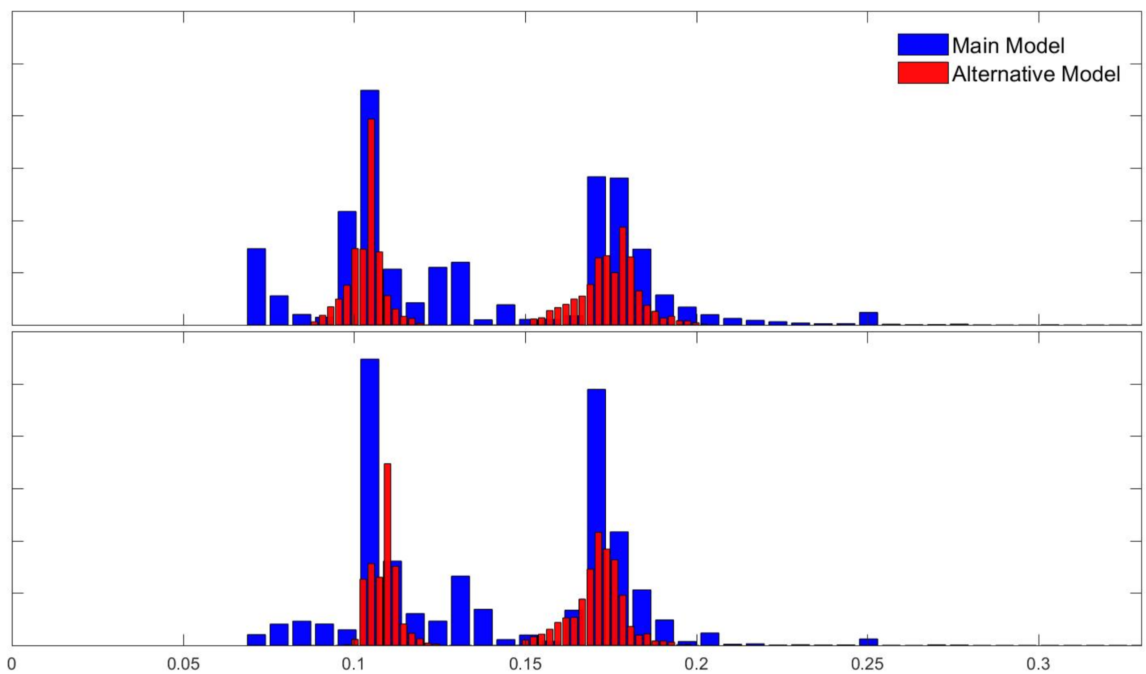
Top panel uses data generated from the main model with a random path, the following panel uses data generated from the same model excluding the bundled capital market, bottom panel presents data using GDP from U.S. Bureau of Economic Analysis and collected data on asset sales and prices.

Figure 5: Unbundled Capital Price (left) and Reallocation (right) following Good (Bad) Aggregate Shocks.



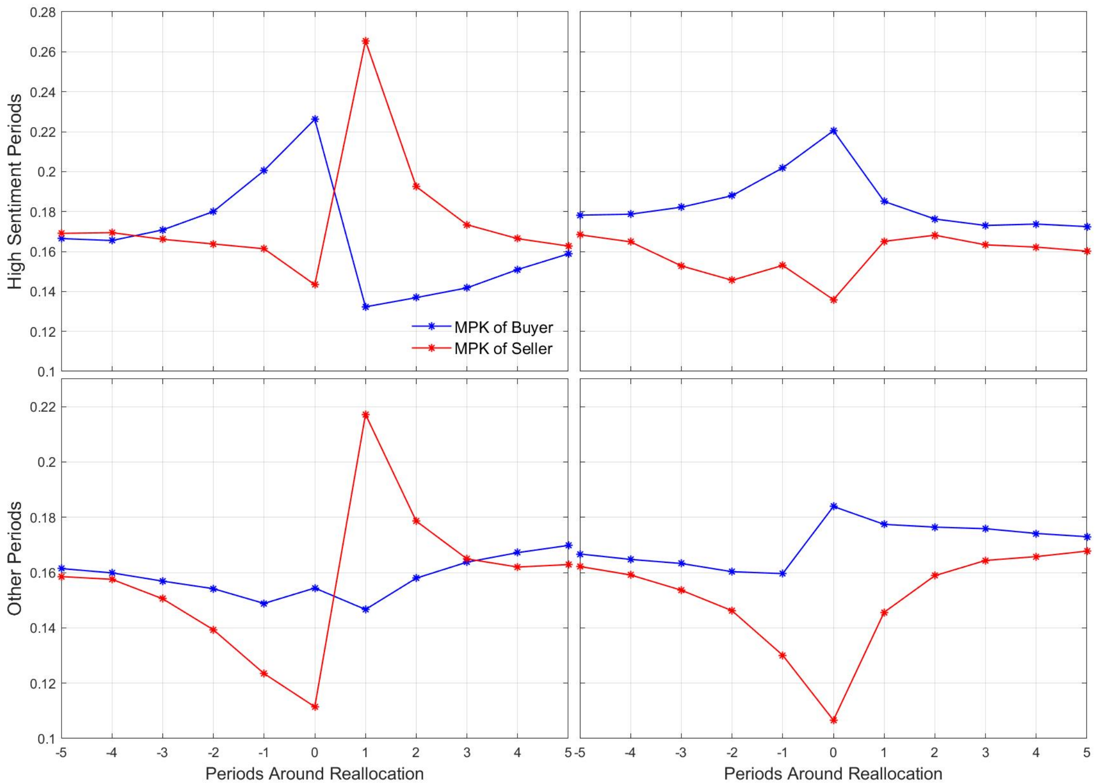
Both price and reallocation normalized to 1 before the shocks. Black line demonstrate price impact as well as reallocation dynamic under the main model, whereas blue line the model with only unbundled market.

Figure 6: Distribution of MPK at the Beginning (top) and End (bottom) of Transitions from $z_a = H$ to $z_a = L$.



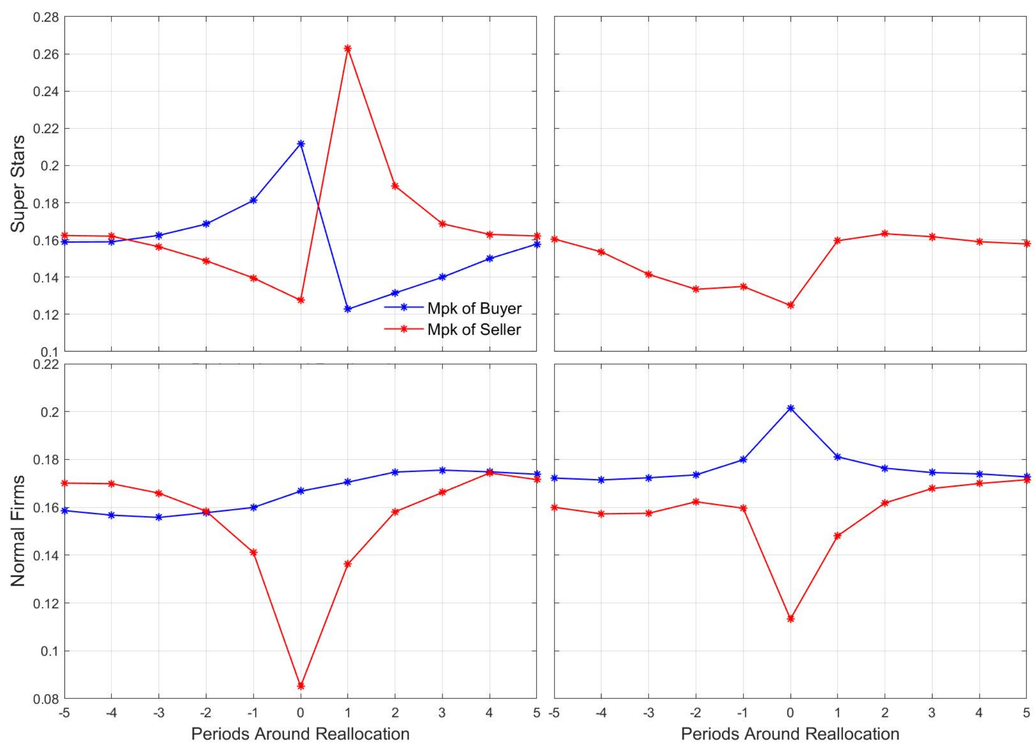
Pictures show histograms, each bar's vertical height corresponds to the amount of capital with marginal product within the range marked by the edges of the bar along the x-axis. Blue bars show distribution under the main model, whereas red bar the Alternative model.

Figure 7: Marginal Product of Buyers/Sellers in the Bundled Market (left) and Unbundled Market (right): by Periods



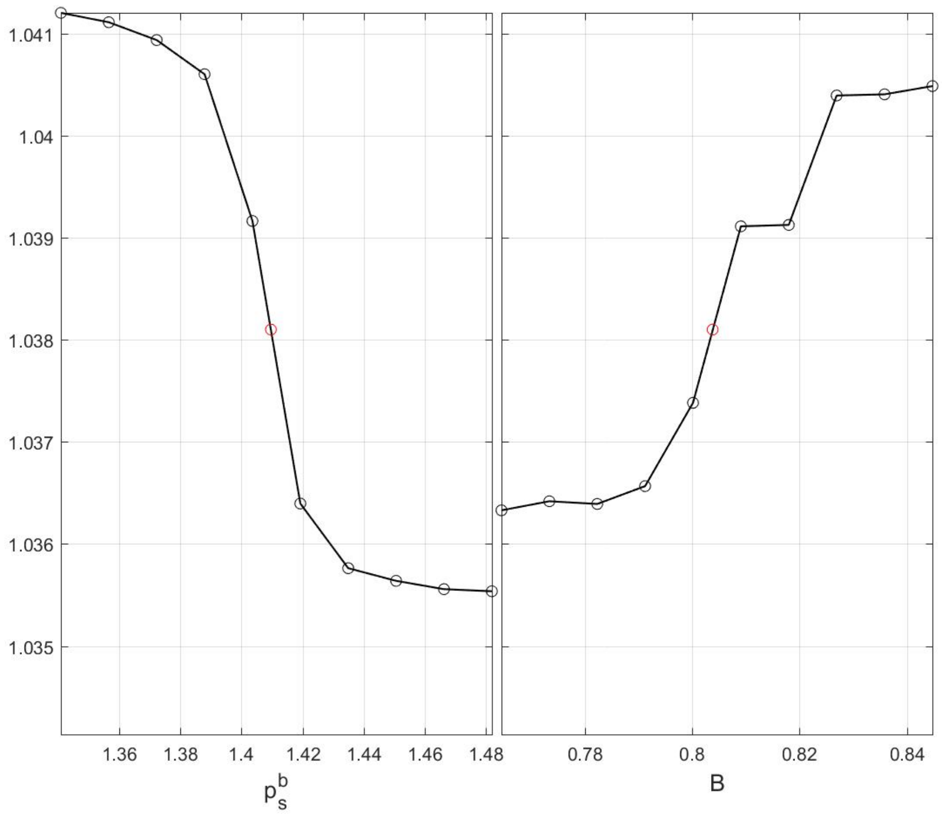
Both price and reallocation normalized to 1 before the shocks. Black line demonstrate price impact as well as reallocation dynamic under the main model, whereas blue line the model with endogenized capital price.

Figure 8: Marginal Product of Buyers/Sellers in the Bundled Market (left) And Unbundled Market (right): by Firm Type



Mpk data averaged over all periods. Missing blue line for buyers in the unbundled market because type II firms do not acquire capital in the unbundled capital market.

Figure 9: Marginal Impact of Equity Valuation (B) And Real Asset Price (p_s^b) On Aggregate Productivity



B captures the extent to which external (irrational) investors overvalue the benefits of certain acquisitions, as a percentage of the capital acquired. p_s^b captures the level of bundled capital price supported by such market euphoria. Red circles mark the original values of aggregate TFP, B, p_s^b from the calibrated economy. Black circles mark changes in aggregate TFP as we vary the x variable with other variables fixed.

Figure 10: Rule 605 Reported Spreads and Realized Profitability

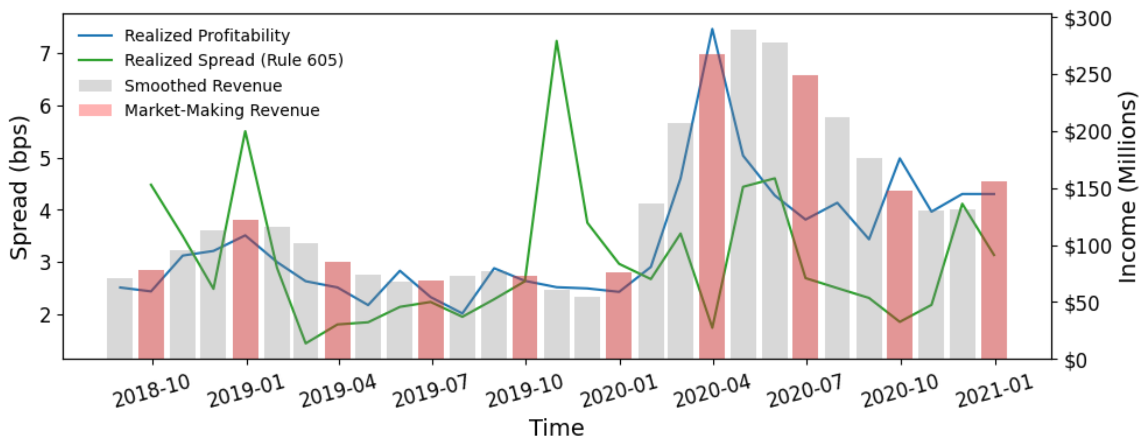
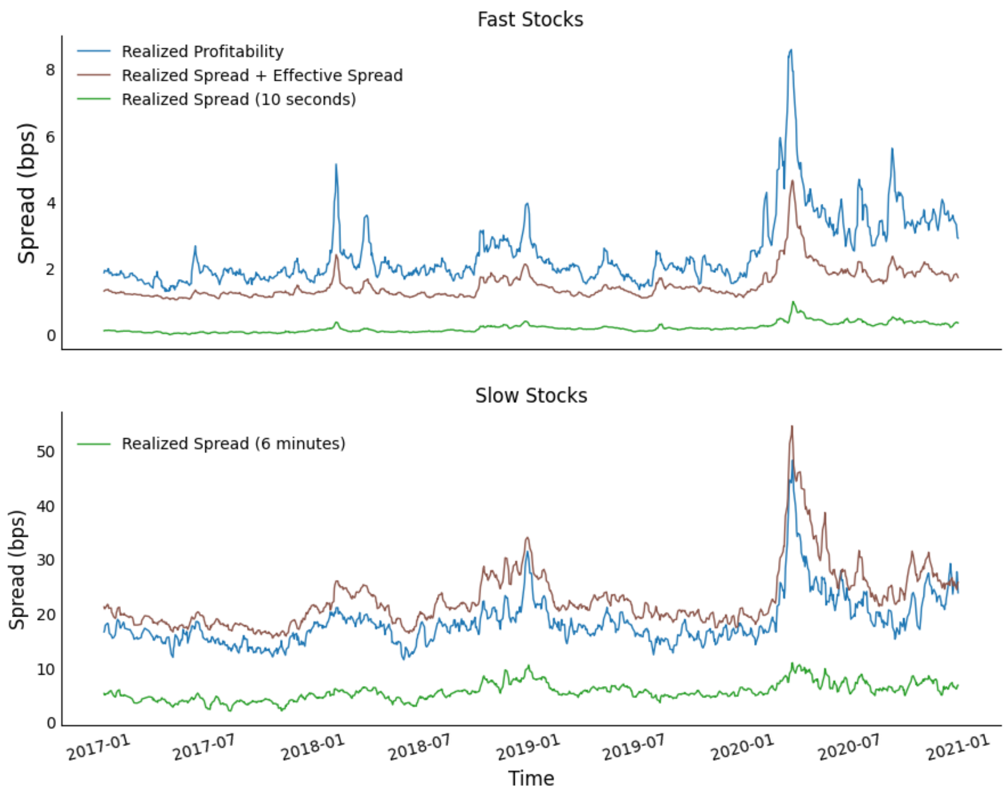


Figure plots the monthly average realized spread (green line), monthly average realized profitability, and Virtu's quarterly market-making revenue (red bar) together with the monthly interpolation of the revenue (grey bar). Average realized spread is computed monthly by aggregating reported realized spreads of a group of matched securities (both in Virtu's Rule 605 and in our sample) using the executed number of shares as weights. Average realized profitability is computed for the same group using our realized profitability data and the same weights. Market-making revenue is the quarterly trading income of Virtu's market-making segment (from Virtu's 10K filings).

Figure 11: Adding Effective Spread to Conventional Realized Spread



The dollar-volume weighted realized profitability rp (blue) for the sample of "fast" securities is plotted in the top panel alongside the dollar-volume weighted realized spread computed with a 10-second horizon with the effective spread (brown) and without (green). The bottom panel plots a similar time series for the "slow" stocks but with the realized spread computed with a 6-minute horizon.

Figure 12: Distribution of τ

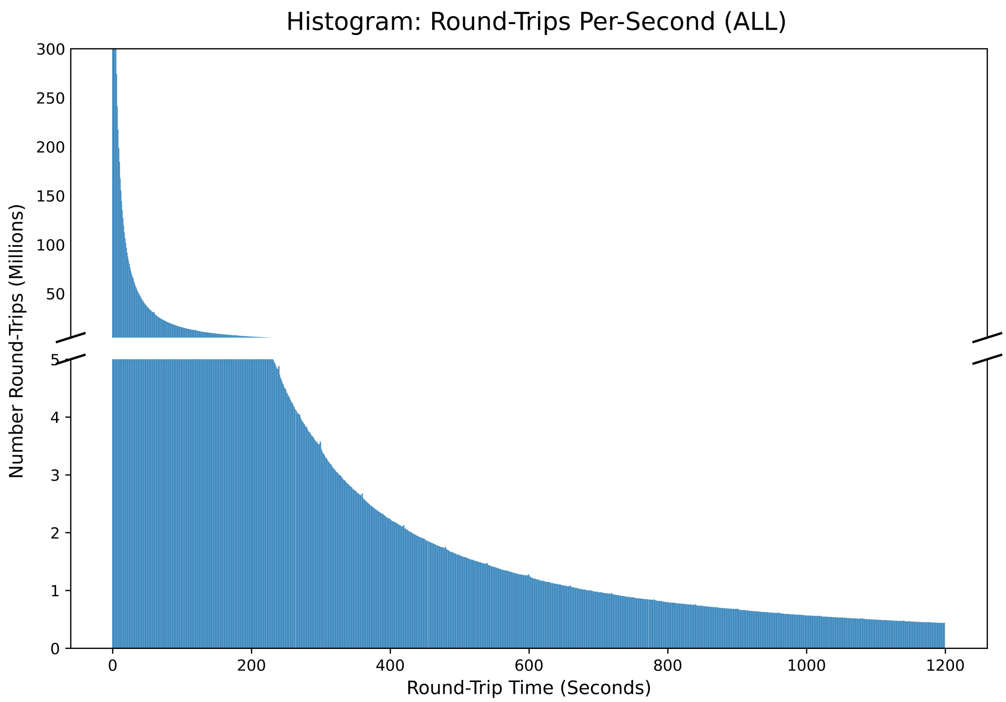


Figure plots the histogram of the round trip time τ (restricted to up to 1200 seconds for visual clarity). The x-axis corresponds to the inventory turnaround time τ, the y-axis the total number of trips that are turned around at τ (x-axis) from their initiation. Using dollar volume instead of the number of trips gives similar distribution.

Figure 13: Deviation of Realized Spreads From Market-making Revenue

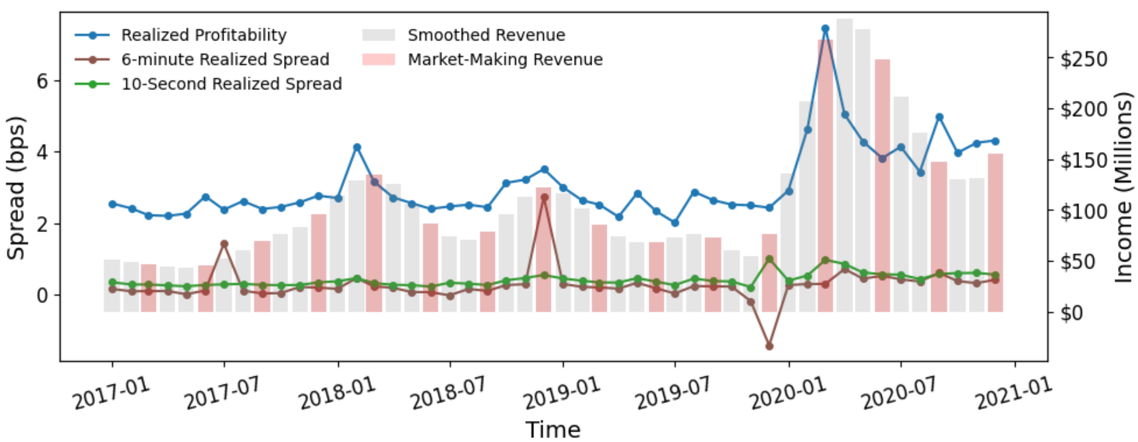
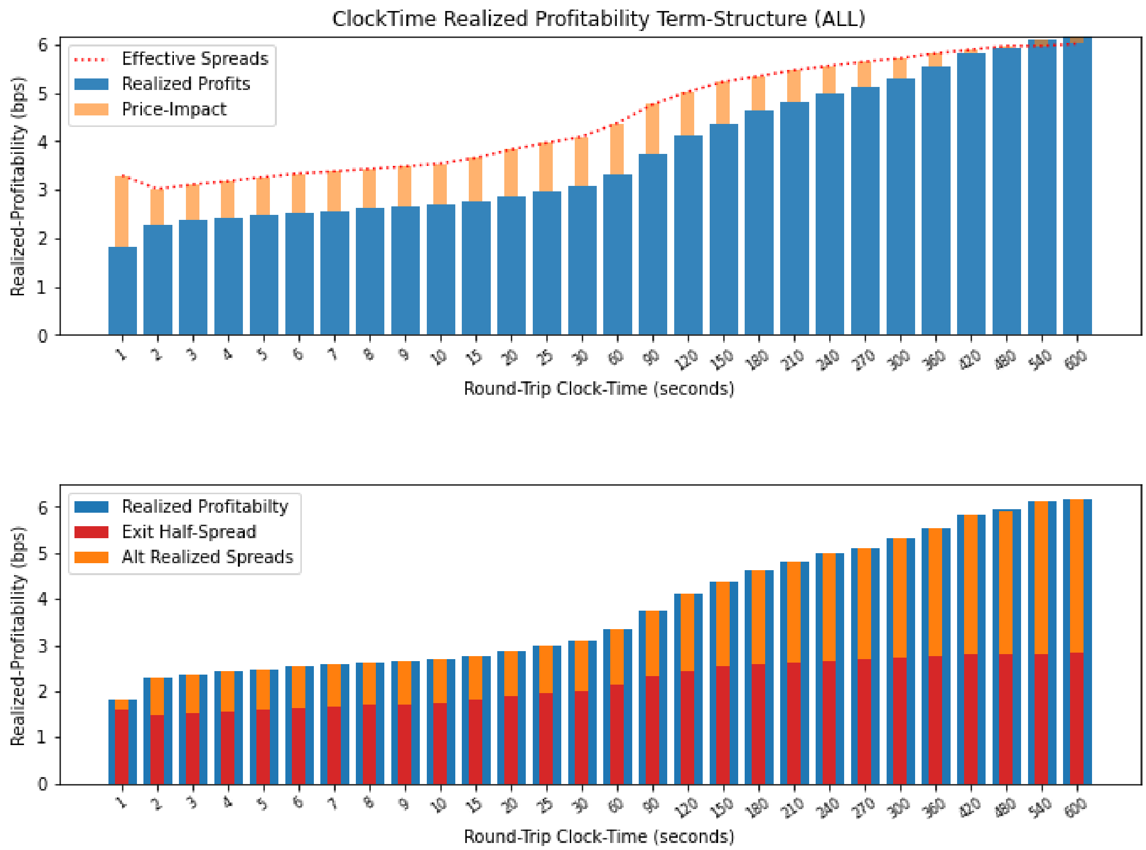


Figure shows the time-series of (dollar-volume-weighted) average realized profitability, average realized spreads under both 10 seconds and 6 minutes, and quarterly market-making revenue (with monthly interpolation). Monthly measures of realized profitability are computed by taking the dollar-volume-weighted average of the realized profitability of all round trips in that month. Monthly measures of realized spread are computed by taking the dollar-volume-weighted average of the realized spread of all trades in that month. Quarterly market-making revenue data comes from Virtu's quarterly financial report: the trading income under the market-making segment.

Figure 14: Aggregate Realized Profitability



The figure plots out the term structure of the realized profitability rp over clock-time horizons. Each bar shows the dollar-volume weighted-average rp (blue bars) of all round trips with a turnaround time between the specified blocks of time. The first two blocks are composed of round trips of 0-1 seconds and 1-2 seconds; the last two blocks are composed of trips that took 480-540 seconds and 540-600 seconds. The top panel decomposes realized profitability into the sum of effective spreads (red-dashed line) and price-impact (orange bars). The bottom panel decomposes rp into the exiting half-spread (red bars) and the alternative realized spread component with endogenous τ (orange bars).

Figure 15: Sharpe Ratio of Liquidity Provision

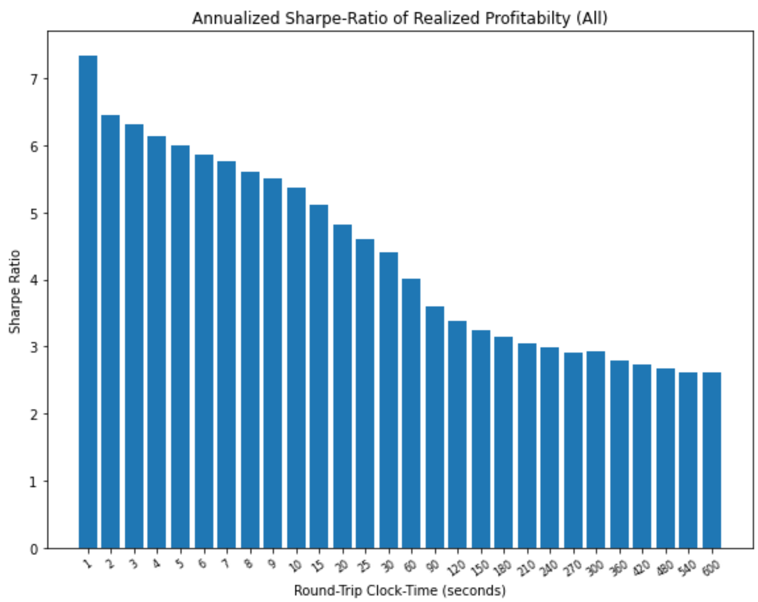
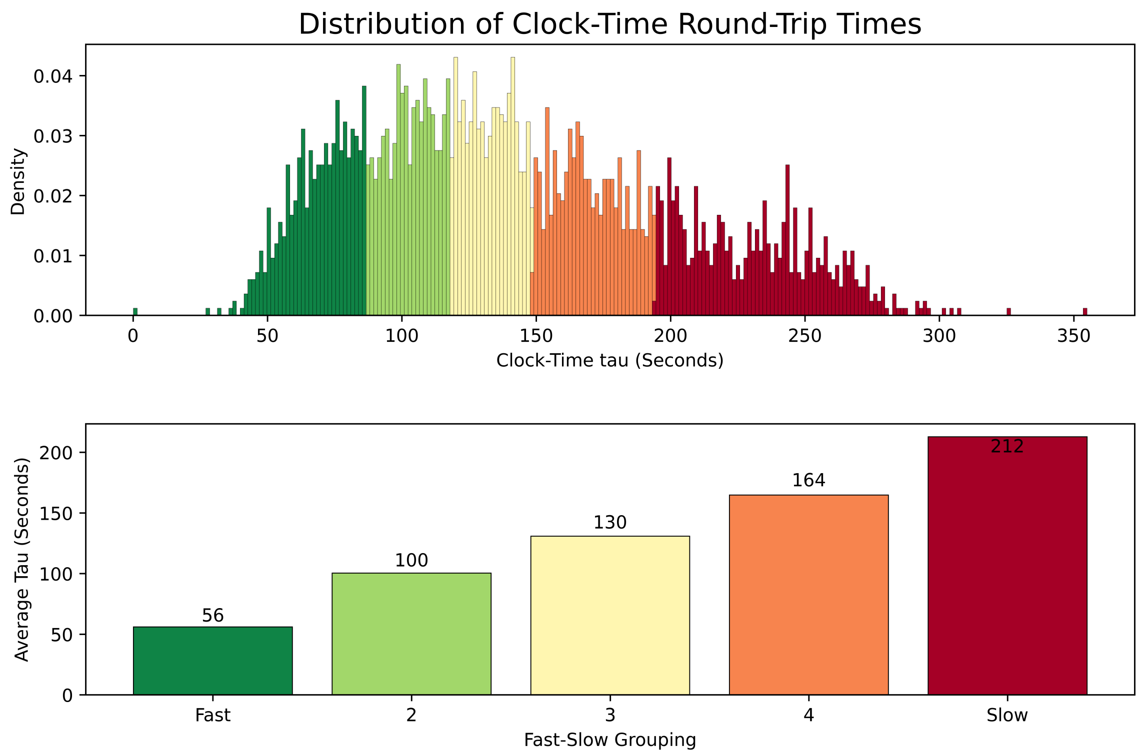
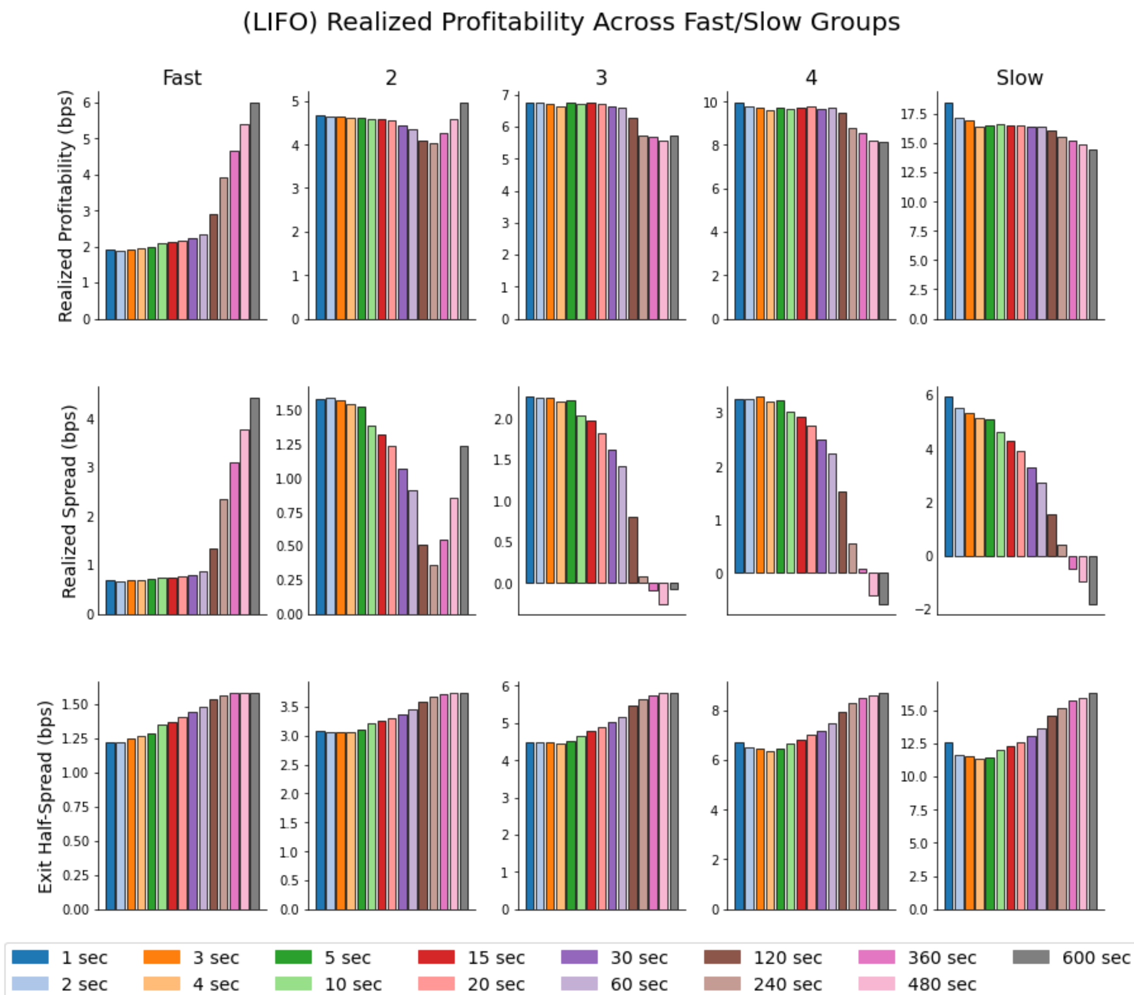


Figure 16: Distribution of τ (Cross-section)



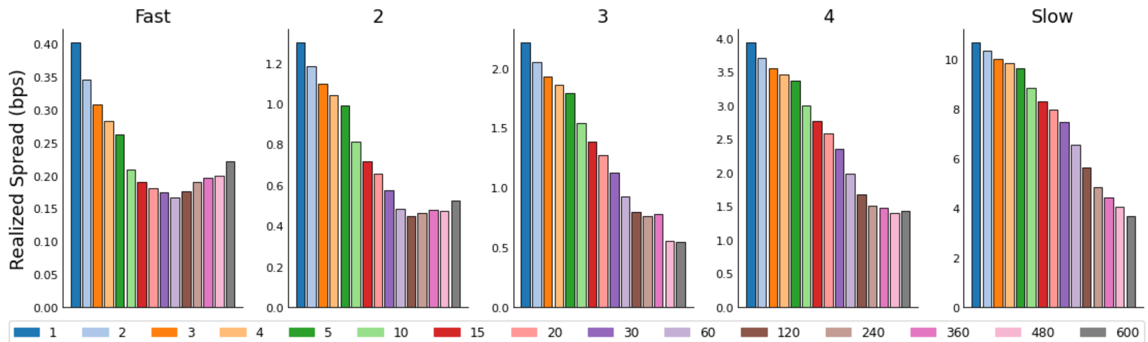
The top panel of this figure plots out the distribution of the average turnaround time τ of the individual stocks in our sample. The y axis denotes the percentage of stocks with an average turnaround time between the range marked by the edges of the bars along the x-axis. The sample is split into quintile grouping based on τ and is color-coated on a fast (green) to slow (red) spectrum. The bottom panel plots out the dollar-volume weighted average turnaround time of each quintile grouping in seconds.

Figure 17: Realized Profitability



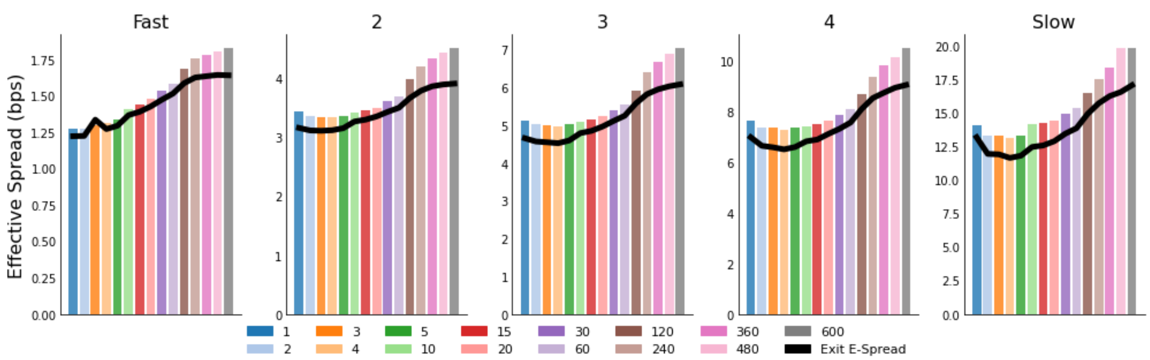
The figure plots out the term structure over clock-time horizons of the realized profitability and its component elements across τ quintile groupings with the fastest securities in the leftmost column and the slowest in the rightmost. The top row shows the term-structure of $rp_{t,\tau}$, the middle row shows the realized spread component $rs_{t,\tau}$, and the final row the exiting effective spread $\delta_t(M_{t+\tau} - P_{t+\tau})$.

Figure 18: Realized Spread Term Structures by Groups



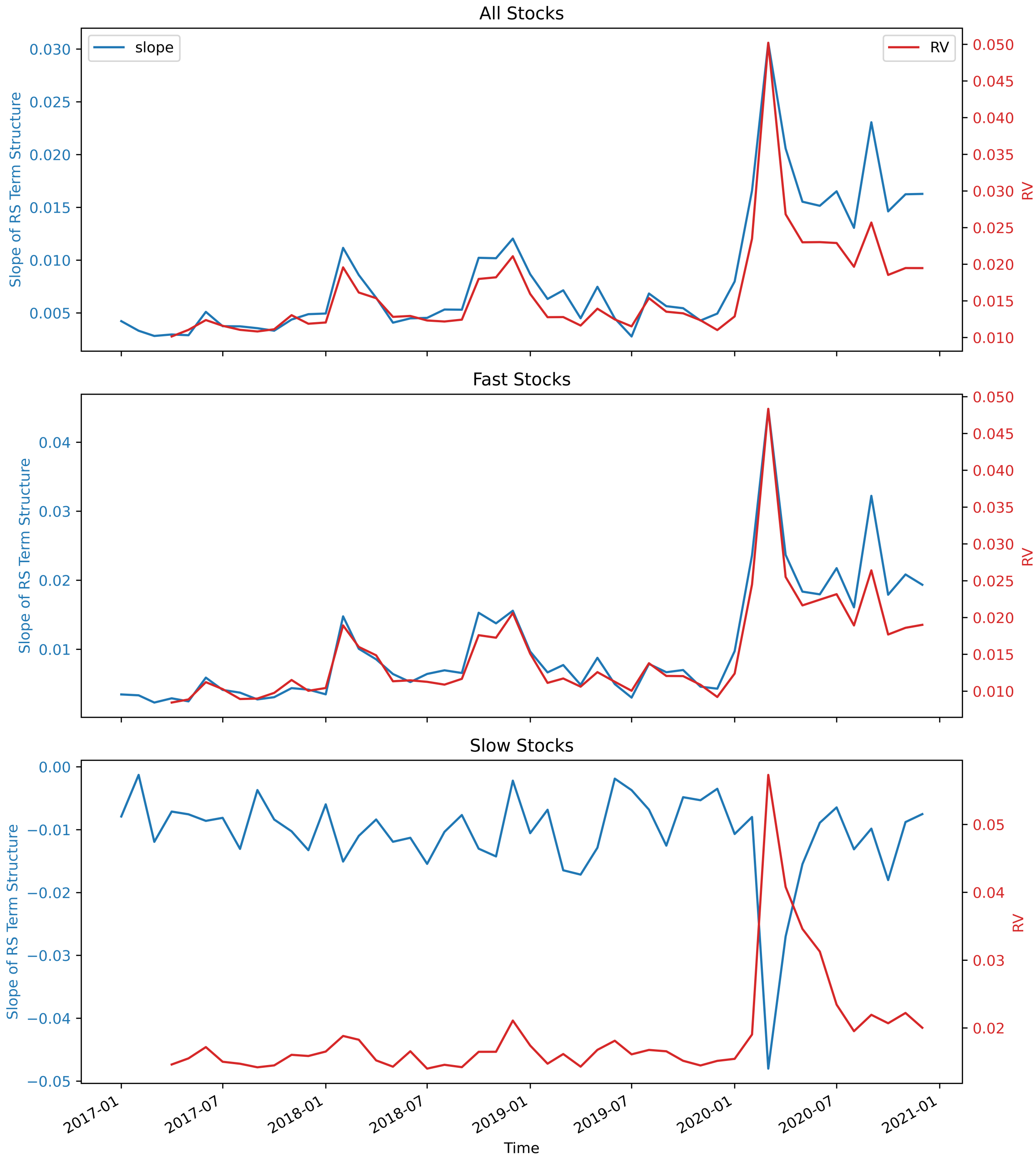
The figure plots the term structure over clock-time horizons of conventionally measured realized spread across τ quintile groupings with the fastest securities in the leftmost column and the slowest in the rightmost.

Figure 19: Effective Spreads by Groups



Here we plot out the term structure of the dollar-volume weighted effective spreads at the beginning of the round-trips at different horizons across τ quintile groupings with the fastest securities in the leftmost column and the slowest in the rightmost. The black solid line outlines the values of the effective spread at the exit of the trips.

Figure 20: Term-Structure Steepness and Volatility



Slope estimates $\hat{\beta}$ from monthly regressions of round-trip profitability onto a constant and turn-around time τ of regression specification: $_{t,\tau} = \alpha + \beta\tau + \epsilon_t$ are plotted alongside the dollar-volume weighted average total realized variation RV for the security subsample over time. The top panel plots out these values for the full sample, the middle panel repeats the exercise for the subset of "fast" stocks while the last panel does so for "slow" stocks.

Figure 21: Realized Profitability Compared with Realized Spreads for Fast Stocks (left) and Slow Stocks (right)

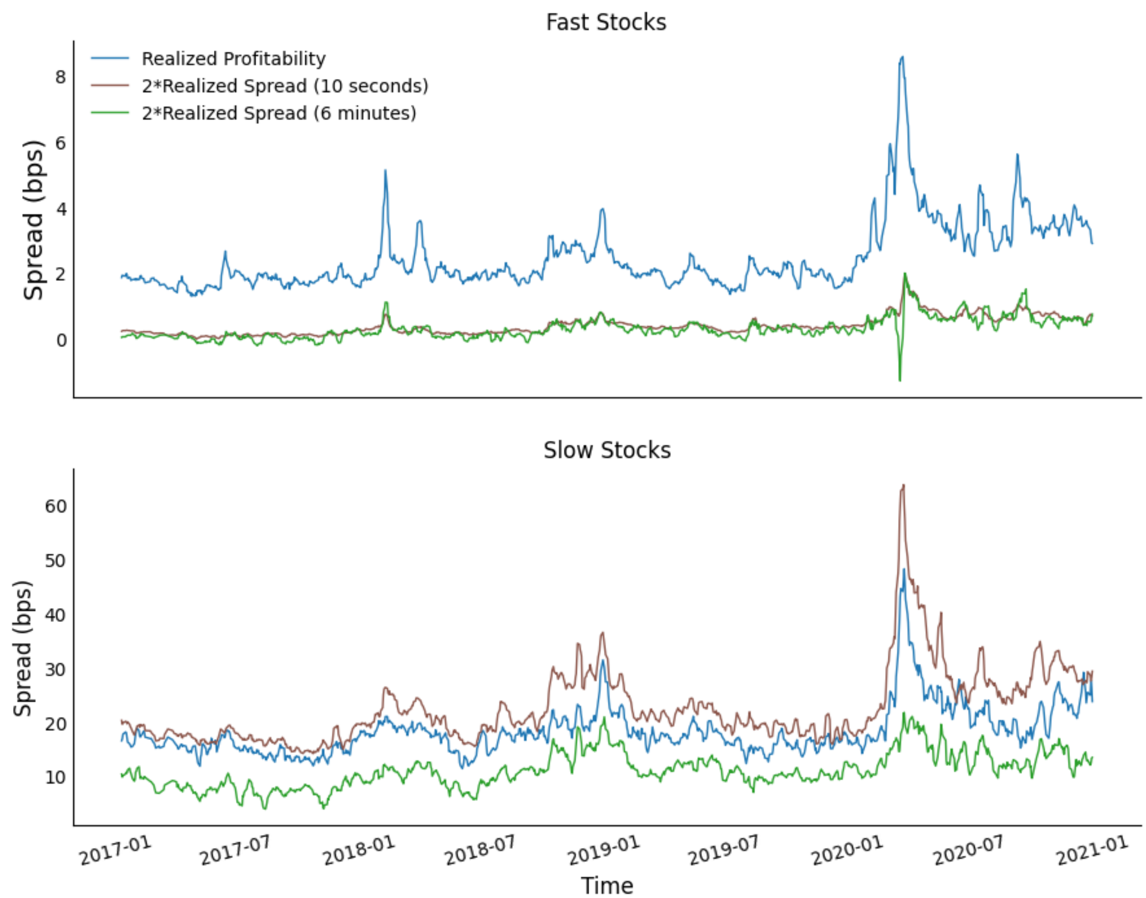


Figure plots the time series of dollar-volume-weighted average realized profitability and dollar-volume-weighted average realized spreads measured with both 10 seconds τ and 6 minutes τ.

Figure 22: Aggregate Realized Profitability (FIFO) across Days Sorted by Order Imbalance

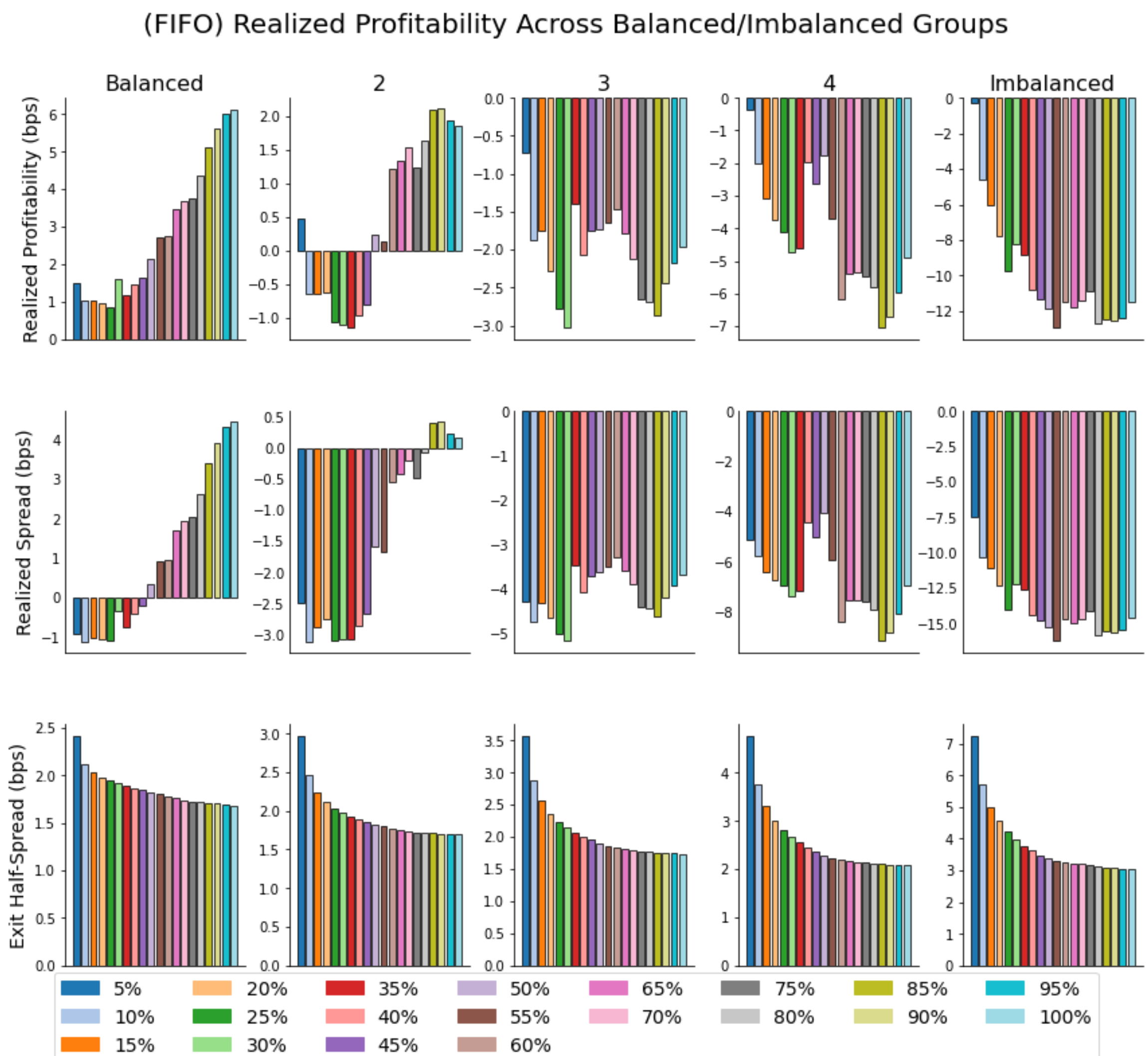
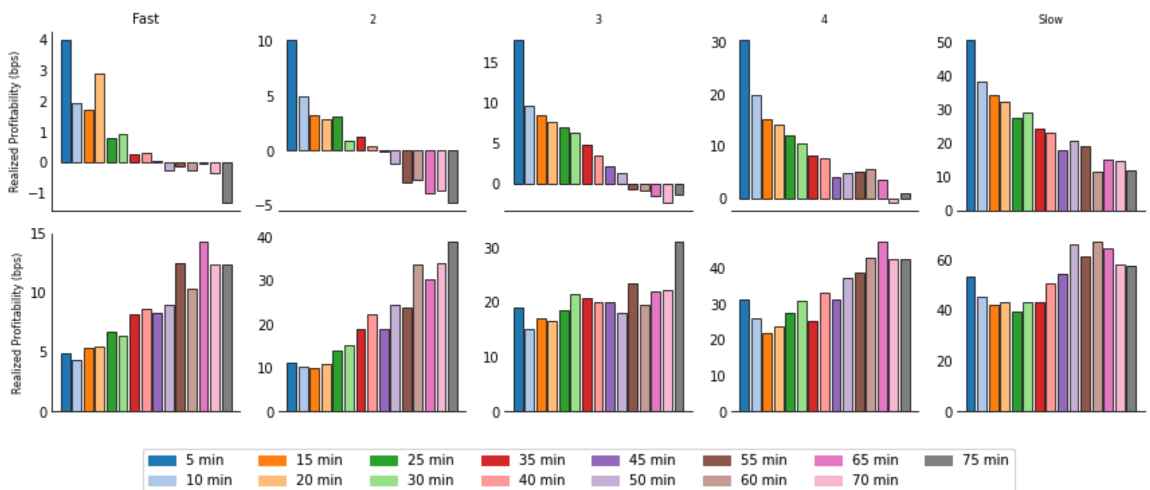


Figure 23: Aggregate Realized Profitability (FIFO) across Fast and Slow Stocks



We use all sample days (top) and sample days with low imbalance days (bottom) to generate the realized profitability term structures for fast/slow stock groupings.

Table 1: Levels and Dynamics of Capital Resale Prices

Panel A presents selected (cross-section) percentiles as well as averages of resale prices for both unbundled and bundled capital respectively. For each year, resale prices are first aggregated at the firm level (ratio of total sales proceeds to book value of the capital sold) for both types of capital. I compute the percentiles of capital prices across all firms using three alternative weighting strategies: book-value weights (Bval); transaction value weights (Tval) or unit weights(S.A). Average prices are computed similarly for each year, e.g, book value weighted average prices use book value of capital sold as weights, whereas unit weighted average prices are simple averages. I then compute the time series averages of these statistics: columns "$P1 - P99$" denote time-series averages of the percentiles/averages across all sample periods. Panel B show correlations with GDP. Standard errors are computed using GMM as using the Hansen-Heaton-Ogaki GAUSS programs and corrected for heteroscedasticity and autocorrelation (one lag) a la Newey West (1987). Log GDP data is stationalized using either Hamilton filter or First-Difference before estimation of cyclical correlations. In Panel B, the time series of aggregate capital price is constructed using book value of capital sold as weights. Sample periods: 1995-2017. Price data are winsorized at 1% by year to alleviate impact of outliers.

Panel A: Summary Statistics of Capital Resale Prices

		Percentiles					Mean
weights		$P1$	$P25$	$P50$	$P75$	$P99$	
Bval	Un-	0.156	0.787	0.967	1.140	2.533	1.015
Tval	bundled	0.360	0.928	1.186	1.598	5.606	1.394
S.A		0.019	0.562	0.948	1.329	10.030	1.221
Bval	Bundled	0.297	0.914	1.165	1.595	4.282	1.375
Tval		0.566	1.102	1.519	2.284	21.559	2.936
S.A		0.162	0.933	1.261	2.019	44.743	2.427

Panel B : Correlation of Output with Capital Resale Prices

	Log GDP, filtered by			
	Hamilton		First-Difference	
corr with	Unbundled	Bundled	Unbundled	Bundled
Resale Price	0.552	0.155	0.594	0.092
	(0.282)	(0.251)	(0.252)	(0.269)

Table 2: Correlations of Capital Resale Prices with Sentiment

Correlations calculated for both the averages as well as selected percentiles. Time series of aggregate resale price constructed using book value of capital sold as weights. Sentiment data from professor Jeffrey Wurgler's website. To alleviate the impact of aggregate economic conditions, the index $SENT^{\perp}$ is used instead of $SENT$. Panel A reports raw correlation estimates and panel B reports regression coefficients of prices on sentiment after controlling for log GDP growth. Sample periods: 1995-2017.

A: Correlation of Sentiment with Capital Resale Prices

	Percentiles					
corr with	$P5$	$P25$	$P50$	$P75$	$P95$	Ps(mean)
	(1)	(2)	(3)	(4)	(5)	(6)
Bundled	-0.388	-0.192	-0.474	-0.112	0.414	-0.158
	(0.351)	(0.251)	(0.206)	(0.212)	(0.338)	(0.190)
Unbundled	0.450	0.392	0.429	0.412	0.154	0.422
	(0.161)	(0.145)	(0.191)	(0.212)	(0.193)	(0.182)

B: Correlation of Sentiment with Prices Controlling for Output

corr with	$P5$	$P25$	$P50$	$P75$	$P95$	Ps(mean)
	(1)	(2)	(3)	(4)	(5)	(6)
Bundled	-0.455	-0.239	-0.537	-0.146	0.428	-0.184
	(0.196)	(0.217)	(0.223)	(0.223)	(0.207)	(0.224)
Unbundled	0.389	0.304	0.332	0.301	0.058	0.310
	(0.192)	(0.185)	(0.169)	(0.166)	(0.198)	(0.167)

Table 3: Cyclicality of Capital Reallocation

Panel A uses asset sales data collected from corporate 10K filings, presents correlations of total output with both quantity and value of capital reallocation (unbundled sales, bundled sales and aggregate reallocation of both). Reallocation quantity (value) is measured as the ratio of book value (transaction value) of capital sold at t to book value of total capital in stock at $t-1$. For unbundled, I use property, plant and equipment as total capital in stock. For bundled, we use asset total as total capital in stock. GDP data is stationalized using two main filters before estimation of its correlation with reallocation: the Hamilton filter and First-Difference. Panel B reports correlations of output with values of property, plant and equipment (PPE) sales and acquisitions from Compustat. PPE sales measured as the ratio: $\textit{Proceeds from sales of } PPE_t / \textit{Book value of PPE in stock}_{t-1}$; Acquisition measured as: $\textit{Proceeds from acquisitions}_t / \textit{Book value of total assets}_{t-1}$. Cyclical correlations for aggregate reallocation computed following existing literature (apply the HF filter on both reallocation and GDP before estimation of cyclical correlations; a smoothing parameter of 100 is used as in Eisfeldt and Rampini (2006)) are also presented in the last column of both panel. Sample periods: 1995-2017.

Panel A: Correlations of Capital Sales Turnover with Output

	GDP, filtered by						
	Hamilton			First-Difference			HP
corr with	Unbundled	Bundled	Aggregate	Unbundled	Bundled	Aggregate	Aggregate
Quantity	-0.403	0.372	0.125	-0.370	0.440	0.202	0.274
	(0.162)	(0.140)	(0.190)	(0.172)	(0.128)	(0.198)	(0.260)
Value	-0.038	0.463	0.350	-0.009	0.523	0.416	0.441
	(0.141)	(0.141)	(0.189)	(0.148)	(0.128)	(0.182)	(0.216)

Panel B: Correlations using Compustat Data for the Main Sample

	GDP, filtered by						
	Hamilton			First-Difference			HP
corr with	SPPE	Acquisition	Aggregate	SPPE	Acquisition	Aggregate	Aggregate
Value	0.021	0.428	0.415	0.016	0.426	0.417	0.594
	(0.207)	(0.188)	(0.194)	(0.207)	(0.203)	(0.208)	(0.142)

Table 4: How Reallocation Relates to Dispersion in Productivity Growth and Q

Panel A reports correlations between reallocation and measures of dispersion in multifactor productivity growth, both across industries and within industry. Dispersion in productivity growth measured three alternative ways: a.standard deviation; b.difference between the top and bottom quartiles; c.difference between the top and bottom percentiles. For cross-industry measures, I use the series "multifactor productivity (percent change)" provided by Bureau of Labor Statistics (BLS) at the 4 digit naics level from 1995-2017. For within-industry measures, I use the activity weighted within-industry productivity dispersion (measured at naics 4 digit industry level) from Dispersion Statistics on Productivity, an experimental product jointly developed & published by the BLS and the Census Bureau (data available from 1997-2016). For all measure, I use value of production as weights in aggregation (averages, percentiles, etc). Panel B reports correlations between reallocation with dispersion in Q across all non-finance/utility firms in Compustat. Dispersion in Q measured as either the standard deviation or the difference between top and bottom quartiles, all computed using lag market capitalization as weights.

Panel A: Correlation of Capital Sales with Dispersion in Productivity (Growth)

	Cross-Industry Dispersion			Within-Industry Dispersion		
corr with	s.d	q3-q1	p90-p10	s.d	q3-q1	p90-p10
Unbundled	0.382	0.131	0.572	0.285	0.396	0.415
	(0.127)	(0.165)	(0.250)	(0.219)	(0.229)	(0.188)
Bundled	0.501	-0.473	-0.040	-0.243	0.146	-0.108
	(0.235)	(0.218)	(0.257)	(0.294)	(0.417)	(0.365)

Panel B: Correlation of Capital Sales with Dispersion in Q

	Unbundled			Bundled		
corr with	$s.d(Q)$	$s.d(Q < 5)$	Q(q3-q1)	$s.d(Q)$	$s.d(Q < 5)$	Q(q3-q1)
	0.028	-0.052	-0.023	0.378	0.437	0.260
	(0.155)	(0.256)	(0.156)	(0.139)	(0.240)	(0.181)

Table 5: How Reallocation Relates to Sentiment

Table presents correlations between reallocation and proxies of valuation sentiment. Reallocation measured as ratio of book value of capital sold to book value of total capital in stock. For unbundled, I use property, plant and equipment as total capital in stock. For bundled, we use asset total as total capital in stock. Columns (1)-(2) use percentage of firms with a Q greater than 1 or 3 as proxies for valuation sentiment. Columns (3)-(5) use the 25th, 50th or 75th percentile of Q. Columns (6)-(7) use average level of Q of firms with Q smaller than 2 or 10. Column (8) use the sentiment index from professor Jeffrey Wurgler's website.

	% of firms		***Percentile.Q***			***Average Q***		***Sentiment***
corr with	$Q > 1$	$Q > 3$	$P25$	$P50$	$P75$	$Q < 2$	$Q < 10$	SENT
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Unbundled	0.05	-0.05	0.03	-0.04	-0.01	0.03	-0.03	0.21
	(0.27)	(0.19)	(0.20)	(0.18)	(0.13)	(0.32)	(0.19)	(0.14)
Bundled	0.47	0.49	0.48	0.42	0.33	0.52	0.54	0.41
	(0.19)	(0.19)	(0.18)	(0.18)	(0.16)	(0.16)	(0.20)	(0.11)

Table 6: Potential Drivers of Capital Sales Decisions

This table presents coefficient estimates from the fixed-effect logit model: $log(\frac{Pr(y_{it}=1)}{1-Pr(y_{it}=1})=\alpha_i + x_{it}\beta + z_t\gamma$. y_{it} is a binary variable indicating the decision to sell unbundled assets for column(1)-(4) or bundled assets for column(5)-(8). x_{it} in a vector containing firm level characteristics (lagged), including APK ((REVT-COGS-XSGA)/lag(AT)), Tobin's Q, Cash holding (CHE/AT), book leverage (LT/AT), interest expense ratio (XINT/lag(LT)). z_t contains variables capturing economy/industry wide information, including dispersion in APK across firms in the Compustat database, average valuation (Q) of the equity market, cross-firm dispersion in Q. Dispersion in Q are orthogonalized against average Q using a modified Gram–Schmidt procedure (Golub and Loan, 2013) to remove impact of highly collinearity. All coefficient estimates are obtained using unbalanced panel fixed effect logit regressions allowing for correlated residuals within panel units. Significance tests for coefficient difference are conducted using heteroskedastic- and cluster-robust standard errors (covariance of estimators obtained from seemingly unrelated regressions). All regressors are scaled by standard deviation before regression for ease of interpretation. Data are yearly from 1995 to 2017.

	Unbundled Sale				Bundled Sale				Test for diff:
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(4) vs (8)
	coeff (s.e)				coeff (s.e)				chi^2 (p-val)
Firm APK	-0.21***	-0.22***	-0.18***	-0.19***	-0.23***	-0.22***	-0.27***	-0.27***	0.91
	(0.06)	(0.06)	(0.06)	(0.06)	(0.05)	(0.05)	(0.06)	(0.06)	(0.340)
Firm Q	-0.13*	-0.11*	-0.14*	-0.12	-0.39***	-0.39***	-0.28***	-0.28***	1.65
	(0.07)	(0.07)	(0.08)	(0.08)	(0.10)	(0.10)	(0.10)	(0.10)	(0.199)
Market Q		-0.04		-0.04		0.15***		0.13***	8.11***
		(0.04)		(0.05)		(0.04)		(0.04)	(0.004)
Q disp		0.12***		0.12***		0.04		0.04	2.85*
		(0.04)		(0.04)		(0.03)		(0.03)	(0.091)
APK disp		0.34***		0.36***		-0.06		-0.06	48.99***
		(0.05)		(0.05)		(0.04)		(0.04)	(0.000)
Cash			0.11	0.13			-0.27***	-0.27***	13.18***
			(0.10)	(0.09)			(0.08)	(0.08)	(0.000)
Leverage			0.13	0.05			0.05	0.04	0.01
			(0.10)	(0.09)			(0.07)	(0.07)	(0.941)
Interest			-0.05	-0.03			0.05	0.05	1.62
			(0.05)	(0.05)			(0.05)	(0.05)	(0.203)
Firm FE	Y	Y	Y	Y	Y	Y	Y	Y	
Year FE	Y	N	Y	N	Y	N	Y	N	
$LR-chi^2$	130.41	80.41	129.60	78.54	79.34	60.39	91.02	68.06	
p-value	$<1\%$	$<1\%$	$<1\%$	$<1\%$	$<1\%$	$<1\%$	$<1\%$	$<1\%$	
N	8404	8404	7790	7790	10084	10084	9668	9668	

Table 7: Characteristics of Capital Reallocation for Private Firms

This table uses capital sales data of private companies from Capital IQ from 2012 to 2019. Panel A estimates correlations of output with both sales of PP&E (SPPE) and divestitures. I measure reallocation value (quantity) as the ratio of proceeds from (book value of) capital sold at time t to total book value of capital in stock at $t-1$. For property, plants and equipment, book value is computed as "$SPPE$"-/+ "gain/loss on sales of asset", I use net property, plants and equipment in stock as denominator. For divestiture and cash acquisitions, I use total asset as denominator. Two alternative filters are used to stationalize GDP before correlation estimation: Hamilton filter and First-Difference. Panel B presents correlations of capital sales with productivity dispersion measured as either the standard deviation of TFP growth across industries, or the difference between the top and bottom quartiles(q3-q1) or deciles (p90-p10). Panel C estimates the correlation of cash acquisition with GDP and Panel D presents correlations of capital reallocation measures with proxies market sentiment, including equity market value based proxies and the sentiment index from professor Jeffrey Wurgler's website.

Panel A: Correlation of Output with Capital Sales

corr with	Log GDP, filtered by			
	Hamilton		First-Difference	
	$SPPE$	$Divest$	$SPPE$	$Divest$
Value	-0.299	0.576	-0.198	0.598
	(0.341)	(0.264)	(0.340)	(0.235)
Quantity	-0.328		-0.223	
	(0.327)		(0.346)	

B: Correlation of Dispersion in TFP Growth with Capital Sales

	SPPE			Divest		
	s.d	q3-q1	p90-p10	s.d	q3-q1	p90-p10
Value	0.804	0.611	0.461	0.158	0.493	0.243
	(0.184)	(0.384)	(0.291)	(0.314)	(0.147)	(0.347)

C: Correlation of Output with Cash Acquisition

	Log GDP, filtered by	
	Hamilton	First-Difference
Value	-0.367	-0.191
	(0.399)	(0.402)

D: Correlation with Sentiment Proxies

	%($Q>1$)	%($Q>3$)	%($Q>5$)	Avg Q(≤ 5)	Avg Q(≤ 10)	SENT
SPPE	-0.172	-0.437	-0.620	-0.428	-0.482	-0.416
	(0.656)	(0.323)	(0.380)	(0.372)	(0.349)	(0.373)
Divest	-0.703	-0.149	-0.112	-0.306	-0.275	-0.160
	(0.090)	(0.346)	(0.441)	(0.252)	(0.274)	(0.280)
Cash	-0.338	-0.788	-0.885	-0.746	-0.767	0.088
Acquisition	(0.482)	(0.138)	(0.089)	(0.169)	(0.153)	(0.511)

Table 8: Model Parameter

This table reports the choices of parameter value in the model.

Adopted:		
α	output elasticity of capital	0.592
β	discount factor	0.930
ρ_a	AR1 coeff for aggregate shock	0.750
σ_a	Std Dev of aggregate shock innovation	0.050
ρ_i^H	AR1 coeff for idiosyncratic shock (high aggregate productivity)	0.550
ρ_i^L	AR1 coeff for idiosyncratic shock (low aggregate productivity)	0.900
σ_i	Std Dev of of idiosyncratic shock innovation	0.100
δ	Depreciation rate	0.100
Calibrated:		
γ	Adjustment cost (convex) for new & used unbundled capital	0.146
f_u	Adjustment cost (fixed) for unbundled capital transfer	0.015
ϕ	Adjustment cost for bundled capital (ratio to capital)	0.043
p_n^b	Price of bundled capital for normal firms	1.059
p_s^b	Price of bundled capital for firms sensitive to sentiment	1.411
P_o	Probability of deal completion (bundled capital transactions)	0.167
P_s	Probability of structural change following bundled acquisition	0.421
S_o	% of firms subject to euphoric sentiment	0.076
δ_s	Increase in S_o following consecutive good aggregate shocks	0.300
b	financing benefits of acquisition as fraction of capital acquired	0.805

Table 9: Model Moments

This table presents statistics on capital resale prices as well as reallocation dynamics both from data and model.

Moments to be matched:		Model	Data
Resale prices			
$E(p^u)$	average unbundled capital price	1.055	1.015
$E(p_a^b)$	average bundled capital price	1.397	1.375
$\rho(p^u, Y)$	correlation of p^u with aggregate output	0.902	0.553
$\rho(p^u, Q_m)$	correlation of p^u with market valuation	0.761	0.410
Reallocation quantities			
$E(U)$	average turnover of unbundled sales	1.266	1.220
$E(B^-)$	average turnover of bundled sales (book value)	0.591	0.730
$E(B^+)$	average turnover of bundled acquisitions (transaction value)	2.279	2.230
$\rho(U, Y)$	correlation of unbundled sales with aggregate output	-0.304	-0.403
$\rho(B^-, Y)$	correlation of bundled sales with aggregate output	0.187	0.372
$\rho(B^+, Y)$	correlation of acquisitions with aggregate output	0.565	0.428
$\rho(B^-, Q_m)$	correlation of bundled sales with market valuation	0.638	0.410
Other model implied statistics:			Model
% unbundled deals with more productive buyers than sellers			91.46%
% bundled deals with productive buyers (less productive sellers)			46.68%
Correlation of unbundled sales with dispersion in productivity change			0.402
Correlation of bundled sales with dispersion in productivity change			-0.093

Table 10: Realized Profitability and Firm Characteristics by Groups

We sort stocks into decile groups based on their average inventory turnaround time. In Panel A we compute the dollar-volume-weighted average realized spread for each group using round trips of all stocks in that group, similarly, we also compute and report the average Sharpe ratio of the realized profitability, average inventory turnaround time (in trade time and clock time) and average effective spreads. In Panel B we describe the characteristics of stocks in each group. All firm characteristics are measured at the end of each fiscal year and then averaged across stocks using lag firm size as weights. MktCap (size) is price times shares outstanding; investment rate is the % change in total asset; book-to-market is the ratio of book equity to size; gross-profitability is revenues minus cost of goods sold over total asset; ROE is income before extraordinary items over lagged book equity; trading turnover is average daily volume over shares outstanding; Market beta is computed annually using daily returns; idiosyncratic volatility is the standard deviation of the residual from the market model regression.

Panel A: Trade Variables					
	Fast	2	3	4	Slow
Realized profitability	2.45	4.43	6.31	9.11	15.53
Sharpe ratio	3.04	3.30	3.74	4.56	5.74
Entering Effective Spread	1.44	3.68	5.68	8.50	16.18
Exiting Effective Spread	1.39	3.43	5.23	7.73	14.36
Realized-Spread Component	1.07	1.01	1.08	1.38	1.17
τ (in # of trades)	211	60	40	27	17
τ (in seconds)	46	100	131	165	213
Panel B: Other Characteristics					
	Fast	2	3	4	Slow
MktCap (Billions)	61.96	5.71	2.25	1.30	0.70
Investment Rate	0.09	0.13	0.14	0.12	0.12
Book-to-Market	0.37	0.44	0.48	0.50	0.62
Gross-Profitabilty	0.28	0.27	0.26	0.26	0.19
ROE	0.25	0.16	0.10	0.12	0.10
Trading Turnover	6.56	9.33	8.16	6.11	4.61
Market Beta	0.98	1.09	1.11	1.09	0.97
Idiosyncratic Vol	0.01	0.02	0.02	0.02	0.02

Table 11: Average Realized Profitability for Double Sorted Groups

Table reports dollar-volume-weighted average realized profitability for stock groups sorted first by size and then average τ (left), and dollar-volume-weighted average realized profitability for stock groups sorted first by book-to-market and then average τ (right). "Small/Large" corresponds to the size grouping and "Low/High" corresponds to the book-to-market grouping.

	Fast	2	3	4	Slow		Fast	2	3	4	Slow
Small	16.02	17.61	19.62	28.63	34.07	Low	2.76	4.11	5.59	6.74	10.75
2	10.33	9.68	9.98	11.75	17.49	2	1.85	3.80	5.68	7.51	12.45
3	5.74	6.37	6.57	7.31	10.02	3	1.94	3.90	5.82	8.47	14.46
4	4.05	3.69	4.20	4.75	6.40	4	1.59	4.29	7.38	12.02	23.68
Large	2.22	1.64	2.28	2.45	4.05	High	1.92	4.27	7.26	10.24	20.39

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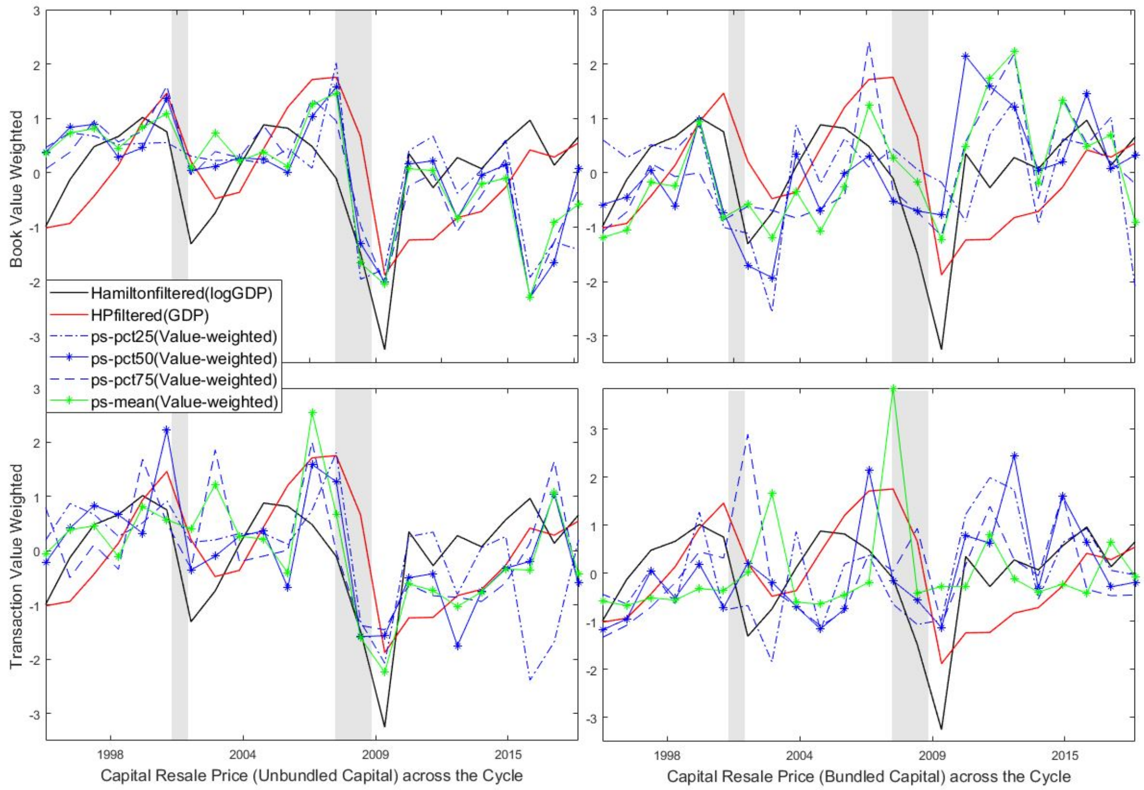
APPENDIX A

APPENDIX TO CHAPTER 1

Figure A.1: Capital Resell Price over the Cycle.



The left panel plots resale price of unbundled capital from 2005 through 2017, using both book-value weights (upper quarter) and transaction-value weights (lower quarter). The right panel if for bundled capital.

Table A.1: Summary Statistics

Panel A reports summary statistics for the sample of firms using both Compustat and collected data from 10Ks. Both transaction value as well as book value of capital sales items are reported when possible. Level data is denoted in 1996 dollors. “Asset” stands for total asset, “PP&E” stands for property, plant and equipment and “CapEx” for capital expenditure. Dollar values are in millions. All sales numbers from 10K filings include non-cash portion of the transaction when available. Panel B summarizes reallocation ratios calculated as the ratio of sample sum of the numerator to the sample sum of denominator. “Reallocation” refers to the sum of acquisition and sales of PP&E for compustat data and the sum of unbundled and bundled capital sales for the 10K data. Book value of sales of PPE is calculated using Compustat item SPPE and SPPIV. Unbundled capital sales typically include sales of property, building, equipment etc. It may also include sales of plants when it's not possible to disentangle plant sales from other property/equipment sales (common in the manufacturing industry). Note that sale-leaseback transaction as well as sales of revenue equipment (e.g. leasing/rental vehicles) are not included as is in Compustat. Bundled capital sales contains sales of business units, (discontinued) operation, facilities, subsidiaries, divestitures, etc. Note that only sales of business whose operation results were consolidated with the parent company before the sale are included in this item. e.g. short-turn equity investment sales not included.

A: Reallocation Levels:	Mean	Median	Std_Dev
Compustat Data(Bookvalue: a,b,d; Mktvalue: c,e,f)			
Assets (a.)	8774.85	2881.00	25131.87
PP&E (b.)	2602.06	569.50	7657.59
CapEx (c.)	459.94	111.58	1315.36
Sales of PP&E* (d.)	28.42	0.00	260.78
Sales of PP&E (e.)	28.21	0.00	263.62
Acquisitions (f.)	186.40	5.22	781.08
10K Data (Bookvalue: g,i; Mktvalue: h,j)			
Unbundled Capital Sales (g.)	29.74	0.05	291.80
Unbundled Capital Sales**(h.)	28.03	0.00	299.92
Bundled Capital Sales(i.)	55.49	0.00	487.01
Bundled Capital Sales***(j.)	68.78	0.00	554.20
B: Reallocation Ratios	Mean	Data Source	
Sales of PP&E/PP&E$_{t-1}$	1.16%	Compustat	
Acquisition/Asset$_{t-1}$	2.23%	Compustat	
Reallocation/PP&E$_{t-1}$	8.56%	Compustat	
Reallocation/Asset$_{t-1}$	2.58%	Compustat	
UnbundledSale/PP&E$_{t-1}$	1.22%	10K	
BundledSale/Asset$_{t-1}$	0.73%	10K	
Reallocation/PP&E$_{t-1}$	3.60%	10K	
Reallocation/Asset$_{t-1}$	1.11%	10K	

Table A.2: Potential Drivers of Bundled Capital Sales

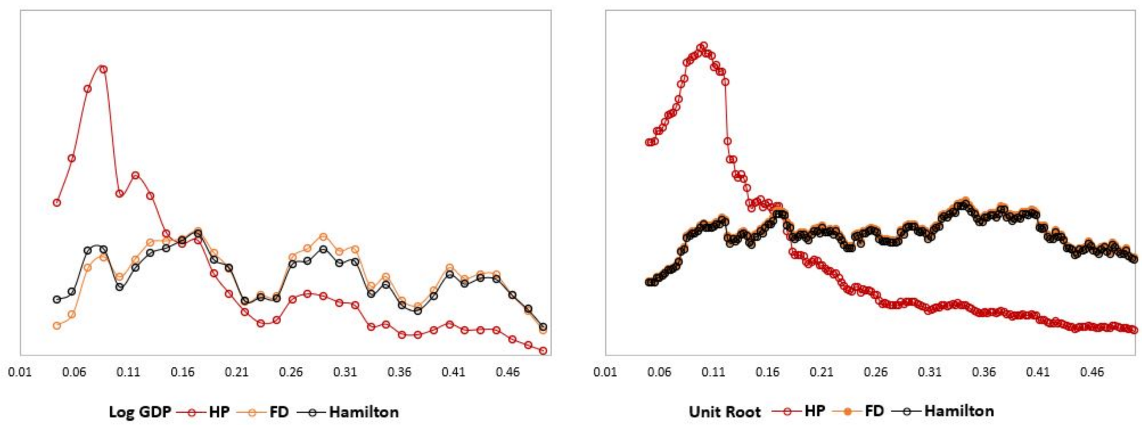
This table presents coefficient estimates from the logit model: $log(\frac{Pr(y_{it}=1)}{1-Pr(y_{it}=1)}) = \alpha + x_{it}\beta + z_t\gamma$. y_{it} is a binary variable indicating the decision to sell unbundled assets for column(1)-(4) or bundled assets for column(5)-(8). x_{it} in a vector containing firm level characteristics (lagged), including APK ((REVT-COGS-XSGA)/lag(AT)), Tobin's Q, Cash holding (CHE/AT), book leverage (LT/AT), interest expense ratio (XINT/lag(LT)). z_t contains variables capturing economy/industry wide information, including dispersion in APK across firms in the Compustat database, average valuation (Q) of the equity market, cross-firm dispersion in Q. Dispersion in Q are orthogonalized against average Q using a modified Gram–Schmidt procedure (Golub and Loan, 2013) to remove impact of highly collinearity. All firm level characteristics are industry and year adjusted. All coefficient estimates are obtained using unbalanced panel logit regressions allowing for correlated residuals within panel units. Significance tests for coefficient difference are conducted using heteroskedastic- and cluster-robust standard errors (covariance of estimators obtained from seemingly unrelated regressions). All regressors are scaled by standard deviation before regression for ease of interpretation. Data are yearly from 1995 to 2017.

	Unbundled Sale				Bundled Sale				Test for diff:
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(4) vs (8)
	coeff (s.e)				coeff (s.e)				chi^2 (p-val)
Firm APK	-0.09***	-0.09***	-0.07***	-0.08***	-0.16***	-0.16***	-0.17***	-0.16***	7.27***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.007)
Firm Q	-0.00	-0.01	-0.01	-0.01	-0.15***	-0.14***	-0.12***	-0.12***	7.22***
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.007)
Market Q		-0.04		-0.03		0.07**		0.07***	8.11***
		(0.02)		(0.02)		(0.03)		(0.03)	(0.004)
Q dispersion		0.06***		0.05**		0.06***		0.06***	0.10
		(0.02)		(0.02)		(0.02)		(0.02)	(0.753)
APK dispersion		0.17***		0.17***		0.01		0.02	17.12***
		(0.02)		(0.02)		(0.03)		(0.03)	(0.000)
Cash holding			0.04	0.04			-0.04*	-0.04	5.51**
			(0.03)	(0.03)			(0.02)	(0.02)	(0.019)
Leverage			-0.00	-0.01			0.04	0.04	1.89
			(0.03)	(0.03)			(0.03)	(0.03)	(0.170)
Interest exp			-0.01	0.00			-0.00	-0.02	0.32
			(0.02)	(0.02)			(0.03)	(0.03)	(0.569)
Year FE	Y	N	Y	N	Y	N	Y	N	
LR-chi2	127.56	67.47	118.72	63.80	124.10	101.87	119.95	94.85	
p-value	< 1%	< 1%	< 1%	< 1%	< 1%	< 1%	< 1%	< 1%	
N	14192	14192	13443	13443	14226	14226	13475	13475	

The Problem with HP Filtering an I(1) process

HP filter, when applied on difference stationary time series, can introduce spurious cyclical dynamics. The main issue boils down to that of over differencing, for example, for a difference stationary process, simple differencing returns white noise, whereas double differencing (as in HP filter) introduce spurious time series dynamics as that of a MA process.

Figure A.2: Periodograms of Filtered GDP Data and Random Walk.



The left panel plots the smoothed periodograms of log GDP data stationalized using HP ($\lambda = 100$), Hamilton and first-difference filter. The right panel plots smoothed periodograms of a random walk stationalized using the same filters. Log annual GDP data used from 1947-2020.

For illustration, Figure A.2 plots the periodogram[1] of log GDP and that of a random walk using all three filters. As can be seen, for difference stationary process such as a random walk, both the Hamilton and first-difference filter generate periodograms close to the theoretical flat-line white-noise spectra. The HP-Filtered series on the other hand produces an exponentially decaying periodogram dominated by low-frequency signals, these spurious frequencies can create systematic bias when we compute correlation between two otherwise independent processes.[2]

Table A.3 illustrates the magnitude of such bias using two simulated random walks with independent shocks. With 30 periods of observation, correlation between the two using Hamilton filtered (first-differenced) data is greater than 0.2 with 16.7% (14.3%) probability whereas using HP filter increases the probability of such false inference by 39% (to 23.2%). Increasing the number of time periods or the threshold of inference helps in reducing such likelihood, but in almost all cases, HP filtering more than doubles the probability of false inference. Importantly, such bias can not

[1] For the usage of periodogram in identifying cyclical behavior of a series not subject to the typical monthly/quarterly seasonality, refer to `https://online.stat.psu.edu/stat510/lesson/6/6.1`.

[2] An intuitive but extreme example being that processes with the same single frequency sine-cosine waves (cycles) almost surely exhibit nonzero correlations.

Table A.3: Probability of Spurious Correlation between Independent I(1) Processes ($y_t = y_{t-1} + \epsilon_t,\ t = 1, ..., T$) under Different Filters

Using estimates from 1000 simulations, the table presents % of simulations where correlation between the two exceed 0.2 or 0.4. The two processes ($\sigma_\epsilon = 0.05$) have length of either 30, 50 or 80 periods, with shocks generated independently. I use $\lambda = 100$ for HP filter. Numbers on the right are average standard errors of the correlation estimates conditional on exceeding the threshold α correcting for autocorrelation and heteroskedasticity of the residuals using specifications in Eisfeldt and Rampini (2006)

% cross correlation (ρ) exceeds threshold α					average(std err of $\rho \| \rho > \alpha$)		
T	α	First-diff	Hamilton	HP	First-diff	Hamilton	HP
30	0.2	14.30%	16.70%	23.20%	0.272	0.275	0.265
30	0.4	1.40%	0.90%	5.90%	0.251	0.265	0.228
50	0.2	7.40%	8.20%	16.00%	0.215	0.219	0.184
50	0.4	0.30%	0.20%	1.60%	0.175	0.183	0.184
80	0.2	3.80%	4.00%	10.0%	0.173	0.176	0.183
80	0.4	0.00%	0.00%	0.20%	.	.	0.166

be easily fixed by employing robust standard errors corrected for autocorrelation or heteroskedasticity as researchers usually do.

Adding to the above issues, the smoothing parameter for HP, which is supposed to be estimated from the data, is typically chosen on an ad hoc basis. Depending on the specific application, this parameter can change the cyclical dynamics of a process substantially.

Data Quality Issues with Compustat

Several issues render Compustat data unsuitable for studies of capital reallocation. First, the item "SPPE" includes sales-leaseback transactions, which does not involve transfer of usership and is in essence a financing activity. Second, because Compustat obtains information about asset sales from corporate cash flow tables by literally matching items that are close to "proceeds from sales of property, plant and equipment", the data quality relies heavily on how standardized the reporting of cash flow items is, both across firms and fiscal periods. In reality, firms have almost no restriction in how they report capital dispositions: e.g., a common practice is to report aggregate sales of all asset (including business and investment sales) under one item, e.g. "Sales of fixed asset and product line", "Proceeds from sale of equipment, property and investments/subsidiaries". As a result, measurement errors are pervasive. For example, McDonald's disposes of hundreds of millions in assets annually. However, the item "Sales of property, plant & equipment (SPPE)" shows zero sales for the 15 years ending 2015, during which the company reported under the aggregate item "Sales of restaurant businesses and property."[3] Similar issue occurs for Wendy's who report asset sales under the aggregate item "dispositions". Another issue with

[3]This issue is more severe for non-manufacturing firms as manufacturing firms tend to use "Sales of property, (plant) and equipment" as a standard item name for reporting asset sales.

SPPE data is that, as a cash flow item, it conveys reliable information about capital dispositions only when the sale is paid fully in cash. For transactions financed partially or fully with non cash methods (e.g., accounts receivable), SPPE provides an incomplete measure of the transaction value or incorrect time of the sale or both. This is potentially important because incorrect timing of capital sales can introduce systematic bias in the estimation of cyclical dynamics if, say, firms are more/less willing to accept non-cash payment during economic downturns. Lastly, as is also mentioned in the introduction, Compustat provides the transaction value of asset sales, which is price times quantity, whereas economic theories are mainly concerned with quantities.

Features of Capital Sales in Certain Industries

Lanteri (2018) reveals intriguing evidence on the reallocation dynamics of two special types of capital: aircraft and ships. He finds that sales of used aircraft are highly procyclical (correlation with GDP of 0.5), sales of ships are also procyclical although the correlation is an insignificant 0.15. These facts are interesting, not only because these two constitute a nontrivial share of the U.S. stock of equipment, but also because of their unique features: e.g. aircraft has high unit value and an enormous leasing market,[4] and just like used vehicles, a very active second hand market. Like car dealers who periodically dispose it's operating fleet, aircraft leasing corporations also regularly upgrade their inventory. Backed by an active second market, price volatility turns aircraft trading into a lucrative side business for leasing companies. The following quote from aersale.com sheds light on the sheer magnitude of such trading.

> "Nearly half of all airplanes in commercial service globally are leased. Those leases give airplane owners and operators a large degree of flexibility, which is demonstrated by increasing annual aircraft trading volumes that have doubled over the past five years. When you consider that the typical leased narrow-body aircraft changes operators and owners an average of four times during its service life, it explains why there is $30 billion worth of commercial aircraft trading annually."

The question here though, is how much of that trading is for routine upgrade, for trading profits, or for productivity reasons? One thing that is for sure is that tradings by leasing companies are least likely to be driven by productivity considerations as they may not even involve the transfer of usership. In fact, opportunistic tradings are norm for aircraft lessors. For example, trading profits on aircraft constitute an important source of annual revenue for the Air Lease Corporation. The company even includes aircraft trading as one of it's main business strategies in 10K.

> "**Aircraft Sales & Trading Strategy:** Our strategy is to maintain a portfolio of young aircraft with a widely diversified customer base. We primarily order new planes directly from the manufacturers, place them

[4] According to CAPA, half of the global aircraft fleet is owned by leasing companies by March of 2018.

on long term leases, and sell the aircraft when they near the end of the first third of their expected 25 year economic useful lives. We typically sell aircraft that are currently operated by an airline with multiple years of lease term remaining on the contract, in order to achieve the maximum disposition value of the aircraft. Buyers of the aircraft may include leasing companies, financial institutions and airlines. We also buy and sell aircraft on an opportunistic basis for trading profits. In the past three years ending December 31, 2016, we sold 93 aircraft. Additionally, we may provide management services to buyers of our aircraft asset for a fee. In 2016, our total revenues were comprised of rental revenues on our operating lease portfolio of 1.34 billion and aircraft sales, trading and other revenue of 80.1 million. During the year ended December 31, 2016, we sold 46 aircraft for proceeds of 1.2 billion, recording gains on aircraft sales and trading activity of 61.5 million."

Even for sales initiated by firms that employ the capital, we can not be sure of the motives, as sales and leaseback transactions are also very common in these industries. For example, the water transportation company "Overseas Shipholding Group INC" actively pursues sale-leaseback transaction in favorable market conditions for monetary gains, as shown in its 10K below

> "**Active Asset Management:** In support of its balanced growth strategy, OSG seeks to balance the mix of owned and chartered-in tonnage of both its operating and newbuild fleet. As noted in the summary of events and transactions by business units above, the Company entered into a number of transactions whereby it sold or sold and leased-back vessels during the year. Fleet disposition activity during 2007 resulted in proceeds on vessel sales of 224 million resulting in 7.1 million in gains. Sale and lease-back transactions allow the Company to monetize assets in a favorable secondhand market, thereby transferring residual risk of older tonnage to third parties while retaining control of the tonnage. Amortization of deferred gains from sale and lease back transactions, which amounted to 47.3 million in 2007, is recorded as a reduction of charter hire expense."

These transactions (aircraft tradings and sale-leasebacks) are fundamentally motivated by financial considerations, be it trading or financing gains, and most likely does not even involve reallocation of capital between users (sale-leaseback certainly does not). In this paper, these transactions are excluded from analysis.

Data Collection & Construction

In this section, I will first briefly introduce the related accounting background and then the main steps of the collection.

Accounting Background

The two main variables this study uses, namely, the proceeds from capital sales and the corresponding gains/losses, are typically reported in a company's cash flow statement. In this section I will briefly go through the structure of a cash flow table and introduce the accounting details with regard to the reporting of these items.

The statement of cash flow shows why a firm's investment/financial structure has changed between two fiscal ends. Typically it contains three sections:

1. Changes in cash flow from operating activities: production & delivery of goods & services;

2. Changes in cash flow from investing activities: investing/disposing of debt or equity securities; purchase or sales of productive assets that are used by a company in the production of goods or services, such as plant and equipment; acquisition or divestitures;

3. Changes in cash flow from financial activities: stocks/bonds issuance, bank loan repayment, etc.

Firms are allowed to choose between two alternative formats for presenting cash flow from operating activities:

1. Direct method: under this method, firms start from cash received from good/services and added/deduct other cash source/income to arrive at cash flow from operating activities;

2. Indirect method: under this method, firms start with accrual-basis net income and adjust for non-cash/cash items to arrive at operating cash flows, non-cash items included revenue earned but not received in cash; gains/losses on the disposal of fixed asset, etc.

Thus, gains on disposal of asset won't show up in cash flow statement for firms that use direct method, however, those non-cash items are required to be disclosed in 10K (in reconciliation of net income to net cash provided by operating activities), e.g., either in the income statement or somewhere else in the 10K. Good thing is, the overwhelming majority of public companies use the indirect method which greatly simplifies the collection.

For the collection, I count on cash flow tables as the main source for locating capital transactions, for the transaction value as well as gain/loss data I supplement the cash flow table with related information provided in the 10K.

Details of the Collection

There are two major steps in the data collection process. First step is the electronic extraction of capital sale items as well as explanatory notes on the sales. As mentioned in the main article, one important issue with Compustat variable SPPE is it's incomplete coverage, due to the restrictive algorithm Compustat used to locate the data (only items that are phrased close to "property, plant and equipment" are collected). In this paper I construct a much more inclusive algorithm (provided below) that captures almost all asset sales from a firm's cash flow table, a random check of 100 sample statements proves 100% completeness. To provide the reader with an idea of how flexible firms can choose to report their asset sales, a raw extraction of asset sales related items (after the remove of similar items) includes more than 400 entries. Most commonly used ones include but not limited to: sales(or disposal) of PPE, sales of assets, Sales of business, sales of joint venture, sales of equity interest, sales of discontinued operations, sales of subsidiary, sales of facilities etc.

I rely on SEC Edgar to first extract corporate 10K filings as well as the financial statements if not contained in the 10K filing (typically companies include their financial tables in the form 10-k, however, separate reporting is not unusual, most of the time separately reported financial statements is included in EX-13(.xx)). Then, for each firm year in my sample, I extract all capital sales items listed on the corporate cash flow table using the constructed text matching algorithm. Figure A.3 contains two simple examples of the output. As can be seen, the algorithm also picks up many items not relevant to capital sales, this is not an issue because the data will be manually cleaned.

Figure A.3: Examples of Extracted Capital Sale Items.

Ex 1

year	2017	2016	2015
mon	12	12	12
unit	m	m	m
Net cash provided by operating activities	2870	1750	2587
Proceeds from sale of property and equipment and sale-leaseback transactions	922	115	26
Sales of short-term investments	5915	6092	8517
Proceeds from issuance of long-term debt	3058	7701	4509

Ex 2

year	2004	2003	2002
mon	12	12	12
unit	t	t	t
Adjustments to reconcile net income to net			
cash provided by operating activities:			
Gains related to Immunex/Amgen common stock transactions		-860554	-4082216
Net gains on sales of assets	-156175	-343064	-329364
NET CASH PROVIDED BY OPERATING ACTIVITIES	2878743	2911103	185730
Proceeds from Amgen acquisition of Immunex			1005201
Proceeds from sales of Amgen common stock		1579917	3250753
Proceeds from sales of assets	351873	402692	798274
Proceeds from sales and maturities of marketable securities	1697864	1217114	2532538
Proceeds from issuance of long-term debt		5820000	

At the same time, from 10K I also extract the most relevant paragraphs (with a proximity score of [check in the code]) in the 10K which provide potential details about the transactions. Sections that frequently appear in those extractions include “Liquidity (and capital resources)”/“Other income (expenses)” from the main body of the 10K as well as “Discontinued operation”/“Dispositions(of xxx)” from the notes to financial statement. Following is an example of a portion of a firm’s explanatory notes:

“2002 net gains primarily resulted from the sale of certain assets related to the Company's generic human injectables product line to Baxter Healthcare Corporation for $305.0 million in cash. This transaction resulted in a pre-tax gain of $172.9 million. The net assets, sales and profits of these divested assets, individually or in the aggregate, were not material to any business segment or the Company's consolidated financial statements as of December 31, 2004, 2003 and 2002"

"During the first quarter of 2002, the Company completed the sale of a manufacturing plant located in West Greenwich, Rhode Island to Immunex (subsequently acquired by Amgen) for $487.8 million. The Company received $189.2 million of these proceeds in 2001 and the remaining $298.6 million during the 2002 first quarter. The Company did not recognize a gain on this transaction because the facility was sold at net book value. In December 2002, the U.S. Food and Drug Administration (FDA) approved the Rhode Island facility, which has been dedicated to expanding the production capacity of Enbrel."

For each firm in my sample, I collect and store these two pieces of information (capital sale items and explanatory notes) across all sample years. The second step of the collection involves manually going through the stored data to collect the following pieces of information on capital sales: fiscal year of the sale, type of asset sold, the transaction value (sale price) as well as the realized gains/losses. Figure A.4 shows you an example of the resulting dataframe, where columns with no shade are electronically generated and the grey shaded columns are either manually checked or entered.

Figure A.4: Examples of the Collected Output

urlID	CIK	File_date	Year	mon	classification	value	unit	fyear	SIC	Notes	URL
0	xxxx	…	Fiscal end year	Fiscal end month	Eg. Gain_unbundled	Eg 1000	"m" for million	xxxx	xxxx	….	https:…
0	xxxx	….			proceeds_bundled		"t" for thousand	xxxx	xxxx		https:…
0	xxxx	….					"" for unit 1	xxxx	xxxx		https:…
0	xxxx	….						xxxx	xxxx		https:…

For each capital sales item in the cash flow table, the collection follows a couple steps:

A. Classify the sale into several categories: unbundled, or bundled, or combined, or others: As mentioned in the main article, the goal of capital classification is to separate out productive capital that serves most similar to a homogeneous factor of production from capital that does not. For this purpose I classify all productive capital transactions into two main types: unbundled or bundled capital sales. I refer to unbundled capital as tangible fixed capital that is not readily operable by itself as a business, e.g., equipment, property, building, land, etc. Bundled capital, on the other hand refers to collections of capital that are organized to be operable as a business, e.g., a subsidiary, (discontinued) operation, business, branch, product line, a whole manufacturing plant, joint venture, etc. By making this distinction, I am exploiting the fact that capital, when sold unbundled, are more likely to be homogeneous whereas when sold in a bundle, are less likely to be so. Here, the meaning of "homogeneous" is two folded, first, it means that the capital sold is homogeneous by itself (equipment sales by a company typically involves equipment of similar usages), it also means that the buyer of the capital has existing capital that is homogeneous/similar to the capital sold.[5] (An important reason why unbundled capital serves better as a homogeneous factor of production: because the buyer employ it under it's own TFP.) In case where firms report combined sales, e.g., aggregate transaction value of unbundled and bundled capital sales, or other assets, refer to the following step 2.B.2. Importantly, I only focus on capital sales that are part of the firm's productive capital investment decisions. Thus, certain types of asset sales are excluded, e.g., sales of equity investment, sale and leaseback transactions, insurance recovery proceeds, sales of real estate investment, sales of revenue equipment[6] of a leasing company (vehicles, aircrafts, vessels), sales of forestland of a timberland company. I also exclude sales that are part of an acquisition, e.g., buying a whole business while divesting portion of it, either due to legal requirements or other concerns.

B. Collect transaction value (price) as well as the realized gain/loss on capital sales by type:

B.1: In cases where the type of asset is clearly stated in the cash flow table: E.g., "Proceeds from sale of property...xxx", check in the notes for potential leaseback or related non-cash proceeds, record the transaction proceeds as xxx plus any non-cash proceeds (e.g., accounts receivable) if available under sales of unbundled capital in case no leaseback is reported. In case the reported proceeds include partial/full leaseback value, deduct from the proceeds the amount from leaseback transactions. For the gain/loss realized on the transaction, record the number from cash flow table (indirect method) if present, if not, locate the gain/loss from income statement or the notes when available. There are cases where firms deduct/accrue gains/loss to depreciation when the amount is small, in those cases, no gain/loss will be recorded.

B.2: In cases where the type of asset cannot be inferred directly from the cash flow table: E.g., "Proceeds from asset sale/dispersion/sales of business and fixed asset...xxx", search in the notes for all capital sales transactions, including the type of asset and corresponding proceeds and gain/loss. For instance, the company in the second example of Figure A.3 report sales of asset of 798 million in 2002, parsing through the notes reveals details of the proceeds. As shown in the example paragraphs in step 1, portion of the proceeds (305.6 million) relates to the sale of a product line (bundled), which results in a gain of 172.9 million. The firm also received 298.6 in 2002 related to a sale initiated in 2001, the sale resulted in no gain/loss.

C. Decide timing of the transaction: In this study, I use fiscal year as timing convention to avoid potential time mismatch. I define a firm's fiscal year as the calendar year during which most of it's operation was conducted (same convention as COMPUSTAT). I classify capital sales under fiscal year t if the sale was initiated in t (rather than completed). In case of the above example, the sale of the manufacturing plant in West Greenwich is initiated in 2001 for $487.8 million, $189.2 was received

[5]For example, while it's not unusual for a car manufacturer to acquire a financing business, it's quite peculiar for it to buy farming equipment

[6]Note that sales of operating capital of

in cash whereas the remaining was paid full in 2002.

Special Issues

This section lists certain special situations occurred during the collection and the corresponding solutions.

1. **Dealing with previous year impairment**.
   Firms typically record realized gains/losses (including related asset impairment) on capital transactions the year the capital is sold. However, in case where the planed sale fails to realize and the firm hold the asset for sale, some firms may separately record impairment (e.g., in early quarters of the year or previous years) before the sale. In those cases, I include these impairment charges in the loss if the impairment can be allocated to the sold asset. However, the data I have typically only allows tracking of impairment charges from the current year (not from previous years)

2. **Deal with aggregate items, special items, equity method investments.**

   - *Aggregate items:*
     when firms report aggregate capital sales items (e.g., "sales of asset"), sometimes disaggregation is infeasible. In those cases, I try to find as much information as possible in the notes about the sale and make classification based on the information found and the firm's previous/future sales reporting (some firms provide extra information in later years on previous transactions). In cases no information/clue can be located about the sale, I ignore the item.

     Reporting practices vary across industries, manufacturing industries, for example, tend to report sales of unbundled capital property, equipment and bundled capital plant together under one item "sales of property, plant and equipment" without providing more details (firms are less likely to provide details when the transactions are small in value). I classify these proceeds under unbundled capital unless disaggregating details are found in the notes. Even though my measure of unbundled sales may contain sales of plants (e.g., manufacturing firms), the economic distinction between these two capital is clear-cut, with the unbundled capital more of homogeneous capital (easier to adapt to different productivity levels) and bundled capital (e.g. a division, a business) less so.

   - *Special items:*
     there are a couple items I excluded from the collection: (1) revenue equipment sold by leasing companies, e.g. vehicles that have served for leasing purpose for a certain amount of time before the sale. (2) sales of forests by lumber companies. (3) franchising sales where the firm continues to manage the asset (typical in the hotel industry).

For gas/oil companies, a common type of asset sold involves reserves, those sales typically include the land as well as the drilling/refining equipment on the land, I classify these as unbundled sales unless the sale was part of a divestiture. (of, e.g., division, subsidiary,jointventure, etc.)

- *Equity method investments:*
  I only include sales of business whose operation was originally incorporated in the parent company's financial statement, thus equity method investment sales are not included as bundled sales. The rule of thumb for determine whether a business constitutes a portion of the firm's operation is to look at the holding stake of the firm in the business, e.g., a subsidiary is part of the firm because the parent company holds a majority stake in it, whereas affiliates are part of equity investments as the company typically holds a minority stake in these entities.

3. **Deal with noncash transactions.**
   Non-cash transactions are deals that involves more than cash payments, e.g, accounts receivable, credit, equity payments, fair value exchanges, etc. Majority of the firms in my sample still receive cash or accounts receivables for sales of unbundled assets and cash constitutes the vast majority of the transaction value. However, usage of noncash payments are much more common for bundled asset sales. I include the noncash portion in the transaction price whenever available for both type of capital. Firms with good practice may report noncash transactions under "other supplemental information" in their cash flow statement but these are the minority. Most of the time this information appears in the notes to financial statements. Noncash payments such as accounts receivables are typically easy to locate, the cases with equity payments and fair value exchanges are more tricky. There are cases Some firms only mention about the asset being exchanged without detailing the transaction value (especially when there is no cash involved, it may not even show up in the cash flow table). There are also cases where the firm pays the asset with equity stocks without detailing the value of the payments. In those cases I look for relevant information in the notes that can aid in the measurement of the proceeds and gain/loss, e.g., for equity payments, in case information about the number of shares and time of the transaction is located, I calculate the value of transaction based on these two pieces of information.

   The case with exchanges is especially tricky for the cable media industry, where like-kind exchanges (typically scheduled for tax purposes) are relatively popular. For those exchanges, firms typically only mention about the gain/loss realized from the exchange but not the value of the asset being exchanged, I ignore exchanges where the target asset value could not be located.

4. **Deal with missing CIK - GVKEY links.**
   The match between CCM firms and my sample is not complete due to changes

in firm CIK over time. To deal with this problem, I adopt different strategies for early years vs later years. For the sample from 2005-2017, I first use a firm's current CIK (from CCM) to extract cash flow information from its 10K report, for all remaining years with missing matches in SEC, I match the firm with the universe of SEC firms based on their EIN number. If I can not find a match in SEC based on EIN, I will match by firms' header names reported in the 10K filings, using levenshtein distince,[7] I use a relatively strict matching rule by requiring a fuzzy ratio[8] to be larger that 0.95. For the remaining unmatched firms, I will do the matching by the firm's header address, similarly using a strict rule with fuzzy ratio of at least 0.95. Those matching added an extra of 20 more firms to the sample per year, but still left a big portion unmatched. Table A.4 presents number of firms with matched CIK by fiscal year using different matching rules.

For earlier years (1995-2004), I manually track the predecessor of a firm that changes it's CIK during it's existence, typically firms change CIK after a merger or divestiture, in those cases information about the predecessor can be easily find in the managerial discussion section of the deal in the current firm's 10K.

[7]refer to `https://en.wikipedia.org/wiki/Levenshtein_distance` for a definition of levenshtein distance.

[8]Fuzzy ratio calculated as $\frac{|a|+|b|=levenshteindist(a,b)}{|a|+|b|}$

Table A.4: Number of Firms with Matched CIK

This table reports the number of firms from the CMM sample that get matched to SEC filing each fiscal year from 2005 through 2017 as well as basic statistics of the main sample thats being used in this study. Note that for each fiscal year t, firms in the CCM are matched to SEC 10Ks filed between July 1st of calendar year t and July 1st of calendar year t+1. Column "Matched" is the number of firms in CCM sample that got matched to a 10K filing; EIN is number of additional firms that get matched using EIN; Name is additional firms that get matched using name; Final is total number of firms got matched to a 10K filing in SEC. Name, address matched are done by a text-based rule using Levenshtein Distance. The last 3 columns are information about the sample of main test in the paper. "W/ table" column documents the number of firms of which we have cash flow and notes data extracted from the 10k, "Non-fin/utili" is the number of firms that are both non-financial and non-utility and the last column demonstrate the market share of the main sample as a percentage of the universe of non-financial/utility firms in CCM.

Year	CCM	Matched	EIN	Name	ADDr	Total	W/ table	Non-fin/utili	% MktCap
2005	907	845	7	16	5	873	808	612	67.7%
2006	872	817	6	15	4	842	808	611	66.8%
2007	868	825	4	10	5	844	809	625	66.6%
2008	856	811	5	14	6	836	806	617	72.8%
2009	849	805	5	13	6	829	822	651	71.3%
2010	854	812	6	12	5	835	811	638	66.7%
2011	851	816	4	12	3	835	835	659	74.7%
2012	878	843	4	10	2	859	843	672	75.0%
2013	898	868	3	7	2	880	865	697	74.9%
2014	929	900	2	7	4	913	889	701	73.9%
2015	965	941	4	5	2	952	934	723	76.4%
2016	916	902	3	2	2	909	882	673	75.4%
2017	914	905	2	2	0	909	836	635	68.8%

Algorithm Model Solution and Estimation

The model is solved by value function iteration and initially estimated using simulated method of moments featuring the following steps and finally calibrated till convergence of the LOMs for both the capital and resale price.

- Step 1. Estimate Φ^m $(\{\gamma, \phi, f_u, f_b, p_n^b, p_s^b, \mathsf{P}_o, \mathsf{P}_s, S_o, \delta_s, b\})$ based on LOMs described by the set of initially guessed values: Φ^k $(\{\alpha_0, ..., \alpha_3, \beta_0, ..., \beta_3\})$ for mean capital level and Φ^p $(\{\gamma_0, ..., \gamma_3, \phi_0, ..., \phi_3\})$ for unbundled capital price.
  - Solve the optimization problem for both types of firms as in equations (1.13) to (1.15) assuming capital and price evolves as in the initialized LOMs, store the resulting value function $V_{ii}(k, z_i, z_a, z_{a,-1}, p^u(\bar{k}))_{ii\in\{I,II\}}$ and decisions rules $\{I_{ii}, U_{ii}, B_{ii}\}$ for later use.
  - Simulate a panel of firms with randomized initial capital and productivity $(\{k_{j0}, z_{ij0}\}_{j=1}^{N})$, simulate the series of aggregate shocks $\{z_{at}\}$ with a randomized initial value. For each period t, with initial productivity $\{z_{it}, z_{at}\}$,

mean capital level ($\bar{k}_t$) and the corresponding capital price, generate firms' decisions based on rules from above:

    * Determine the set of firms that are type I/II based on the aggregate shocks from current and one period before. Use corresponding policy rules for each type.
    * For new or unbundled capital, decisions are equivalent to realizations. For bundled capital, generate random number to determine whether transactions of each firm complete successfully: with probability $1-\mathsf{P}_o$, decision to buy/sell bundled capital B_t may not realize (does not result in changes of firm level capital).
    * Based on realized decisions, compute the resulting mean capital level of the economy for the next period.
    * Conditional on the current state of aggregate productivity shock z_{at}, generate idiosyncratic shock for next period according to Equation (1.4).
        · For firms that did not or failed to acquire bundled capital, next period shock depends on current productivity $z_{it+1} = f(z_{it})$.
        · For firms that successfully acquired bundled capital, the next period shock will be generated from $f(z_{it})$ with probability $1 - \mathsf{P}_s$, or from $f(\tilde{z}_i \in \omega_{-z_{it}})$ with probability P_s, here $\omega_{-z_{it}}$ is the complement of z_{it} in the state space of z_i. With two levels of shocks $\omega = \{z_i^H, z_i^L\}$, $\tilde{z}_i$ will be z_i^H (z_i^L) if z_{it} is z_i^L (z_i^H). Generate random number to determine whether the firms will experience such a structural changes in the state variable.
    * Repeat the above process to complete the panel in the time series, store the output of the cross-section (capital distribution, policy decisions, firm values, etc.) at each point in time. Calculate simulated moments from the stored output.
  - The structural parameters are estimated using ParticelSwarm to minimize the euclidean distance between model simulated moments and empirical moments.

- Step 2. Based on estimated structural parameters and LOMs from Step 1, resolve the model to generate new value function and policy rules and then simulate the economy.
  - Simulate a panel of firms with the same initial capital and productivity levels as in Step 1 and the same series of aggregate shocks. For each period t,
    * determine the composition of firm types as in Step 1, for each type, use corresponding value and policy functions.
    * generate firms' decisions based on above policy rules, determine realized decisions and compute next period mean capital level according to the realized decisions as in Step 1, save the time series of mean capital $\{\bar{k}_t\}$.

  - ∗ solve for the market clearing price of unbundled capital using the algorithm provided below based on policy functions of the firm, save the time series $\{p_t^u\}$
  - ∗ determine occurrence of structural changes among bundled acquirers and then generate the next periods idiosyncratic shocks for all firms as in Step 1.
  - ∗ repeat till completing the panel.

- Step 3. Re-estimate LOMs using capital and price data ($\{\bar{k}_t\}$,$\{p_t^u\}$) generated from Step 2, skipping the first 50 time periods for stationary concerns. Compare the perceived LOMs ($\{\Phi^k, \Phi^p\}$) with the realized LOMs ($\{\hat{\Phi}^k, \hat{\Phi}^p\}$), if the euclidean distance between the two exceed certain threshold, update the guess according to the following rule:

$$\tilde{\Phi}^i = (1-\lambda^i)\Phi^i + \lambda^i\hat{\Phi}^i, \quad \lambda^k = 0.3,\ \lambda^p = 0.2 \tag{A.1}$$

  Return to Step 1 and repeat the process till initial convergence of $\{\Phi^k, \Phi^p\}$.[9] Once initial convergence achieved, proceed to Step 4.

- Step 4. Fix the estimated parameters $\hat{\Phi}^m$, repeat Step 2 through Step 3 till final convergence of $\{\Phi^k, \Phi^p\}$.[10]

The market clearing price in the unbundled market is the price at which net asset supply (demand) turns to zero. Since net demand is nonincreasing in the price, I estimate the market clearing price using the following algorithm, of which a simple example is illustrated in Figure A.5.

- Step 1. Pick a lower bound and upper bound for the price to be solved.
  - Use varying bounds depends on the aggregate states $\{z_{at}, z_{at-1}\}$, namely, for states combinations of $\{H,H\}, \{H,L\}, \{L,H\}, \{L,L\}$, the lower bounds (lbd) are $\{1, 1, 0.9, 0.9\}$ and upper bounds (ubd) are $\{1.12, 1.15, 1.05, 1.06\}$ respectively.
  - Estimate the net asset demand (negative being supply) at the bounds, denote the net demand as π, if any of the bounds results in a net demand of zero, set it as the market clearing price and exit. Otherwise, $\pi(lbd)$ should be positive and $\pi(ubd)$ be negative, if not, adjust the bounds accordingly, e.g., if $\pi(lbd) < 0$, adjust downward the lbd and reset ubd as the original lbd. Repeat until either market clears at a new boundary and exit or the following holds $(\pi(lbd) < 0)\&(\pi(ubd) > 0)$.

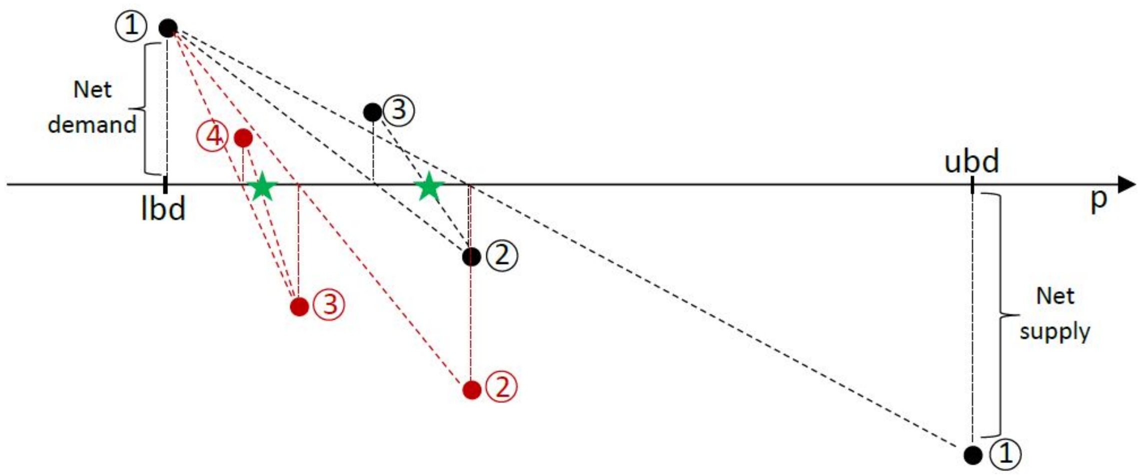
- Step 2. Locate the next searching point as $s = \pi(lbd)(upd - lbd)/(\pi(lbd) - \pi(ubd)) + lbd$, estimate $\pi(s)$, if $\pi(s) = 0$, set s as the market clearing price and exit, otherwise, determine the new boundaries for next search: if $\pi(s) > 0$, new boundaries as $\{s, upd\}$, else, $\{lpd, s\}$

[9] Initial convergence achieved when norm of the difference as a ratio of norm of the initial LOMs less than 0.1.

[10] Final convergence achieved when norm of the difference as a ratio of norm of the initial LOMs less than 0.01.

- Step 3. Return to Step 1 with the new boundaries, repeat the process for a maximum of n times (I find n=5 is very effective in achieving market clearing).

Figure A.5: Examples of Solving Market Clearing Price



Starting with a set of boundary prices $\{lbd, upd\}$, the graph demonstrate two possible routes (indicated by black and red dashed lines respectively) the algorithm could potentially follow to arrive at the market prices. The numbers marks the sequence of searching points evaluated by the algorithm in both scenarios and the green stars denote the solutions (market clearing prices), upon the 4^{th} evaluation for one route (black) and 5^{th} evaluation for the other (red).

APPENDIX B

APPENDIX TO CHAPTER 2

LIFO and FIFO

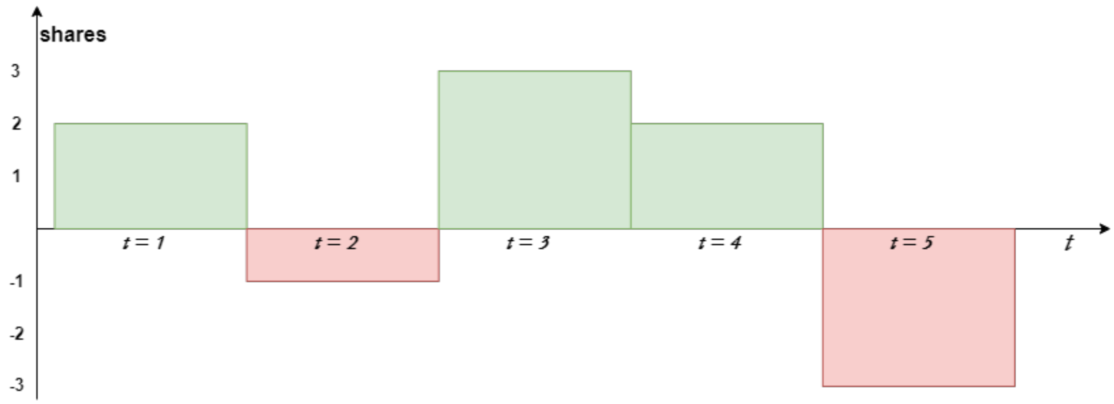
Under the LIFO system each inventory reversing trade is matched to the newest inventory entries in a sequential manner whereas under FIFO the offsetting trade is matched to the oldest pieces of inventory. The difference between the entry and exit time of each inventory entry will be the round trip time (τ) for the trade that initiated that inventory. Figure B.1 illustrates the identification of round trips under the LIFO and FIFO methods using a simple example.

Over any period of time in which all of the LP's inventory positions are completely turned around, the average round trip time τ and dollar-volume-weighted average realized profitability under LIFO would be exactly equal to that under FIFO. However, whenever the LP does not fully turn around it's inventory position, LIFO estimates will deviate from that of FIFO. This discrepancy results from the difference in the set of matched trades between LIFO and FIFO. To illustrate the difference in the selection of trades between these two tracking systems during days with order imbalance, we use an extremely simplified example as shown in Figure B.2. As in the figure, during days with large order imbalance, LIFO matches offsetting trades that are temporally closer to each other than FIFO: average turnaround time is 2 hours under LIFO ($(1 + 3)/2$) and 5 hours under FIFO ($(5 + 5)/2$).[1] This feature of LIFO is economically appealing: market makers are more likely to provide liquidity when trades can be turned around faster; given this preference and rational expectations (about the expected time to turnaround a trade) it is reasonable to expect that round trips matched under LIFO were more likely executed by market makers than ULPs.

The advantage of LIFO over FIFO is especially prominent during days when there is large order imbalance. In Table B.1 we sort our stock days into decile groups based on the daily order imbalance level and then report the average round trip time and realized profitability of all round trips from each group. Under LIFO, the average τ increases from 62 seconds for the days with the lowest level of order imbalance to 116 for the days with the highest level of order imbalance. Under FIFO, average turnaround times are much larger and also very sensitive to order imbalance (it increase from 711 seconds for low imbalance day to 5808 seconds for high imbalance day). In terms of realized profitability, the estimates are very close—around 2.7bps—under both LIFO and FIFO during days with small order imbalances (the first two decile groups). However, as we move towards large order imbalance stock days, realized profitability increases gradually to 4.85 bps for the 9th decile group and jump to 8.26 for the group with the largest order imbalance. By contrast, it drops to a dramatic -18.18 bps for the group with the highest order imbalance. Compared to FIFO, LIFO produces much more reasonable estimates of τ across days with and without large order imbalances. Consider the fact that market makers—especially high frequency ones—are extremely averse to holding inventory, we believe the high sensitivity of FIFO estimates to daily order imbalance results from FIFO's tendency to capture trades by ULPs: trades that took extremely long to turnaround were most likely intermediated by long term investors rather than market makers; during days with large order imbalance, FIFO disproportionately select these trades because it

[1] Note that in our analysis we only keep trades that are turned around within a day: during days with order imbalance, the trades, or circles that are not connected by pink dashed lines are omitted from our sample.

Figure B.1: Tracking Round Trips (LIFO and FIFO)



	Trades:	Inventory book:	Round trips (LIFO):	Round trips (FIFO):
t = 1	+2 shares	entry at 1, book: (+2, t = 1)	none	none
t = 2	-1 shares	exit at 2, book: (+1, t = 1)	Trip1: stime = 1, etime = 2 tau = 1, eQ = -1	Trip1: stime = 1, etime = 2 tau = 1, eQ = -1
t = 3	+3 shares	entry at 3, book: (+1, t = 1) (+3, t = 3)	none	none
t = 4	+2 shares	entry at 4, book: (+1, t = 1) (+3, t = 3) (+2, t = 4)	none	none
t = 5	-3 shares	exit at 5, book: (+1, t = 1) (+2, t = 3)	Trip2: stime = 4, etime = 5 tau = 1, eQ = -2 Trip3: stime = 3, etime = 5 tau = 2, eQ = -1	Trip2: stime = 1, etime = 5 tau = 5, eQ = -1 Trip3: stime = 3, etime = 5 tau = 2, eQ = -2

Figure illustrates the identification of round trips (how to match off-setting trades to form a round trip) under LIFO and FIFO using an example with 5 trades over a 5-minute window. Light green bars denote market sell orders—or equivalently the LP's buy orders—with sizes shown on the y-axis; light red bars denote the LP's sales similarly. The inventory book records entries of inventory positions with information on the size, direction as well as time of the entry. Under LIFO, off-setting trades are matched with the newest inventory to form a round trip: e.g., at $t = 5$, part of the market buy order is matched with the newest inventory, the 2 shares acquired at $t = 4$, to form the round trip Trip2, which has a turnaround time of 1 minute (exit time 5 – entry time 4). Under FIFO, off-setting trades are matched with the oldest inventory: e.g., at $t = 5$, part of the market buy order is matched with the oldest inventory, the 1 share acquired at $t = 1$, to form the round trip Trip2, which has a turnaround time of 5 minute (exit time 5 – entry time 1).

matches offsetting trades with the oldest inventory.

Aside from being economically meaningful, LIFO also produce estimates of realized profitability that are statistically more robust to order imbalances than FIFO. In the following section we demonstrate how FIFO can introduce mechanical bias in the estimates of realized profitability across market making horizons when there exists large order imbalance.

Figure B.2: Matched Trades under LIFO (left) and FIFO (right)

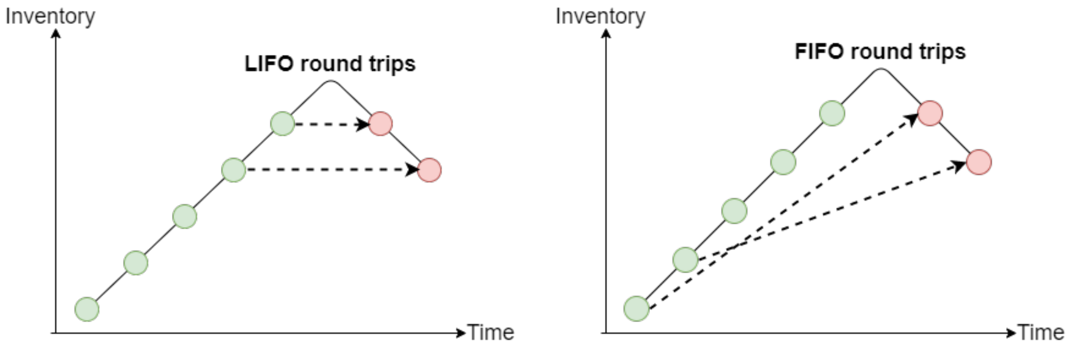


Figure compares the set of trades matched to form round trips under LIFO with the set matched under FIFO in a hypothetical day with 7 trades and order imbalance. The solid black line tracks the cumulative inventory level of the LP throughout the day as shown on the y-axis; light green balls denote market sells (the LP's buys) and light red balls denote market buys, all of unit size and evenly distributed across time (elapsed time between consecutive trades is one hour). The dashed black lines with arrows connect trades to form round trips under LIFO on the left and FIFO on the right. Unmatched trades—the first trades under LIFO and the 3^{rd} through 5^{th} trades under FIFO—show up in the end-of-day inventory as order imbalance.

Table B.1: Average Inventory Turnaround Time and Realized Profitability by Order Imbalance

Table reports average inventory turnaround time τ and realized profitability rp for decile groups of stock days sorted by order imbalance. The sorting variable order imbalance is computed for each stock day as the total order imbalance scaled by the total trading volume $\frac{|\$Buy-\$Sell|}{|\$Buy+\$Sell|}$. For each decile group of stock days, we compute the average τ as the dollar-volume-weighted average τ of all round trips from that group, and the average rp as the dollar-volume-weighted average rp using all round trips from the same group. First row reports average τ using round trips matched under FIFO and second row reports average τ using round trips matched under LIFO. Similarly, the third and fourth row report average rp using round trips matched under FIFO and LIFO respectively. The last row reports the dollar-volume-weighted average value of the sorting variable for each group. Column "All" reports full sample averages (dollar-volume-weighted).

Decile	1	2	3	4	5	6	7	8	9	10	All
FIFO τ (s)	711	875	1,110	1,436	1,801	2,236	2,740	3,368	4,303	5,808	1,567
LIFO τ (s)	62	62	63	64	65	68	72	78	89	116	66
FIFO rp (bps)	2.64	2.54	1.00	0.06	-1.20	-2.49	-3.62	-5.35	-8.63	-18.18	-0.16
LIFO rp (bps)	2.68	2.78	2.68	2.91	2.91	3.12	3.37	3.91	4.85	8.26	2.99
Imbalance (%)	0.8	2.3	3.8	5.5	7.4	9.5	12.0	15.4	20.5	30.2	4.6

Statistical Sensitivity to Order Imbalance: LIFO vs FIFO

In this section, we use a simplified example to show how FIFO can generate statistical bias—that has no economic meaning—in the estimates of realized profitability compared to LIFO. We examine the case where the LP's inventory is built up over the first n trades of the day followed by D reversing trades—there are a total of D round-trip trades during the day. For simplicity we assume each trade is either an aggressive sale or purchase for 1 share. The LP begins with zero inventory and the initial price of the security is P_0.

To illustrate the statistical bias, we shut down economic sources that can potentially cause differences in the estimates of LIFO and FIFO by assuming that each trade has same price impact Δ in the direction of the trade ($+\Delta$ for buyer-initiated trades and $-\Delta$ for seller-initiated trades), and the occurrence of order imbalance does not convey information about future trades. The first n trades are seller-initiated trades for the security meaning that the LP builds up a cumulative inventory position of $+n$ at time $t = n$ with the security price falling to $P_n = P_0 - n\Delta$. Following the build up, all D subsequent trades are assumed to be aggressive purchases which progressively reverse the LP inventory. In the case when $D = n$ the LP's inventory is completely turned around and there's no trade-imbalance; when $D < n$ the LP ends the day holding $n - D$ shares in inventory.

Figure B.3: LIFO/FIFO Term-Structure Sensitivity

t	Aggressive Sellers	LP	Aggressive Buyers	LP Inventory	ΔPrice	Price
1	Sell →	Buy		+1	$-\Delta$	$P_1 = P_0 - \Delta$
2	Sell →	Buy		+2	$-\Delta$	$P_2 = P_0 - 2\Delta$
3	Sell →	Buy		+3	$-\Delta$	$P_3 = P_0 - 3\Delta$
⋮	⋮	⋮		⋮	⋮	⋮
n-1	Sell →	Buy		+(n-1)	$-\Delta$	$P_{n-1} = P_0 - (n-1)\Delta$
n	Sell →	Buy		+n	$-\Delta$	$P_n = P_0 - n\Delta$
n+1		Sell →	Buy	+(n-1)	$+\Delta$	$P_{n+1} = P_0 - (n-1)\Delta$
n+2		Sell →	Buy	+(n-2)	$+\Delta$	$P_{n+2} = P_0 - (n-2)\Delta$
⋮		⋮	⋮	⋮	⋮	⋮
n+(D-2)		Sell →	Buy	n-D+2	$+\Delta$	$P_{n+(D-2)} = P_0 - (n-D+2)\Delta$
n+(D-1)		Sell →	Buy	n-D+1	$+\Delta$	$P_{n+(D-1)} = P_0 - (n-D+1)\Delta$
n+D		Sell →	Buy	n-D	$+\Delta$	$P_{n+D} = P_0 - (n-D)\Delta$

If one were to use FIFO to track the round-trip trades, the presence of an order-imbalance, ceteris paribus, would mechanically generate a downward slopping term-structure. Under FIFO, the trade resulting in the first decrease in inventory at time

$t = n + 1$, is matched with the trade which first increased the inventory position at time $t = 1$. According to FIFO, the LP entered into the position by buying the share at P_1 and later sold it at P_{n+1} to yield a realized profitability of $P_{t+1} - P_1$. More generally FIFO will match the exit trade at time $t = n + d$ with the entering trade at time $t = d$ with realized profitability given by $P_{n+d} - P_d$; note that every round-trip has the same turn-around time of n under FIFO. The average proceeds for a trading day with D round trip trades can be calculated as:

$$\frac{1}{D}\sum_{d=1}^{D}(P_{n+d} - P_d) = \Delta(D + 1 - n) \tag{B.1}$$

Whenever there's trade imbalance, the average turn around time would be decreasing in the average FIFO turn around time n; for example letting $D = \lambda n, \quad \lambda \in (0, 1)$:

$$\partial_n[\Delta(D + 1 - n)] = -(1 - \lambda) < 0$$

So long as there are trade-imbalance days, the FIFO system would have a mechanically downward-sloping term-structure. For days with no-trade imbalance $D = n$, the average turn around time would be n with average proceeds of Δ, regardless of what n is.

Unlike FIFO, LIFO does not have any variation in the realized profitability term structure mechanically introduced by trade imbalance. Since every trade is of the same size, and the inventory reversal begins at time $t = n + 1$, LIFO would match the entering trade at $t = n - d$ with the exit at $t = n + 1 + d$ for $d = 0, 1, 2, \ldots, D$. The round trip times τ for the D trips under LIFO are given by $1, 3, 5, ..., (2D - 1)$. When $D = n$ (no imbalance) the average τ would be the same as FIFO, $\tau_{LIFO} = n = \frac{1}{D}\sum_{d=1}^{D}(2d - 1)$. On days where D is much smaller than n (so imbalance is large) the FIFO τ would be much larger than the LIFO τ, $\tau_{LIFO} = \frac{1}{D}\sum_{d=1}^{D}(2d - 1) << n = \tau_{FIFO}$. Given that each 1-share trade has a price impact of $\pm\Delta$, the price at the entrance and exit may be computed as:

$$P_{n-d} = (P_0 - n\Delta - d\Delta) \text{ and } P_{n+1+d} = (P_0 - n\Delta + d\Delta) + \Delta$$

Meaning that the round trip profits, $P_{n-d} - P_{n+1+d} = \Delta$ is constant for every round-trip, resulting in a flat term-structure. Even when trade imbalance is introduced with $D < n$, the realized profitability for every round trip would still remain constant at D. This is to show that in-contrast to FIFO, the combination of price-impact with trade-imbalance does not mechanically generate a downward (or upward) sloping term-structure under LIFO.

APPENDIX C

CO-AUTHORSHIP STATEMENT

Chapter 2 of this dissertation, titled The Profitability of Liquidity Provision, forms the core of a paper of the same name, co-authored with Ariel Lohr and included in this document with his permission.