# Customer Capital*

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**Abstract**

Firms spend substantial resources on marketing and selling. Interpreting this as evidence of frictions in product markets, which require firms to spend resources on customer acquisition, this paper develops a search theoretic model of firm dynamics in frictional product markets. Introducing search frictions generates long-term customer relationships, rendering the customer base a state variable for firms, which is sluggish to adjust. This affects: the level and volatility of firm investment, sales, profits, value and markups, the timing of firm responses to shocks, and the relationship between investment and Tobin's $q$. We document support for these predictions in firm-level data from Compustat, using cross-industry variation in selling expenses to quantify differences in the degree of friction across markets.
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# 1 Introduction

Firms spend substantial resources on marketing and selling, with marketing expenditures recently estimated to make up as much as five percent of GDP (see Arkolakis Forthcoming). Interpreting this as evidence of frictions in product markets, which require firms to spend resources on customer acquisition, this paper develops a search theoretic model of firm dynamics in frictional product markets. Introducing search frictions generates long-term

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customer relationships, rendering the customer base a state variable for firms, which is sluggish to adjust. We use this framework to study the implications of frictional product markets and customer base concerns for firm dynamics: the level and volatility of firm investment, sales, profits, value and markups, the timing of firm responses to shocks, as well as the relationship between investment and Tobin's $q$. Moreover, we document support for these predictions in firm-level data from Compustat, using cross-industry variation in selling expenses to quantify differences in the degree of product market friction across markets. Our paper contributes to a newly developing literature – both theoretical and empirical – emphasizing the role of customer base concerns in a variety of settings,[1] by studying the direct implications for firm dynamics.

To understand the implications of product market frictions for firms, we begin by developing a tractable search-theoretic general equilibrium model of frictional product markets. The model builds on the Mortensen-Pissarides matching model, and nests the neoclassical adjustment cost model of investment. In the model, a continuum of firms produce goods which are sold through a product market affected by informational frictions concerning product characteristics. To overcome these frictions, firms must hire sales people to meet with potential customers, and consumers spend time searching for suppliers. Search frictions render customer relationships long-term in nature, and the customer base thus a state variable for firm decision-making. To allow firms to influence customer acquisition through pricing, we incorporate directed/competitive search into the model, with firms using optimal pricing schedules to attract new customers. Equilibrium pricing schedules involve an initial discount to new customers, with firms charging existing customers a price which leaves them indifferent between continuing the customer relationship or not.[2] Three features of the model are important for the results we emphasize: long-term customer relationships, customers purchasing a fixed quantity per period, and convex costs of customer acquisition.

[1]We discuss these papers in Section 5.

[2]Examples of products motivating our model are newspapers subscriptions and cell phone services. Newspapers offer discounts to new customers, subsequently charging a price above the marginal cost of production for an extended period of time. Similarly, cell phone providers often offer an initial discount in the form of a free phone. In these industries it appears common to evaluate the value of a firm based on the number of customers, the customer retention rate, and the margin per customer. We believe the main insights of our analysis to apply also to markets where contracts are implicit, however.

Product market frictions have a number of implications for firms, which we find non-trivial in magnitude:

First, they generate a form of intangible capital embodied in the customer base. When customer relationships are long-term in nature and the costs of customer acquisition paid up-front, the present value of firm profits from a new customer relationship must make up for the initial costs of attracting the customer. This turns existing customers into valuable assets for firms. Frictional product markets thus raise firm value above the value of physical capital, profit rates above the cost of capital, as well as generating positive markups.[3]

Second, product market frictions affect firm dynamics. On the one hand, by effectively imposing an additional adjustment cost on firm expansion, they work to dampen firm responses to shocks. On the other, by slowing down expansion in sales, they generate hump-shaped responses in a number of variables. In the neoclassical adjustment cost model, an increase in firm productivity leads to an instantaneous increase in firm sales and investment. In a frictional product market, however, the increase in production capacity leaves the firm short of customers to sell to, as the convex costs of customer base expansion slow down the increase in sales in the short run. Investment rises on impact, but continues to rise further as the firm accumulates customers (and eventually finds itself short of production capacity), generating a hump-shaped response. These changes in firm dynamics make frictional product markets promising for understanding the evidence on hump-shaped responses of macro-aggregates – in particular investment – to aggregate shocks.[4] The complementarity of customer capital with physical capital plays a key role in generating hump-shaped responses in investment.

Third, product market frictions affect the widely-studied relationship between investment and Tobin's $q$. A large literature documents that the simple prediction of the neoclassical

[3]The paper is thus related to the literature emphasizing the importance of intangible capital, such as Hall (2001b), Atkeson and Kehoe (2005), McGrattan and Prescott (2010a, 2010b), Eisfeldt and Papanikolaou (2009), Ai, Croce, and Li (2010). Relative to this literature, which generally considers a broader notion of organizational capital, we model and study a particular form of intangible capital more closely. An exception within the finance literature is Belo, Lin, and Vitorino (2011), who study the relationship between brand capital and firm riskiness.

[4]See e.g. Cogley and Nason (1995), Christiano, Eichenbaum, and Evans (2005), Basu, Fernald, and Kimball (2006), Smets and Wouters (2007). Such hump-shapes are generally at odds with the neoclassical growth model, where variables respond to shocks on impact, and recent literature resorts to non-standard adjustment cost functions to replicate these patterns within a model (e.g. Christiano, Eichenbaum, and Evans 2005, Jaimovich and Rebelo 2009).

adjustment cost model – that Tobin's $q$ be a sufficient statistic for firm investment – has little success empirically.[5] Frictional product markets offer a potential explanation for this evidence by breaking the perfect correlation between investment and Tobin's $q$ implied by the neoclassical model. Plausibly parameterized, these frictions reduce the coefficient estimate in an investment-$q$ regression by a factor of four. Moreover, as found in the data, the model predicts firm profits to have stronger explanatory power for investment than Tobin's $q$: Profits share the hump-shaped response of investment to shocks, while Tobin's $q$ does not.

To establish the empirical relevance of the model mechanism across a range of markets, we turn to firm-level data from Compustat. Because product market frictions are likely to be more important in some markets than others, it is natural to use this cross-sectional variation to test the predictions of the model. The model associates greater frictions with greater overall selling expenses within a market. Sorting markets according to selling expenses thus allows us to compare markets characterized by differing degrees of friction. We document support for each of the main predictions discussed: the levels and volatility of firm investment, sales, profits, value and markups, the timing of firm responses to shocks, and the relationship between investment and Tobin's $q$ – both at the firm, industry, and aggregate level.

The paper is organized as follows. Section 2 presents our model. Section 3 fleshes out the implications of the model, which we study empirically in Section 4. Section 5 relates our paper to recent work emphasizing the role of the customer base in various contexts, and Section 6 concludes.

## 2 The Model

This section introduces a model designed for analyzing the effects of frictional product markets on firm investment, sales, profits, value and their dynamic responses to shocks. The

[5] Caballero (1999) and Chirinko (1993) survey this literature. A number of alternative explanations have been proposed for the empirical failure of $q$-theory (as discussed in Sections 3 and 4). Although all of these alternatives imply that $q$-theory not hold exactly, in many models it nevertheless works well as an approximation (see e.g. Gomes 2001).

model economy is populated by a representative household and a cross-section of firms facing idiosyncratic shocks to their productivity. We begin by examining a stationary competitive equilibrium, together with a corresponding planning problem, but the analysis is straightforward to extend to allow aggregate shocks as well.[6] We return to discuss our modeling choices at the end of the section.

**Firms** Production is carried out by a continuum of measure one firms, each producing a differentiated good with a Cobb-Douglas production technology $y = f(k, l^p, z)$. Firms sell the goods through a frictional market to the household, which converts them one-for-one into a homogenous good used for consumption and investment. The homogenous good acts as both the medium of exchange and the numeraire in the economy.[7] Firms accumulate capital according to the law of motion $k' = (1 - \delta_k)k + i$, with existing capital depreciating at rate $\delta_k$. New investment entails a cost $\phi(i, k)$, which includes both the purchase price of capital and a standard convex adjustment cost. Firms hire production labor $l^p$ from a frictionless labor market. Finally, productivity $z$ is independent across firms, and follows a Markovian stochastic process with a bounded support and a continuous and monotone transition function.

**Representative household** The representative household consumes the homogenous good and leisure, with preferences

$$\sum_{t=0}^{\infty} \beta^t u(c_t, 1 - l_t^m - l_t^b). \tag{1}$$

Here $u$ is strictly increasing and concave, and satisfies Inada conditions. The household allocates its time between leisure, market work $l_t^m$, and buying activity $l_t^b$. The household's per-period budget constraint (with the price of the homogenous good normalized to one)

[6]Appendix C describes the version of the model where we replace the idiosyncratic shocks with aggregate shocks.

[7]To fix ideas, one can think of each firm as producing the same good in different colors. Due to idiosyncratic differences in tastes, not all buyers will accept all colors. Once a buyer has accepted to buy a good, however, for all practical purposes the color becomes irrelevant. Assuming that the goods become perfectly substitutable ex-post allows capturing the frictions in creating purchasing relationships, while keeping the model as simple as possible.

reads

$$c_t \leq w_t l_t^m + w_t^b l_t^b + \Pi_t, \tag{2}$$

for all $t \geq 0$.[8] The household's income, on the right, consists of the wages on market work $w_t l_t^m$ and the aggregated dividends $\Pi_t$. In addition, buying activity also yields a positive payoff $w_t^b l_t^b$, discussed in detail below. Note that the budget constraint is formulated in terms of a frictionless market in the homogenous good. The supply of the good to this market is determined by the frictional product market, discussed next.

**Frictional product market** The measure $l^b$ infinitesimal household members engaged in buying activity are each aware of all firms producing goods, but due to idiosyncratic differences in tastes, they are not each willing to buy all firms' goods. Informational frictions imply that in order for a household member to determine whether he or she is willing to buy a particular firm's good, the household member must meet with the firm's sales person. To allow these meetings to take place, firms hire sales people. The sales people are placed in separate sales locations differing in centrality, starting from the most central toward the less central. Formally, this idea is captured by assuming that the measure of sales people generating $l^s$ efficiency units of sales people is given by an increasing and convex function $\kappa(l^s)$.[9]

We assume household members decide on the sales locations to visit independently, and that sales people have finite capacity to handle potential buyers. Meetings between sales people and potential buyers are thus subject to coordination frictions: Each period some sales locations go without any potential buyers arriving, while others get more than the sales person can handle. We capture this formally with a firm-level matching function. If a firm hires $l^s$ efficiency units of sales people, with $l^b$ potential buyers arriving across sales locations, then the measure of new customer relationships is given by $m(l^b, l^s) = \xi(l^b)^\gamma(l^s)^{1-\gamma}$,

[8]We could include a saving/portfolio-choice decision, allowing the household to choose how much to invest in each firm. It would not change allocations, however, as in equilibrium the household owns all the firms. Doing so would make explicit the usual observation that the rate of return on the household portfolio must equal $1/\beta - 1$ in a stationary equilibrium.

[9]The assumption that $\kappa$ is convex is important for the firm dynamics we emphasize later. We discuss this, and other, modeling choices at the end of the section.

where $\xi > 0$ and $\gamma \in (0, 1)$. This measure is a product of the exogenous probability of a meeting leading to a new customer relationship, and the measure of meetings taking place. We use $\theta = l^b/l^s$ to denote the (firm-specific) average queue-length of potential buyers across a firm's sales people.[10] With this, the probability of matching per sales person, $\eta(\theta) = \xi\theta^\gamma$, becomes an increasing function of the queue length. Similarly, the probability of matching per potential buyer, $\mu(\theta) = \xi\theta^{\gamma-1}$, becomes a decreasing function of the queue length. These expressions capture the idea that an increase in potential buyers per sales person increases matches per sales person, but at a diminishing rate because these buyers are more likely to arrive in locations with sales people occupied.[11]

For thinking about the payoff to buying activity, it is useful to start from existing customer relationships, where *one* unit of the differentiated good changes hands per period. Existing relationships end with probability $\delta_n$ each period, for idiosyncratic reasons. Apart from this exogenous customer depreciation, a customer relationship continues as long as the customer is willing to continue to buy a unit of the good per period, and the firm to produce it. Because the customer values the differentiated good at one unit of the homogenous good (and there is no additional cost of continuing the relationship), that is how much he or she is willing to pay for it. To maximize profits, the firm charges the highest price it can without driving the customer away. In principle these payments could be scheduled in different ways over time, but because we assume firms cannot commit to future prices, it follows that they optimally price at exactly one unit of the homogenous good per period.[12]

To allow firms influence over customer acquisition through their pricing decisions, we assume firms can commit to an initial discount to new customers. Firms use these discounts to compete for new customers as follows: Each period each household member engaged in

[10] To be exact, $l^s, l^b$ are in units of selling and buying time, so $\theta$ captures average buying time per unit of selling time.

[11] This discussion is based on Stevens (2007), who describes a matching process that generates an approximately Cobb-Douglas matching function: Sales people are situated in separate sales locations and handle potential buyers at a finite Poisson rate. Potential buyers contact these sales people at a finite Poisson rate, but cannot coordinate among themselves on which sales people to contact. This means that upon contacting a sales person, a potential buyer may find them occupied with another buyer. Increasing the number of potential buyers per sales person increases the number of matches per sales person (as sales people spend less time idle), but at a diminishing rate (as idle time is limited).

[12] We assume the firm can refuse attempts by customers to re-bargain prices, as doing so would not be in the firm's interests.

buying activity optimally chooses a firm based on the discounts $\varepsilon$ and queue lengths $\theta$ across firms. The payoff $w^b$ must be consistent with this optimization, implying that

$$w^b = \max_{\{(\varepsilon,\theta)\}} \mu(\theta)\varepsilon. \tag{3}$$

Choosing a firm with discount $\varepsilon$ and queue length $\theta$ leads to a new customer relationship forming with probability $\mu(\theta)$. The present value of the relationship to the household member is $\varepsilon$: the customer gets one unit of the homogenous good per period,[13] and pays back $1-\varepsilon$ units in the first period, and one unit in later periods.

Note that equation (3) implies that potential buyers can be indifferent between low discount firms and high discount firms, if the queues in the low discount firms are sufficiently shorter than in the high discount firms. In equilibrium different firms indeed generally offer different discounts, depending on their desire to expand sales (with potential buyers indifferent across firms).

**Firm problem** With this, we can write the firm problem in a stationary equilibrium, where $w$ and $w^b$ are constant, as

$$v(k,n,z|w,w^b) = \max_{y,i,l^p,l^s,\theta,\varepsilon} y - l^s\eta(\theta)\varepsilon - wl^p - w\kappa(l^s) - \phi(i,k) + \beta E_z v(k',n',z'|w,w^b), \tag{F}$$

$$y \le n + l^s\eta(\theta), \tag{4}$$

$$y \le f(k,l^p,z), \tag{5}$$

$$n' \le (1-\delta_n)y, \tag{6}$$

$$k' \le (1-\delta_k)k + i, \tag{7}$$

$$w^b \le \mu(\theta)\varepsilon, \tag{8}$$

where all choice variables except investment are non-negative. In addition to capital and productivity, the state variables of the firm now include the size of the customer base. We use $n$ to denote the measure of existing customers at the beginning of the period. Hiring

[13] The customer receives one unit of the differentiated good per period, but converts it one-for-one into the homogenous good.

$\kappa(l^s)$ units of labor to work in sales (with $l^s$ efficiency units resulting), the firm attracts $l^s\eta(\theta)$ new customers this period. Here the queue length $\theta$ depends on the choice of discount $\varepsilon$, as explained below. Equations (4) and (5) state that total units sold $y$ cannot exceed the size of the customer base, nor production output, respectively. In fact, because producing excess output cannot be optimal, (5) must hold with equality, determining how much labor $\ell^p(k, y, z)$ is needed to produce $y$ units of output. Equation (6) is the law of motion for the customer base, which limits next period's customer base to the fraction of current customers who remain with the firm. Equation (7) is the law of motion for capital. Finally, as standard in competitive search, equation (8) imposes rational expectations regarding the queue length attracted by the firm's choice of discount $\varepsilon$. The firm takes as given the market-determined payoff to buying activity $w^b$, and expects a queue which leaves customers indifferent between choosing this firm versus attaining the market payoff somewhere else.

The firm's objective is to maximize the present discounted value of dividends. Current dividends are given by sales revenue $y$ net of discounts to new customers $l^s\eta(\theta)\varepsilon$, wages of production and sales labor, as well as the costs of investment – all in terms of the homogenous good.[14] Finally, the present value of future dividends is given by $\beta E_z v(k', n', z'|w, w^b)$.

Notice that despite constant returns to scale in production, the convex costs of capital adjustment (as usual) imply that firms face decreasing returns in the short run. As a result, production will not be taken over by whichever firm has the highest productivity realization in the current period. Here the convex costs of customer acquisition only serve to reinforce this. In practice, we will assume that the customer depreciation rate $\delta_n$ is large enough to guarantee that the firm hires some sales people each period, even when a low productivity realization causes it to contract overall. This affords us the following first order conditions for characterizing decision-making.

The firm problem implies that the marginal value of an additional customer is forward-

[14] Note that investment takes the form of the homogenous good, rather than the differentiated good, and therefore must also be procured through the frictional market. Firms purchase investment goods from the same frictionless market in consumption goods described in the household problem.

looking, satisfying the envelope condition

$$v_n(k,n,z|w,w^b) = 1 - w\ell_y^p(k,y,z) + \beta(1-\delta_n)E_z v_n(k',n',z'|w,w^b). \tag{9}$$

An additional customer increases today's sales revenue by one unit, and production costs by $w\ell_y^p(k,y,z)$. Moreover, with probability $1-\delta_n$ the customer stays with the firm also into the following period, delivering the continuation value $\beta E_z v_n(k',n',z'|w,w^b)$.

The firm hires sales people until the marginal cost of an additional customer equals the marginal value, as reflected in the first order condition for $l^s$:

$$w\frac{\kappa'(l^s)}{\eta(\theta)} + \varepsilon = v_n(k,n,z|w,w^b). \tag{10}$$

The marginal cost of an additional customer, on the left, consists of both the wages of additional sales people, as well as the discounts used to attract new customers. These up-front costs of customer acquisition generally imply that existing customers are valuable assets the firm (i.e. $v_n(k,n,z|w,w^b) > 0$). Because the value of a customer depends on the firm's state – both its production capacity (determined by capital and productivity) and its existing customer base – so does the measure of sales people the firm hires.

The firm chooses the discount to minimize the costs of customer acquisition, resolving a trade-off between the two costs involved. Increasing the discount attracts more potential buyers per sales person, increasing customer acquisition per sales person, but at the same time it also reduces the profitability of those customers. The firm raises the discount to a point where the percentage increase in new customer relationships just compensates for the percentage drop in profitability per customer, as reflected in the first order condition for $\varepsilon$:

$$\frac{1}{v_n(k,n,z|w,w^b) - \varepsilon} = \frac{\gamma}{1-\gamma}\frac{1}{\varepsilon}. \tag{11}$$

Here $v_n(k,n,z|w,w^b) - \varepsilon$ is the value of the marginal relationship to the firm and $\varepsilon$ that to the customer. A marginal increase in the discount increases the value to the customer by $1/\varepsilon$ (in percentage terms), leading to a percentage increase in new customer relationships of $\gamma/(1-\gamma) \times 1/\varepsilon$. The matching function elasticity $\gamma$ governs the extent to which it is profitable to offer low prices to attract more customers. A low value of $\gamma$ implies that sales people cannot handle more customers per unit of time, so competition does not lead to large discounts.

Combining equations (8), (10), and (11) yields the following result, which implies that in equilibrium firms hiring more sales people also offer bigger discounts and attract longer queues:

**PROPOSITION 1.** *A firm's queue length and discount are increasing in its sales personnel* $l^s$*:* $\theta = \gamma/(1-\gamma) \times \kappa'(l^s)$ *and* $\varepsilon = w\theta^{1-\gamma}/\xi$.

**Investment** The firm invests according to the familiar rule, implied by the first order condition for $i$,

$$\phi_i(i,k) = \beta E_z v_k(k', n', z'|w, w^b), \tag{12}$$

which equates the marginal cost of investment to the discounted value of additional capital next period, also known as marginal $q$. Together with a standard quadratic adjustment cost for investment, this equation implies a linear relationship between the investment rate $i/k$ and marginal $q$. If the product market is frictionless, marginal $q$ then equals Tobin's $q$ (i.e. $v(k', n', z'|w, w^b)/k'$), which implies a linear relationship between the investment rate and Tobin's $q$.[15] Product market frictions break the linear relationship by introducing a time-varying wedge between marginal $q$ and Tobin's $q$, offering a potential explanation for the weak correlation between these variables in the data. We discuss these changes in dynamics, and their implications for investment-$q$ regressions, in Section 3.

**Aggregation** Before defining an equilibrium, we need to define a number of aggregate variables. To simplify notation, we denote a firm's state as $x = (k, n, z)$. The cross-sectional distribution of firms across capital, customers and productivity can then be denoted by $\lambda(x)$. The distribution evolves over time according to a law of motion $\lambda' = T(\lambda|w, w^b)$, determined by the productivity process and firm decision rules, but we focus on a sta-

[15]Hayashi (1982) shows that with constant returns to scale, marginal and average $q$ are the same.

tionary distribution where $\lambda' = \lambda$. Integrating over the stationary distribution yields aggregate output $Y(\lambda|w, w^b) = \int y(x|w, w^b)d\lambda(x)$, and costs of investment $\Phi(\lambda|w, w^b) = \int \phi(i(x|w, w^b), k)d\lambda(x)$. The aggregate demand for labor, used in production and sales, is $L^d(\lambda|w, w^b) = \int \ell^p(k, y(x|w, w^b), z) + \kappa(l^s(x|w, w^b))d\lambda(x)$. Finally, aggregate dividends are $\Pi(\lambda|w, w^b) = \int \pi(x|w, w^b)d\lambda(x)$, where $\pi$ denotes the firm-level dividend.

**DEFINITION 1.** A stationary competitive search equilibrium[16] specifies: i) household decision rules $C(w, w^b, \Pi)$, $L^m(w, w^b, \Pi)$, $L^b(w, w^b, \Pi)$, ii) firm decision rules $y(x|w, w^b)$, $i(x|w, w^b)$, $l^p(x|w, w^b)$, $l^s(x|w, w^b)$, $\theta(x|w, w^b)$, $\varepsilon(x|w, w^b)$, and value function $v(x|w, w^b)$, iii) aggregates $Y(\lambda|w, w^b)$, $\Phi(\lambda|w, w^b)$, $L^d(\lambda|w, w^b)$, $\Pi(\lambda|w, w^b)$, iv) wage $w$, v) payoff to buying $w^b$, and vi) distribution of firms $\lambda$, such that

1. The firm decision rules and value function solve the firm problem (F).
2. The household decision rules maximize (1) subject to (2), and optimal buying behavior solves problem (3).
3. The goods market clears: $C(w, w^b, \Pi(\lambda|w, w^b)) + \Phi(\lambda|w, w^b) = Y(\lambda|w, w^b)$.
4. The labor market clears: $L^m(w, w^b, \Pi(\lambda|w, w^b)) = L^d(\lambda|w, w^b)$.
5. Consistency: $L^b(w, w^b, \Pi(\lambda|w, w^b)) = \int l^s(x|w, w^b)\theta(x|w, w^b)d\lambda(x)$.
6. Stationarity: The distribution of firms $\lambda$ is stationary.

**Planning problem** To understand the allocations in the competitive equilibrium more concretely, it is useful to spell out a corresponding planning problem, subject to the same

[16] We incorporate the competitive search equilibrium of Moen (1997) and Shimer (1996) into a stationary equilibrium with a cross-section of firms (e.g. Gomes 2001).

frictions:

$$
\begin{aligned}
V(\lambda) = & \max u(c,l) + \beta E_z V(\lambda') && \text{(P)}\\
& c + \int \phi(i(x), k) d\lambda(x) \leq \int y(x) d\lambda(x), && (13)\\
& l + \int [l^p(x) + l^b(x) + \kappa(l^s(x))] d\lambda(x) \leq 1, && (14)\\
& y(x) \leq f(k, l^p(x), z), \ \forall x, && (15)\\
& y(x) \leq n + m(l^b(x), l^s(x)), \ \forall x, && (16)\\
& n'(x) \leq (1-\delta_n) y(x), \ \forall x, && (17)\\
& k'(x) \leq (1-\delta_k) k + i(x), \ \forall x. && (18)
\end{aligned}
$$

Here the choice variables are $c$, $l$ and functions $y(x)$, $i(x)$, $l^b(x)$, $l^p(x)$, $l^s(x)$, $n'(x)$, $k'(x)$, for all $x \in supp(\lambda)$. All choice variables except investment are assumed non-negative. The planner maximizes the utility of the representative household, allocating goods between consumption and investment (across production units), and time between leisure, production, selling and buying (across production units). The planner faces the same frictions in bringing together customers and producers, requiring keeping track of the customer bases of production units. The planner allocates investment, as well as selling and buying time, for each production unit separately, depending on their productivity, capital stock and customer base. Equation (13) states that the sum of consumption and investment (across production units) cannot exceed total output across production units. Equation (14) states that the sum of time allocated to leisure, production, selling and buying cannot exceed the total time endowment. Equations (15) and (16) state that the output of a production unit cannot exceed what the production technology, nor the customer base, of the producer allow. Equations (17) and (18) are laws of motion for the customer base and capital stock.

The planning problem is concave, with first order conditions that coincide with those of the competitive equilibrium.[17] Useful for familiar reasons, this implies that not only is a competitive equilibrium constrained efficient, but that we can use the planning problem to understand equilibrium outcomes. For a more detailed analysis of the connection between

[17] See Appendix A.

the two problems we refer the reader to Kaas and Kircher (2011), who analyze a related environment with frictional labor (rather than product) markets.

**Discussion of modeling approach** Before proceeding to study the model implications, we briefly discuss four key elements of our modeling approach. First, the buyers in our model spend time searching for products because of differences in tastes over product characteristics. An alternative approach would be to assume identical tastes, with buyers searching for low prices instead. Although we view both frictions as relevant, it is substantially simpler to begin with the former. Equilibrium models of price dispersion, such as Burdett and Judd (1983) or Burdett and Mortensen (1998), typically focus on stationary environments abstracting from dynamics in production costs. Because we specifically seek to analyze the effects of product market frictions and long-term customer relationships on firm dynamics, a natural framework to turn to instead is the Mortensen-Pissarides model.[18] While this framework lends itself well to thinking about search for the right products, determining prices through bargaining seems less natural in the context of product (than labor) markets. For this reason, we introduce directed search into the model, allowing firms to optimally choose prices based on trading off attracting more (new) customers against greater profits per (new) customer.

Second, as recent work using the Mortensen-Pissarides model to analyze firm dynamics in frictional labor markets (Kaas and Kircher 2011, Garibaldi and Moen 2010), we too have adopted a convex cost function ($\kappa$) to curb firm responses to idiosyncratic shocks. This convexity is important for the dynamics we emphasize in Section 3, rendering the customer base a bottleneck for firm expansion. The other central element capturing frictions in the model – the matching function – turns both selling and buying time into necessary inputs for producing matches, but does not limit reallocation in response to firm-level shocks. The matching function elasticity governs the shares of these two inputs in the production of matches, as well as the extent to which it is profitable to offer low prices to attract more customers. A low value of $\gamma$ implies that: i) sales people cannot handle more customers per unit of time, so competition does not lead to large discounts, but also that ii) total

[18] See Pissarides (2000).

equilibrium buying time is low.[19]

Third, in the Mortensen-Pissarides model, the path of prices within a match is generally not allocative (beyond its present value). Similarly, although our assumptions determine a path of prices within each customer relationship, the close connection between the planner's allocation and the market equilibrium underlines the fact that this particular path is not essential for allocations. With this feature of the modeling framework in mind, we have sought to (whenever possible) emphasize the implications for allocations rather than prices. Note that the way the path of prices is determined in the model – effectively implementing two-part pricing – has the advantage of avoiding additional state variables for keeping track of different price-schedules for different cohorts of customers: All existing customers pay the same price (which is identical across firms), while new customers get an initial discount, which depends on the firm's desire to expand (which varies across firms).

Finally, we explicitly focus on the extensive margin of firm demand, abstracting from the intensive margin of demand per-customer – the polar opposite of the standard case in the literature. Abstracting from the intensive margin has the advantage of simplifying the model substantially, allowing us to highlight the role of the extensive margin for firm dynamics.[20]

# 3 Implications of Customer Capital

How do product market frictions affect firm investment, sales, profits, value and their dynamic responses to shocks? This section demonstrates the effects, focusing on the idiosyncratic shocks which dominate at the firm-level first, and turning to aggregate shocks at the end of the section.

**Parametrization** To illustrate the impact of frictions, as well as to get a rough idea of magnitudes, we parameterize and solve the model numerically. Appendix B discusses our numerical approach in more detail. Parameterizing is straightforward for a number of

[19]In the limiting case with $\gamma = 0$, discounts disappear altogether, but this case also implies that equilibrium buying time becomes zero.

[20]As most of the literature, we also abstract from inventories.

the parameters, which are standard in the literature, but requires more thought for the parameters governing the frictional product market.

We begin with a conventional parametrization of the neoclassical adjustment cost model.[21] The annual discount rate is set to $\beta = 0.95$. We set the capital depreciation rate to $\delta_k = 0.1$, and the capital share in production to $\alpha = 0.3$. The capital adjustment cost is quadratic, $\phi(i,k) = i + \varphi_k/2 \times (i/k - \delta_k)^2 k$, with $\varphi_k = 10$. This adjustment cost parameter represents the middle ground of a wide range of estimates: for example Gilchrist and Himmelberg (1995) estimate a value around 6, while Erickson and Whited (2000) a value around 20.[22] We adopt the preferences $u(c,l) = \log c + A \log l$, where $A$ is set such that market work comes to a third of total time (Hansen 1985).[23] Finally, the $AR(1)$ process for productivity $z$ follows the estimates of Hennessy and Whited (2005), with an $AR(1)$ coefficient of 0.74 and a standard deviation of the shock of 0.123.

The remaining parameters pertain to the frictional product market: the customer depreciation rate $\delta_n$, the matching function parameters $\xi$ and $\gamma$, along with the function $\kappa(l^s)$. We use available evidence to set values for these parameters, returning to examine sensitivity later.

The customer depreciation rate $\delta_n$ is an important parameter for the impact frictional markets have. Although firms in some industries regularly announce customer turnover rates, and such rates play an important role in the marketing literature on customer equity, systematic evidence on the topic appears scant. Some examples include the following:[24] Cell phone service providers are recently reporting monthly turnover rates of $1-2.5$ percent, translating into annual rates of $11-26$ percent. In online banking, the corresponding annual rates are in the $10-20$ percent range. Both are examples of products with contractual long-term customer relationships, which makes the customer turnover rate a natural statistic for firms to follow. For an example in a non-contractual setting, survey evidence on the frequency at which consumers switch their primary super market suggests annual customer

[21]The model is solved on a monthly frequency, but we report annual values here.

[22]By contrast, the direct investment-$q$ regression evidence suggests a parameter around 30.

[23]The form of preferences is irrelevant for responses to firm-level shocks, but plays an important role for responses to aggregate shocks.

[24]See Raice (2010), Ackermann (2010), FMI (1994), FMI (2004).

turnover rates of $10 - 25$ percent. Acknowledging that there exists significant heterogeneity on this dimension, we adopt an annual customer depreciation rate of $\delta_n = 0.15$.

Next, the parameters $\gamma$ and $\xi$ of the matching function $m(l^b, l^s) = \xi (l^b)^{\gamma} (l^s)^{1-\gamma}$ are determined based on evidence on total time spent in buying and selling activities at the aggregate level, corresponding to $L^b$ and $\int \kappa(l^s) d\lambda$ in the model. Our targets for these two values are 0.53 and 2.13 percent of total time, respectively. (Note that these values are very small compared to the one third of total time we attribute to market work, as standard in the literature.) To arrive at these targets we use data on the share of the labor force in sales-related occupations from the Occupational Employment Statistics (OES) survey, and the amount of time consumers spend shopping from the American Time Use Survey (ATUS).

According to the OES survey, 11 percent of US workers are employed in sales-related occupations.[25] Examples of such occupations include sales representatives, retail salespersons, cashiers, real estate brokers, and advertising agents. Because workers in other occupations are likely to spend a share of their time in selling activities also, we attribute 10 percent of their time to selling as well. Examples of other occupations with a significant selling component are waiters, marketing and sales managers, and advertising and promotions managers. Overall, this implies that 20 percent of working time is spent in selling activities.[26] With working time making up a third of total time, this yields a share of total time in selling of 6.5 percent. Finally, in reality not all of this time is spent on new customers. To take this into account, we attribute a third of selling time to new customer acquisition, leading to our 2.13 percent number for selling time.

Turning to our target for buying time, time-use data document that Americans spend on average 0.4 hours per day shopping. If we again attribute a third of this time to the new-customer margin, our target for buying time becomes 0.53 percent of total time. Finally, we adopt a quadratic specification for the function $\kappa(l^s) = \kappa_0 (l^s)^2/2$, where the value of $\kappa_0$ can be normalized to one.[27] With this, the targets for buying and selling time determine unique values for $\gamma$ and $\xi$.

[25] Data source: `ftp://ftp.bls.gov/pub/special.requests/lf/aat11.txt`
[26] 11 percent + 10 percent of 89 percent = 19.9 percent.
[27] See Appendix B.

Table 1: Parametrization

| | |
|---|---|
| Discount rate $\beta$ | 0.95 |
| Persistence of productivity $\rho_z$ | 0.74 |
| Standard deviation of productivity $\sigma_z$ | 0.123 |
| Share of capital $\alpha$ | 0.30 |
| Depreciation of capital $\delta_k$ | 0.10 |
| Adjustment cost function coefficient $\varphi_k$ | 10 |
| Depreciation of customers $\delta_n$ | 0.15 |
| Matching function elasticity $\gamma$ | 0.11 |
| Matching function coefficient $\xi$ | 0.096 |

*Notes:* The table reports annual values.

Table 1 summarizes our parametrization. Next, we turn to study the effects of product market frictions on firms.

**Level effects** Product market frictions affect firms in a number of ways. Most directly, the greater the frictions, the more firms spend on customer acquisition. The top left panel in Figure 1 illustrates this by plotting steady-state selling expenses as a function of the matching function coefficient $\xi$. In the frictionless limit, shown on the left, the model reduces to the neoclassical adjustment cost model, where selling expenses are zero. In our benchmark parametrization (indicated by the vertical line), on the other hand, these expenses make up as much as five percent of sales revenue.

Product market frictions turn the customer base into a form of intangible capital, which manifests itself in increased firm value, profits, and markups. In the frictionless limit, Tobin's $q$ equals one (as firm value equals the value of physical capital), markups equal zero, and the profit rate equals the cost of capital, $r + \delta_k = 0.15$. In a frictional market, competition for new customers drives the value of the marginal new customer to zero, but firm value still exceeds the value of physical capital for two reasons. First, the value of the average new customer exceeds that of the marginal, due to the convex costs of customer acquisition. Second, existing customers are valuable assets to the firm because, to make up for the initial costs of attracting them, the firm charges a positive markup on these customers later. As a result, Tobin's $q$ is as high as 1.9 in our benchmark parametrization, with an average markup of 15 percent. Similarly, averaging across new and existing customers leads to a firm profit rate which, at 20 percent, exceeds the cost of capital.[28] Perhaps surprisingly, these changes have no effect on the investment rate, however, which continues to equal the depreciation rate of capital.[29]

These changes in levels make the testable predictions that *ceteris paribus* in markets with greater product market frictions, we should see greater average Tobin's $q$, profit rates and markups, than in markets with lesser frictions. Investment rates, on the other hand, should remain unaffected. Moreover, the increasing relationship between product market frictions and selling expenses suggests using data on selling expenses to quantify the degree of friction.

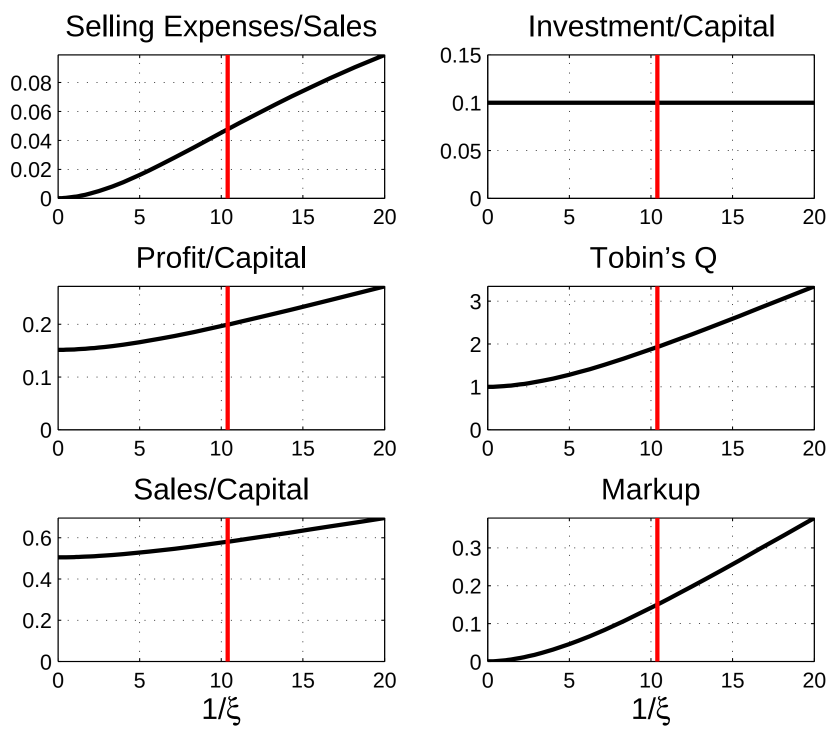


Figure 1: Impact of Friction on Steady State

*Notes:* The figure plots the steady state as a function of the matching function parameter $\xi$. The frictionless limit is on the left, and the vertical line indicates our baseline parametrization. Selling expenses refer to $w\kappa(l^s)$, sales to $(1 - l^s\eta(\theta)\varepsilon)y$, profit to sales net of labor costs of production and selling, and the markup to sales per unit sold $1 - l^s\eta(\theta)\varepsilon/y$ over the marginal cost $wl^p/y \times 1/(1-\alpha)$.

[28] Recall that even if the present value of future profits the firm makes off of a customer just makes up for the up-front costs of getting that customer, discounting implies that average profits across new and existing customers must be positive.

[29] The markups do translate into an increase in sales revenue per unit of capital, however, a statistic we consider in our empirical work.

**Firm dynamics** For thinking about the effects of product market frictions on firm dynamics, it is useful to start from the frictionless limit i.e. the neoclassical adjustment cost model. In a frictionless product market, an increase in firm productivity leads to an instantaneous increase in firm sales and profits. Investment increases because the marginal product, and shadow value, of capital increases, but the capital adjustment costs smooth this investment response over time. As illustrated in Figure 2 (dashed line), investment rises on impact, decaying with productivity. In this frictionless product market, the responses of investment and Tobin's $q$ are identical, because Tobin's $q$ is proportional to the shadow value of capital.[30]

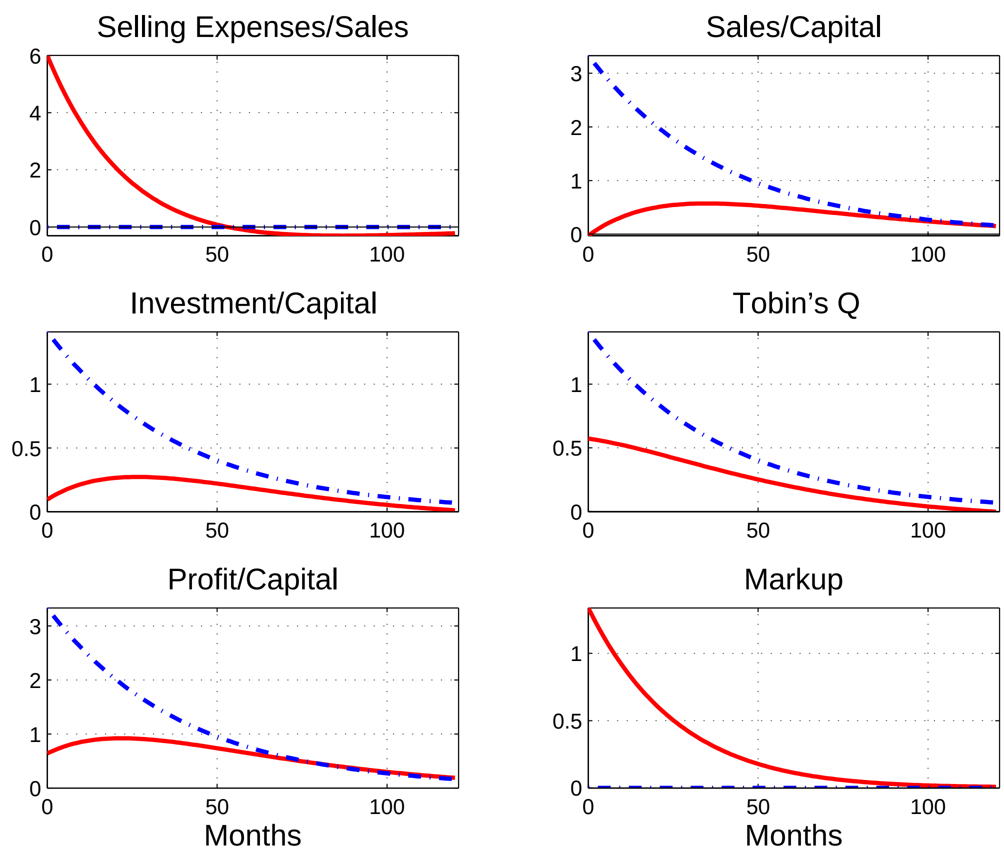


Figure 2: Impulse Responses to Firm-Level Productivity Shock

*Notes:* The responses are in percentage deviations from steady state. Selling expenses refer to $w\kappa(l^s)$, sales to $(1 - l^s\eta(\theta)\varepsilon)y$, profit to sales net of labor costs of production and selling, and the markup to sales per unit sold $1 - l^s\eta(\theta)\varepsilon/y$ over the marginal cost $wl^p/y \times 1/(1-\alpha)$.

Introducing product market frictions has two main effects on these firm dynamics. First, by effectively imposing an additional adjustment cost on firm expansion, they work to

[30] As shown by Hayashi (1982).

dampen firm responses to the shock. Second, by slowing down the expansion in sales, they generate hump-shaped responses in a number of variables. Figure 2 illustrates these changes by plotting our benchmark parametrization (solid line) side-by-side with the frictionless limit (dashed line).

In a frictional product market, the increase in productivity increases the firm's production capacity, but leaves the firm short of customers to sell to. This shortage of customers curbs the increase in sales, as well as investment, in the short run. The first order of business following the shock is an increase in selling expenses to expand the customer base, smoothed over time by the convex costs of customer base expansion.[31] Investment rises on impact, but continues to rise further as the firm accumulates customers (and eventually finds itself short of production capacity), generating a hump-shaped response.[32] The response of firm profits is also hump-shaped: Despite the increase in selling expenses, profits rise on impact as production costs fall, but they also continue to rise as the surge in selling expenses subsides and the customer base grows. Finally, product market frictions introduce a time-varying wedge between the shadow value of capital and Tobin's $q$, explaining the differing responses of investment and Tobin's $q$ in the figure. The response of Tobin's $q$ reflects the response of the shadow value of capital, but also the appreciation of the firm's customer base in the face of falling costs of production.

Overall, these changes in dynamics make the testable predictions that *ceteris paribus* in markets with greater product market frictions, we should see: i) dampened firm responses to shocks, and ii) investment, profits and sales lag Tobin's $q$ and selling expenses more strongly.

**Investment regressions** These dynamics suggest that product market frictions may be useful for understanding the investment-$q$ regression evidence, which appears at odds with the neoclassical adjustment cost model: A large literature documents that firm investment

[31] The convexity of $\kappa(l^s)$ is important for this smoothing when studying responses to firm level shocks, as otherwise firms would expand the customer base on impact. To see this, note that the reduced form of the left hand side of the first order condition (10) for $l^s$ is $\gamma^{-\gamma}(1-\gamma)^{\gamma-1}w\kappa'(l^s)^{1-\gamma}/\xi$.

[32] The main role of the convex capital adjustment cost here is to prevent instantaneous adjustments in the firm's capital stock in response to shocks, a seemingly implausible feature. Without convex capital adjustment costs, the short run response to a positive productivity shock would be to abruptly disinvest, leading to a drop in capital, until the customer base expands sufficiently. The expansion in sales and profits would continue to be hump-shaped, however, with Tobin's $q$ rising on impact.

is only weakly correlated with Tobin's $q$, appearing more correlated with firm cash flow instead. These findings have sometimes been interpreted as evidence of firms facing financial constraints, leading to capital misallocation.[33]

To study the predictions of the model for investment-$q$ regressions, we run the following regressions on simulated data from the model:

$$i_{jt}/k_{jt} = a_0 + a_1 q_{jt} + \varepsilon_{jt}, \text{ and} \tag{19}$$

$$i_{jt}/k_{jt} = a_0 + a_1 q_{jt} + a_2 \pi_{jt}/k_{jt} + \varepsilon_{jt}, \tag{20}$$

where $q_{jt} = \beta E_t v_{jt+1}/k_{jt+1}$ is Tobin's $q$ and the profit rate reflects firm cash flow. Figure 3 shows how the results of the first regression depend on the degree of friction in the product market. In the frictionless limit (on the left) the model generates the results expected for the neoclassical adjustment cost model: the coefficient on Tobin's $q$ coincides with the inverse of the adjustment cost parameter, $1/\varphi_k = 0.1$, and the $R^2$ equals one. But as frictions increase, both the slope coefficient and $R^2$ fall, taking significantly lower values at our benchmark parametrization (depicted by the vertical line). While the lower $R^2$ reflects the weaker correlation of investment with Tobin's $q$ (as illustrated by the impulse responses), the slope coefficient is attenuated further by the reduced volatility of investment relative to Tobin's $q$.[34]

Figure 4 shows how the results change when we include firm cash flow in the regression. In the frictionless limit cash flow is irrelevant, and investment perfectly explained by Tobin's $q$. But as frictions increase, the coefficient on Tobin's $q$ falls, while the coefficient on cash flow quickly becomes significant. This reflects the similar responses of investment and profits to shocks (illustrated by the impulse responses), relative to that of Tobin's $q$. The model would thus seem to predict non-trivial cash flow effects even for small frictions. As the figure shows, the degree of friction has relatively little effect on the $R^2$ from this regression, however, because the two right-hand-side variables together explain investment well in the model.

[33]Caballero (1999) and Chirinko (1993) survey this literature.

[34]Recall that the coefficient on Tobin's $q$ is a product of the correlation between investment and Tobin's $q$ and the standard deviation of investment relative to Tobin's $q$.

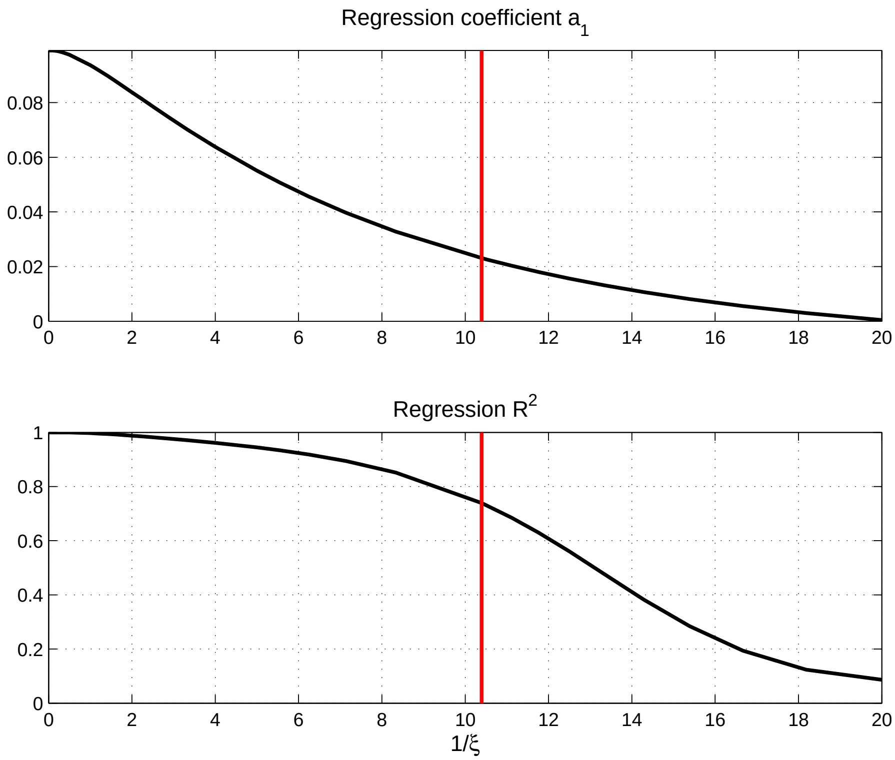


Figure 3: Impact of Friction on Investment-$q$ Regression

*Notes:* The figure plots the results from regression (19) on model simulated data, as a function of the matching function parameter $\xi$. The frictionless limit is on the left, and the vertical line indicates our baseline parametrization.

The coefficient estimates from these regressions are sometimes used to infer the magnitude of capital adjustment costs – an approach which leads to the conclusion that these costs are very high. Following the reasoning of Gilchrist and Himmelberg (1995) or Hall (2001a): A typical coefficient on Tobin's $q$ of 0.025 in an annual regression suggests adjustment costs high enough for it to take a firm $1/0.025 = 40$ years to double its capital stock. Figures 3 and 4 illustrate that this approach can lead to substantial overestimates for firms in frictional product markets. Our benchmark parametrization yields a similar coefficient on Tobin's $q$ with substantially smaller capital adjustment costs, roughly implying $1/0.1 = 10$ years for a firm to double its capital stock.[35]

[35] The aspect of the empirical evidence that the model will necessarily have difficulty replicating are the very low $R^2$'s in both panel and time series regressions. This is natural given that the model abstracts from many other factors likely to influence the empirical results, including measurement error. With a simple mechanism, the model generates quite low $R^2$'s in the single regression of investment on Tobin's $q$, but this is much harder to accomplish in the multiple regression with cash flow included. In this sense, our results are complementary with the literature emphasizing the importance of measurement error in Tobin's $q$ (Erickson and Whited 2000, Eberly, Rebelo, and Vincent 2009), and finding more empirical success when other proxies

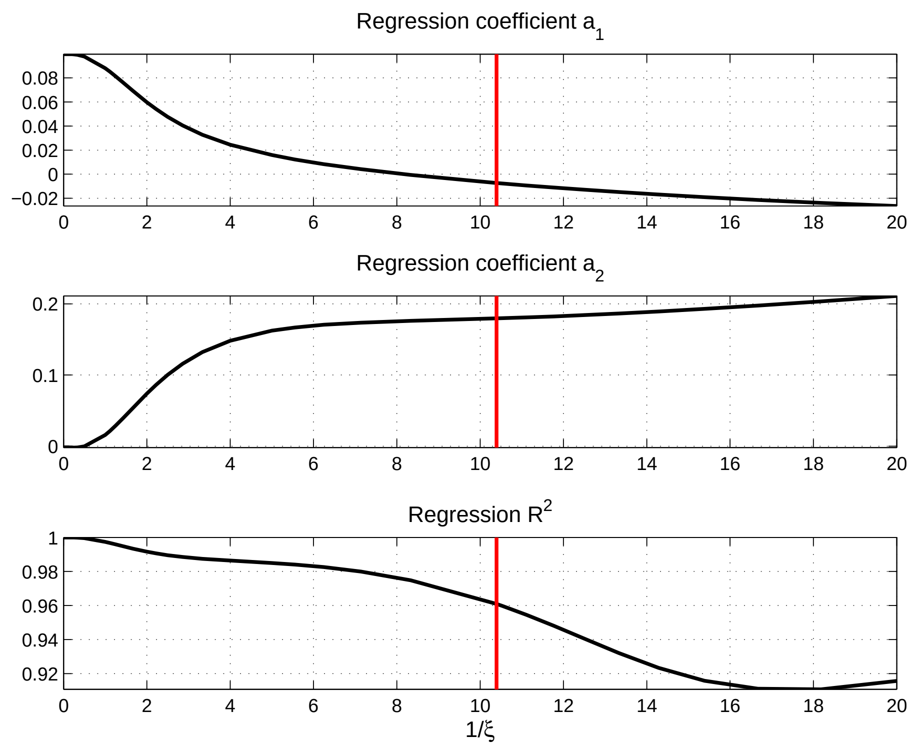


Figure 4: Impact of Friction on Investment-$q$ Regression with Cash Flow

*Notes:* The figure plots the results from regression (20) on model simulated data, as a function of the matching function parameter $\xi$. The frictionless limit is on the left, and the vertical line indicates our baseline parametrization.

Our theory makes the testable predictions that *ceteris paribus* in markets with greater product market frictions, we should see regressions of investment on Tobin's $q$ yield: i) lower coefficient estimates on Tobin's $q$ and ii) lower $R^2$'s.

**The mechanism: long-term customer relationships** In the model product market frictions lead to long-term customer relationships, as long as $\delta_n < 1$. But one could also consider frictional markets without long-term relationships, by setting $\delta_n = 1$. To highlight that such relationships play an important role for our results, Figure 5 compares firm responses in frictional product markets *with* long-term customer relationships (solid line), to those in frictional product markets *without* long-term customer relationships (dashed line). Introducing frictions dampens firm responses to shocks in both cases but, as the figure shows, long-term customer relationships are essential for the hump-shaped responses emphasized. Table 2

than stock prices are used to measure $q$ (Abel and Blanchard 1986, Gilchrist and Himmelberg 1995, Cummins, Hassett, and Oliner 2006, Philippon 2009).

confirms that this feature of the model is important also for our investment-$q$ regression results. By attenuating the relationship between investment and Tobin's $q$, it significantly reduces both the slope coefficient and $R^2$ in these regressions.[36]

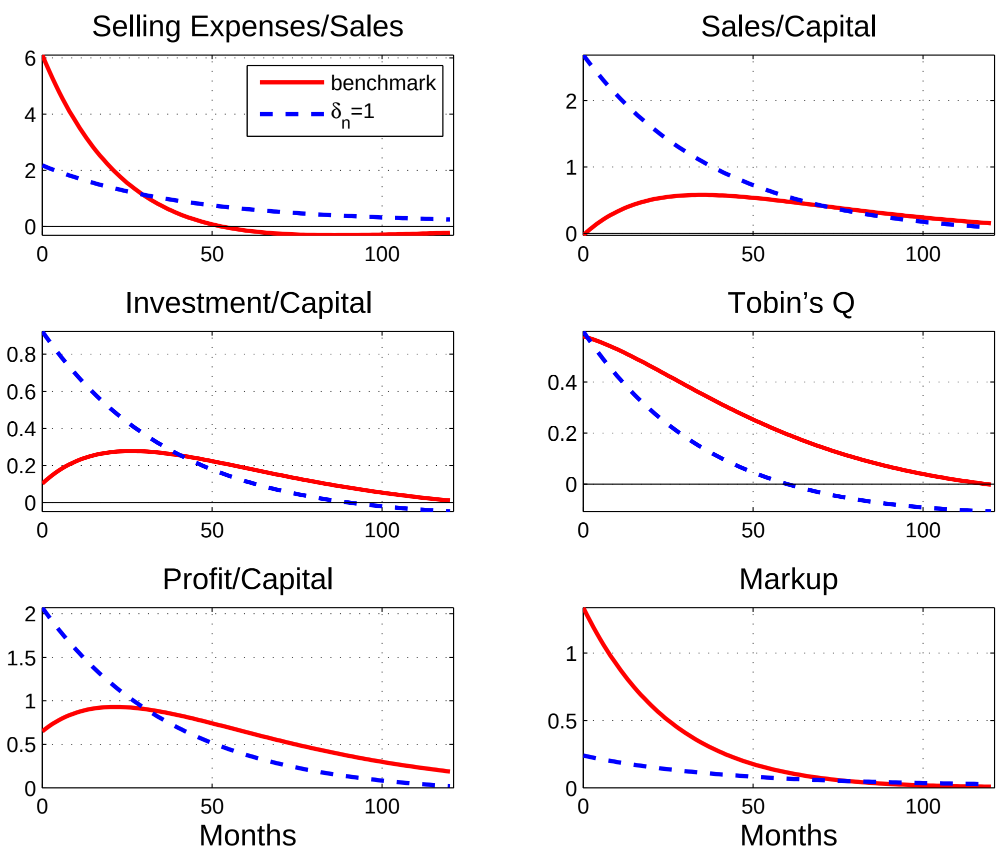


Figure 5: Impulse Responses to Firm-Level Productivity Shock with $\delta_n = 1$
*Notes:* The responses are in percentage deviations from steady state. The model with $\delta_n = 1$ is parameterized to match the same targets for buying and selling time as the benchmark model. Selling expenses refer to $w\kappa(l^s)$, sales to $(1 - l^s\eta(\theta)\varepsilon)y$, profit to sales net of labor costs of production and selling, and the markup to sales per unit sold $1 - l^s\eta(\theta)\varepsilon/y$ over the marginal cost $wl^p/y \times 1/(1-\alpha)$.

**Sensitivity** Finally, although the effects illustrated in the figures appear non-trivial in magnitude, will they remain so if we change the parametrization to a plausible degree? To examine this issue, Appendix B considers the sensitivity of our results to lower targets for buying and selling time, as well as higher customer depreciation rates. We find that our results are not strongly sensitive to the specifics of the parametrization used.

[36]It is this role of long-term customer relationships that differentiates ours from the decreasing-returns, or monopolistic-competition, based explanations of the investment-$q$ evidence pursued by Cooper and Ejarque (2003) and Abel and Eberly (2009).

Table 2: Impact of Long-Term Relationships on Investment-$q$ Regressions

| | Frictionless | Benchmark | Frictional with $\delta_n = 1$ |
|---|---|---|---|
| Coefficient $a_1$ | 0.099 | 0.024 | 0.098 |
| Regression $R^2$ | 1.000 | 0.758 | 0.973 |

*Notes:* The table reports results from regression (19) on simulated data. The model with $\delta_n = 1$ is parameterized to match the same targets for buying and selling time as the benchmark model.

**Aggregate shocks** These changes in dynamics make frictional product markets promising also for understanding the hump-shaped responses of macro-aggregates to aggregate shocks, documented in a number of studies.[37] Such hump-shaped responses are generally at odds with the neoclassical growth model, where variables respond to shocks on impact. In the case of investment in particular, recent literature has turned to non-standard capital adjustment costs to generate hump-shaped responses to shocks.[38] But are the model's hump-shaped responses preserved in the face of aggregate, instead of idiosyncratic, shocks?

There is a straightforward way to adapt the model for analyzing aggregate dynamics, by assuming firms are identical in productivity – and consequently also in their capital and customer base. The main changes involve: i) assuming firms are identical, ii) introducing stochastic discount factors that capture aggregate variation in marginal utility, and iii) allowing variables such as wages, queue lengths, and discounts to vary over time.[39] In this case, the model implies that in times when firms hire more sales labor, both queue lengths and discounts are greater.

Figure 14 in Appendix C illustrates model dynamics in response to an aggregate productivity shock, under frictional, as well as frictionless, product markets. The figure confirms that the main predictions regarding volatility and hump-shaped responses of investment and sales continue to hold also in the face of aggregate shocks. The main difference would seem to be a weaker hump-shape in profits, likely due to the smaller increase in sales labor at the aggregate, as well as a change in the shape of the response of Tobin's $q$, likely due to differences in discounting.

[37] See e.g. Cogley and Nason (1995), Christiano, Eichenbaum, and Evans (2005), Basu, Fernald, and Kimball (2006), Smets and Wouters (2007).

[38] For example, Christiano, Eichenbaum, and Evans (2005) and Jaimovich and Rebelo (2009) impose adjustment costs directly penalizing the rate of change in investment.

[39] See Appendix C for details.

# 4 Evidence of Customer Capital

The model makes a number of predictions about the effects of product market frictions on firm investment, sales, profits, value and their dynamic responses to shocks, which appear promising for understanding documented patterns in the data. But is there any evidence linking product market frictions to these patterns? In this section we turn to firm-level data to document the evidence, using the model to make the link to product market frictions. Seeking to establish relevance from a macroeconomic point of view, we consider a broad range of industries.[40]

**Data** Our primary data source is Compustat, which provides annual accounting data on publicly listed US firms. It is the standard data source for studying firm-level investment, sales, profits and Tobin's $q$. We restrict our analysis within Compustat to a balanced panel of 648 firms from 1983 to 1999. Balancing simplifies the analysis of firm-level dynamics significantly, but the results are largely robust to extending the sample to the full unbalanced Compustat data (where possible). We exclude foreign firms, utilities and financial firms, as commonly done in the investment literature, as well as mergers and observations with extreme values. Appendix D describes the sample construction more closely.

**Measuring frictions** Because product market frictions are likely to be more important in some markets than others, it is natural to use this cross-sectional variation to test the predictions of the model. The non-trivial challenge in doing so is finding a way to measure the degree of friction across markets with available data. The theory suggests a simple approach to this measurement problem, however, by predicting that in markets with greater frictions, firms spend more on selling. Among the accounting variables reported in Compustat is "selling, general and administrative" (SGA) expenses, which we use as a proxy for selling expenses. Interpreting a market as a two-digit SIC industry, we compute a time-series average of total industry SGA expenses over total industry sales, and sort industries into two groups based on this measure: above and below median. We can then compare the two

[40] A complementary approach, more in the spirit of industrial organization, would be to focus on a particular industry, tailoring the model to fit the specifics of that market.

subsamples on the various predictions of the model discussed in Section 3.

Our sorting variable, SGA expenses, includes selling expenses such as sales people's salaries, commissions and travel expenses, advertising and marketing expenses, shipping expenses, depreciation of sales buildings and equipment, etc, but also general and administrative expenses such as executives' salaries, legal and professional fees, insurance, office rents, office supplies, etc. To gauge the extent to which variation in SGA expenses is driven by selling expenses, we make use of the advertising expense data which is available separately for a subset of firms. The two are relatively strongly correlated for firm-level data: For the subset of firms reporting both, the cross-sectional correlation between firm-level advertising and SGA expenses is 0.35, while the firm-level time-series correlation between the two is 0.41. The industries falling into our high and low SGA expense samples are given in Tables 11 and 12 in Appendix D. Consistent with intuition, commodities, for which product market frictions are likely to play a smaller role, fall into the lower selling expense group, while tobacco products and clothing retailers are examples of high selling expense markets. With these considerations in mind, from this point on we refer to SGA expenses as selling expenses (SE).

Table 3 provides summary statistics for our data, comparing the two subsamples we study. Note that the firms in the sample are quite large overall, and although a large share of firms are in manufacturing, a substantial share are not. The high selling expense sample is slightly smaller, both in terms of numbers of firms, and share of total sales or assets. Perhaps surprisingly, it is also more manufacturing intensive. The main message of the table is that the two subsamples are relatively similar in firm attributes like size and growth rate, although the high selling expense firms are perhaps slightly larger and faster-growing. There are substantial differences in selling expenses across samples, with high selling expense firms spending significantly more on advertising.[41]

Next, we turn to study the predictions of the model in this data. We examine, in turn, the relationship between the level of selling expenses and: i) the levels and ii) volatility of investment, sales, Tobin's $q$, profits, and markups, iii) the lead-lag patterns, and iv) the

[41] The advertising figure is calculated for the subset of firms with separate data on advertising.

Table 3: Summary Statistics

| Medians | Low SE | High SE |
|---|---|---|
| Selling Expenses/Sales | 0.160 | 0.268 |
| | (0.007) | (0.010) |
| Advertising/Sales | 0.017 | 0.031 |
| | (0.002) | (0.003) |
| Sales | 503.9 | 652.5 |
| | (55.2) | (70.2) |
| Equity | 267.9 | 454.9 |
| | (42.4) | (63.1) |
| Assets | 385.1 | 467.8 |
| | (39.6) | (56.6) |
| Growth rate of assets | 4.694 | 5.055 |
| | (0.210) | (0.234) |
| Debt/Assets | 0.179 | 0.157 |
| | (0.007) | (0.008) |
| Dividends/Assets | 0.013 | 0.017 |
| | (0.001) | (0.001) |
| Number of firms | 391 | 257 |
| Share of manufacturing firms | 52% | 48% |
| Share of total sales | 60% | 40% |
| Share of total assets | 57% | 43% |

*Notes:* Sales, assets and equity value reported in millions of 2005 dollars. Bootstrapped standard errors – computed over 200 replications – are reported in parenthesis.

investment-$q$ regressions.[42]

**Levels** The model predicts a positive relationship between the degree of product market friction and the levels of Tobin's $q$, profits, sales, and markups. To study this prediction, we first compute, for each firm, time-series medians of Tobin's $q$, profits/capital, sales/capital, and markups.[43] We then compute, for each subsample, medians across firms of these time-series medians. Table 4 reports the results, revealing a significant increase in each of these

[42]Note that the experiment we conduct in the model differs somewhat from the one in the data: The empirical experiment considers an economy with a number of goods, each demanded separately, where the degree of friction in each particular good's market varies across goods. The model, on the other hand, abstracts from this heterogeneity for the sake of tractability. The implications of product market frictions we have emphasized do not hinge on this simplification, however.

[43]Note that our empirical measure of markup is a rather crude one, revenue over the production cost of goods sold. The absolute levels of the sales/capital ratio are also significantly higher in the data than in the model. The model abstracts from intermediate inputs, which raise the overall level of the sales/capital ratio in the data.

variables from the low to the high selling expense sample, as the model would predict. Also consistent with the model, the investment rate remains similar across the subsamples.

Table 4: Medians

| | Low SE | High SE |
|---|---|---|
| Investment/Capital | 0.103 | 0.112 |
| | (0.002) | (0.002) |
| Profit/Capital | 0.210 | 0.302 |
| | (0.008) | (0.010) |
| Sales/Capital | 1.954 | 2.531 |
| | (0.078) | (0.101) |
| Markup | 1.376 | 1.605 |
| | (0.017) | (0.023) |
| Tobin's $q$ | 1.014 | 1.648 |
| | (0.046) | (0.062) |

*Notes:* The table reports, for each subsample, medians across firms of the time-series medians of firm investment/capital, profit/capital, sales/capital, sales/cost of goods sold, and Tobin's $q$. Bootstrapped standard errors – computed over 200 replications – are reported in parenthesis. The differences across samples are significant at the one percent level for each variable.

Sorting industries into two groups has the advantage of leaving two relatively large samples to study. But it is useful to examine the evidence on an industry-by-industry basis as well, even if sample sizes diminish in doing so. To this end, we compute medians across firms of the above time-series medians also *for each industry separately.* The top panels in Figure 6 illustrate the results by plotting these measures of industry Tobin's $q$ and profits against industry selling expenses. The figure reveals a clear positive relationship in both cases, as well as significant variation across industries.

**Volatility** The model predicts a negative relationship between the degree of product market friction and firm-level volatility. To study this prediction, we first compute, for each firm, time-series standard deviations of investment/capital, sales/capital, profits/capital, Tobin's $q$ and markups. We then compute, for each subsample, medians across firms of these time-series standard deviations. The left column of Table 5 reports the results, revealing, instead of a decrease, a modest to large increase in firm volatility from the low to the high selling expense sample.

The intensity of idiosyncratic shocks varies across industries, however. One way to control

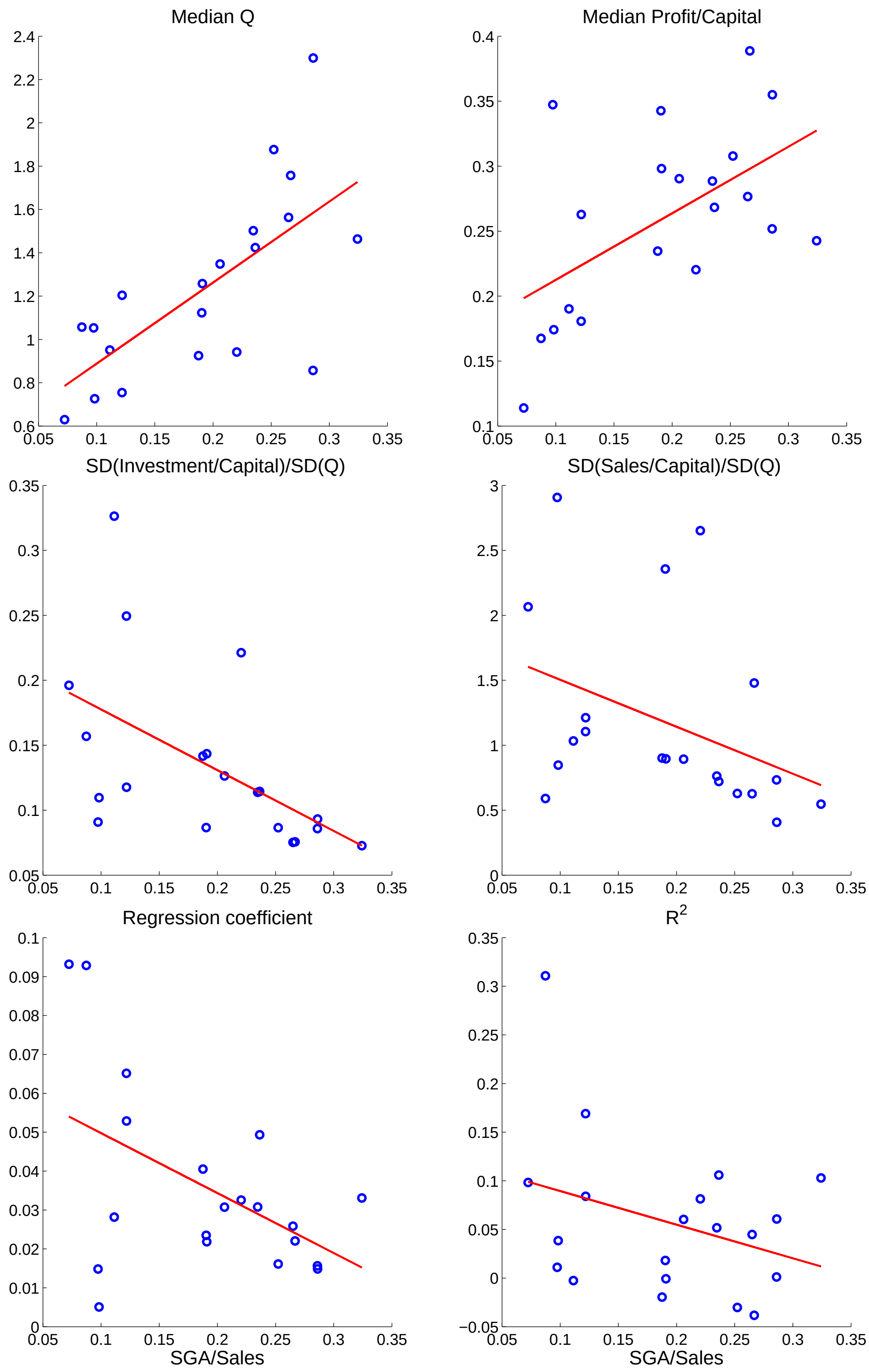


Figure 6: Industry Selling Expenses vs Firm-Level Evidence: Levels, Volatilities, Regressions
*Notes:* Each circle corresponds to a 2-digit SIC industry with ten or more firms. The horizontal axis is the time-series average of industry selling expenses relative to industry sales. The top two panels plot, for each industry, medians across firms of time-series medians of firm Tobin's $q$ and profit/capital. The middle two panels plot, for each industry, medians across firms of time-series standard deviations of firm investment/capital and sales/capital. The bottom two panels plot, for each industry, the slope coefficient and $R^2$ from regression (21) (with both time and fixed effects). We include a fitted line for reference.

Table 5: Firm-Level Time-Series Standard Deviations

| | Absolute | | Relative to Tobin's $q$ | |
|---|---|---|---|---|
| | Low SE | High SE | Low SE | High SE |
| Investment/Capital | 0.065 | 0.062 | 0.149 | 0.082 |
| | (0.002) | (0.003) | (0.008) | (0.010) |
| Profit/Capital | 0.085 | 0.114 | 0.192 | 0.141 |
| | (0.011) | (0.011) | (0.008) | (0.010) |
| Sales/Capital | 0.440 | 0.552 | 0.932 | 0.696 |
| | (0.086) | (0.116) | (0.038) | (0.061) |
| Markup | 0.062 | 0.094 | 0.142 | 0.115 |
| | (0.020) | (0.026) | (0.008) | (0.008) |
| Tobin's $q$ | 0.492 | 0.847 | - | - |
| | (0.054) | (0.064) | - | - |

*Notes:* The table reports, for each subsample separately, medians across firms of the time-series standard deviations of firm investment/capital, profit/capital, sales/capital, sales/cost of goods sold, and Tobin's $q$. Bootstrapped standard errors – computed over 200 replications – are reported in parenthesis. Relative to Tobin's $q$, the differences across samples are significant at the one percent level for each variable.

for this is to scale these measures of volatility by the volatility of idiosyncratic shocks. While identifying these idiosyncratic shocks poses a non-trivial problem in itself, the model dynamics suggest a simple approach: using Tobin's $q$ as a proxy for the shock. On the one hand, Tobin's $q$ responds to shocks on impact, independent of the degree of friction. On the other, it is relatively straightforward to measure given our data.[44] We use Tobin's $q$ to study changes in firm volatility as follows. For example in the case of investment we compute, for each firm, the ratio of the time-series standard deviation of the investment rate to the time-series standard deviation of Tobin's $q$. We then compute, for each subsample, medians across firms of these ratios.

The right columns of Table 5 report the results for firm volatility, revealing a significant drop in the volatility of investment, sales as well as profits from the low to the high selling expense sample, as the model would predict. For reference, Figure 10 in Appendix B plots these relationships in the model.[45] What is not consistent with the model is the observed

[44]Moreover, Vuolteenaho (2002) argues that cross-sectional variation in Tobin's $q$ is largely driven by variation in expected future cash flow. Firm-level variation in $q$ should thus largely reflect variation in fundamentals.

[45]As frictions increase, the volatility of investment/capital, sales/capital and profits/capital fall, in absolute terms as well as relative to the volatility of Tobin's $q$. The volatility of markups, on the other hand, increases independent of the measure.

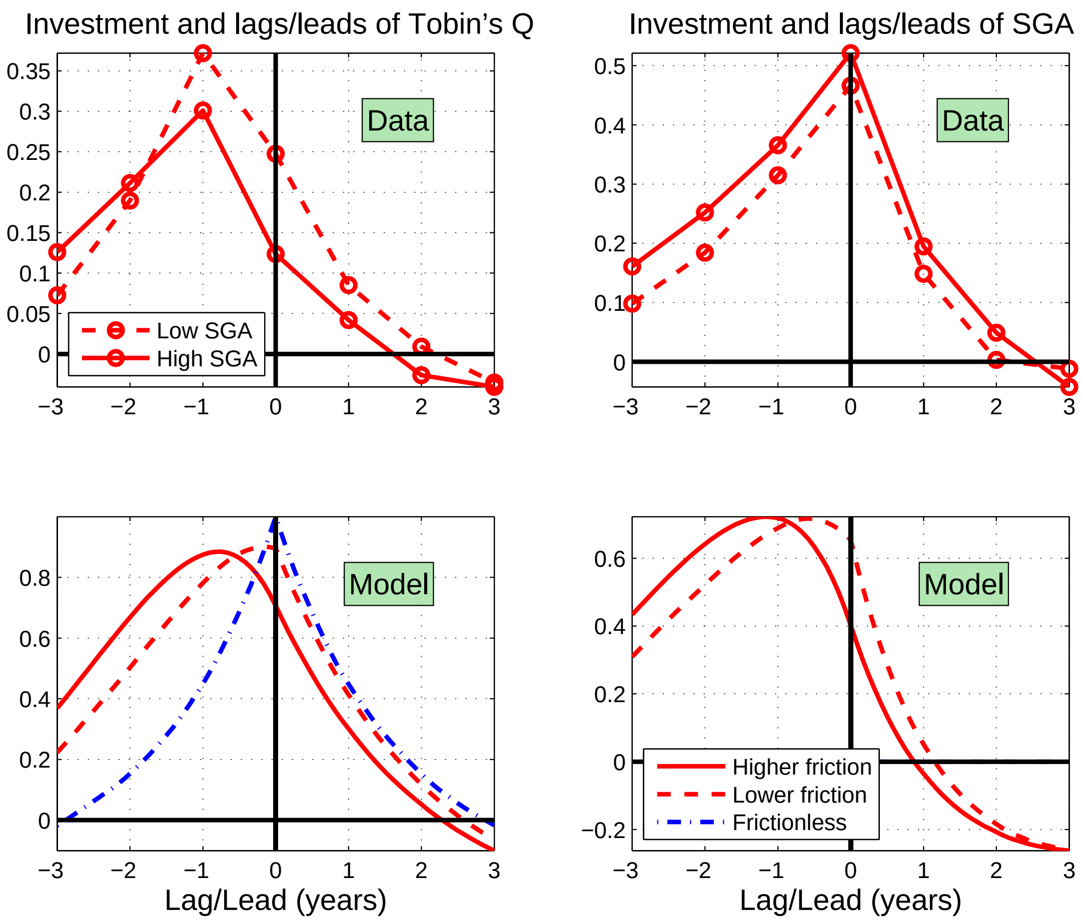


Figure 7: Firm-Level Cross-Correlations of Investment with Tobin's $q$ and Selling Expenses
*Notes:* The top left panel plots, for each subsample separately, medians across firms of the time-series cross-correlation of firm investment/capital with lags and leads of firm Tobin's $q$. The top right panel plots the same for investment/capital and selling expenses/capital. The bottom panels plot the same moments for model-generated data for the fictionless model, the model with frictions, and the model with frictions parameterized with slightly lower frictions than our benchmark. Tables 13 and 14 in Appendix D report the numbers, including standard errors.

drop in the volatility of markups.

Finally, to examine the evidence on an industry-by-industry basis, we compute medians across firms of the above ratios *for each industry separately.* The middle panels in Figure 6 illustrate the results by plotting these measures of firm-level volatility in investment and sales against industry selling expenses. The figure reveals a clear negative relationship in both cases.

**Timing of responses** We have emphasized that frictional product markets turn investment into a lagging variable. To study this prediction we compute, for each firm, time-series correlations of investment with lags and leads of Tobin's $q$, as well as selling expenses. We then compute, for each subsample, medians across firms of these correlations. The top panels in Figure 7 plot the results.

To help compare model and data, the bottom panels in Figure 7 plot the same correlations in model-simulated data for versions of the model *without frictions* (dash-dotted line), *with frictions* (solid line), as well as slightly *lower frictions* than our benchmark parametrization (dashed line). As the figure shows, the model without frictions predicts a contemporaneous relationship between investment and Tobin's $q$, and no relationship between investment and selling expenses. In the model with frictions, on the other hand, a lag pattern emerges: investment becomes positively correlated with past values of Tobin's $q$ and selling expenses, and much less so with future values.

The model with frictions clearly outperforms the model without frictions, by capturing the lag-patterns in the data. Investment is, in both subsamples, positively correlated with past values of Tobin's $q$ and selling expenses, and much less so with future values. These lag-patterns are also somewhat stronger in the high selling expense sample, as the model would predict, but the standard errors are too large to allow distinguishing the samples statistically.[46]

**Investment regressions** Finally, turning to the predictions for investment-$q$ regressions, we run the panel regression

$$i_{j,t}/k_{j,t-1} = a_0 + a_1 q_{j,t-1} + d_t + f_j + \varepsilon_{j,t}, \tag{21}$$

in both subsamples.[47] Here $d_t$ controls for time effects and $f_j$ firm fixed effects. Table 6 reports the results, replicating the low slope coefficients and $R^2$'s documented in the

[46]Tables 13 and 14 in Appendix D report bootstrapped standard errors. As an alternative story, time-to-build also generates lead-lag patterns, but renders investment dependent future Tobin's $q$ rather than past, as investment decisions reflect the future value of capital. Time-to-plan has the opposite effect, offering an alternative explanation for the overall lag pattern. It is not clear that time-to-plan would have any implications for selling expenses, however.

[47]We follow the standard timing of investment regressions in the empirical literature, by using lagged values of Tobin's $q$. The model regressions were instead run with the timing which is correct in the model.

literature. Comparing the two subsamples reveals that the results line up with our theory: both the estimated slope coefficient and $R^2$ fall significantly from the low to high selling expense sample, independent of the specification.[48] Running these panel regressions for each industry separately only confirms this negative relationship between industry selling expenses and both coefficient estimates and $R^2$'s. The bottom panels of Figure 6 plot these industry-by-industry results.

To relate our results to the literature emphasizing cash flow effects, we also run the cash-flow augmented panel regression

$$i_{j,t}/k_{j,t-1} = a_0 + a_1 q_{j,t-1} + a_2 \pi_{j,t-1}/k_{j,t-1} + f_j + d_t + \varepsilon_{j,t}, \tag{22}$$

in both subsamples. The results, reported in Table 7, line up with our theory also here. Comparing the two subsamples, the slope coefficient on Tobin's $q$ drops significantly from the low to high selling expense sample. Cash flow is clearly significant across the board, but not necessarily increasing in selling expenses. Lastly, the differences in $R^2$ across subsamples are relatively small. These patterns are consistent with the predictions of the model, illustrated in Figure 4.

Many studies of firm investment focus on manufacturing industries. Our sample, in contrast, includes a substantial share of non-manufacturing firms as well, because we view the model as well-suited for analyzing a broader set of industries than manufacturing alone. To relate our findings to studies focusing on manufacturing, Tables 15 and 16 in Appendix D report the results restricting the sample to manufacturing firms only. The main conclusions continue to hold in this subsample.

**Alternative theories** A number of alternative theories have been proposed for the investment-$q$ regression evidence. The main ones relax key assumptions of the neoclassical model, by introducing financing constraints (Gomes 2001, Lorenzoni and Walentin 2007, DeMarzo, Fishman, He, and Wang Forthcoming), market power (or decreasing returns to scale) (Cooper

[48] In addition to being robust to including time and/or fixed effects in the regression, these results appear to also be robust to changes in the definition of Tobin's $q$, as well as changes in the timing and specification of the regressions (levels versus logs).

Table 6: Firm-Level Regression of Investment on Tobin's $q$

| | Simple regression | | Time effects | | Fixed effects | | Both effects | |
|---|---|---|---|---|---|---|---|---|
| | Low SE | High SE | Low SE | High SE | Low SE | High SE | Low SE | High SE |
| $a_1$ | 0.032 | 0.017 | 0.032 | 0.019 | 0.044 | 0.023 | 0.045 | 0.026 |
| | (0.004) | (0.002) | (0.004) | (0.002) | (0.004) | (0.003) | (0.004) | (0.003) |
| $R^2$ | 0.085 | 0.058 | 0.085 | 0.058 | 0.072 | 0.052 | 0.071 | 0.044 |

*Notes:* The table reports results from panel regression (21) in each subsample, with and without firm fixed effects and time effects. Robust standard errors are reported in parenthesis. The differences in slope coefficient $a_1$ across samples are significant at the one percent level.

Table 7: Firm-Level Regression of Investment on Tobin's $q$ and Cash Flow

| | Simple regression | | Time effects | | Fixed effects | | Both effects | |
|---|---|---|---|---|---|---|---|---|
| | Low SE | High SE | Low SE | High SE | Low SE | High SE | Low SE | High SE |
| $a_1$ | 0.022 | 0.005 | 0.024 | 0.008 | 0.031 | 0.012 | 0.034 | 0.018 |
| | (0.004) | (0.003) | (0.004) | (0.003) | (0.004) | (0.003) | (0.004) | (0.003) |
| $a_2$ | 0.087 | 0.132 | 0.067 | 0.108 | 0.139 | 0.133 | 0.109 | 0.092 |
| | (0.025) | (0.023) | (0.024) | (0.022) | (0.027) | (0.023) | (0.025) | (0.022) |
| $R^2$ | 0.096 | 0.100 | 0.096 | 0.099 | 0.072 | 0.091 | 0.076 | 0.081 |

*Notes:* The table reports results from panel regression (22) in each subsample, with and without firm fixed effects and time effects. Robust standard errors are reported in parenthesis. The differences in slope coefficient $a_1$ across samples are significant at the one percent level.

and Ejarque 2003, Abel and Eberly 2009), or non-convex capital adjustment costs (Abel and Eberly 1994, Caballero and Leahy 1996, Dixit and Pindyck 1994). The results of this cross-industry comparison – showing that investment-$q$ regressions work less well in industries with higher selling expenses – are particularly valuable in distinguishing our theory from these alternatives. The concern that remains, however, is the possibility of a systematic relationship between these alternative theories and selling expenses, which could explain the results.

First, it seems quite plausible that firms in more frictional product markets might be more affected by financing constraints, due to a larger share of firm value deriving from intangible capital (arguably less likely to work as collateral). To assess the role of financing constraints for our results, we examine the relationship between selling expenses and both debt level and dividend payout. We find that firms in the high selling expense sample indeed have slightly less debt (see Table 3), but because they also pay somewhat greater dividends,

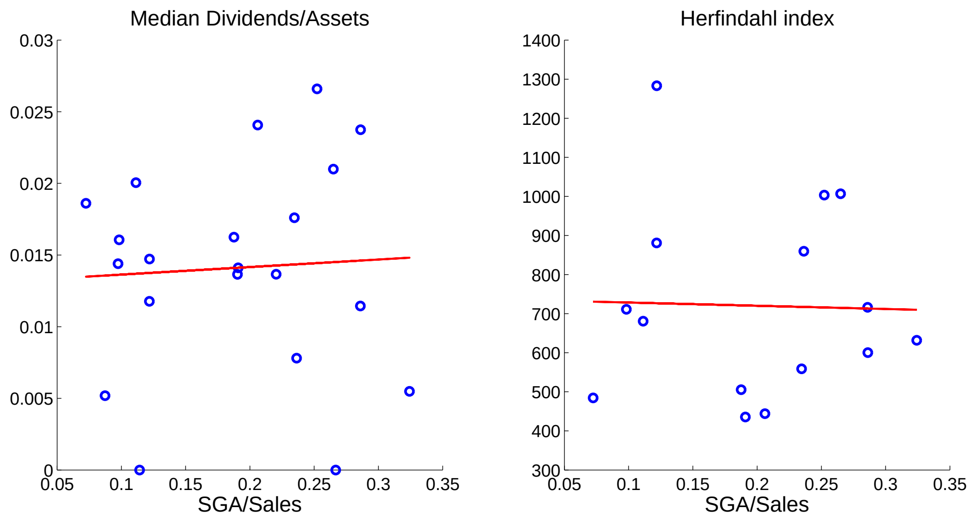


Figure 8: Industry Selling Expenses vs Dividend Payout, Industry Concentration

*Notes:* Each circle corresponds to a 2-digit SIC industry with ten or more firms. The horizontal axis is the time-series average of industry selling expenses relative to industry sales. The left panel plots, for each industry, the median across firms of time-series medians of firm dividends/assets. The right panel plots the Herfindahl index of industry concentration, available from `http://www.census.gov/epcd/www/concentration.html`. We include a fitted line for reference.

it seems unlikely that financing constraints account for our results. The left panel of Figure 8 illustrates this relationship on an industry-by-industry basis. Second, to assess the role of market power for our results, we examine the relationship between selling expenses and industry concentration, as measured by the Herfindahl index.[49] As the right panel of Figure 8 illustrates, this relationship is relatively weak and generally negative. Market power is thus unlikely to account for our results. Finally, fixed costs are unlikely to play an important role here because the firms in our sample are quite large.

**Aggregate shocks** In addition to firm-level shocks, we can use the same data to study responses to more aggregate-level shocks as well. The empirical variation we measure when aggregating is, of course, very different from that at the firm level, offering an almost orthogonal test of the model predictions. To that end we compute, for each subsample, aggregate time series of investment, sales, profits, and our other variables of interest by adding up the firm-level observations at each point in time. Because the aggregate time series are relatively short, we move to the quarterly data in Compustat for this exercise. As standard with ag-

[49]The Herfindahl index is available at `http://www.census.gov/epcd/www/concentration.html`, along with some alternatives. These alternative concentration indexes yield similar results.

Table 8: Aggregate-Level Time-Series Standard Deviations

| | Absolute | | Relative to Tobin's $q$ | |
|---|---|---|---|---|
| | Low SE | High SE | Low SE | High SE |
| Investment/Capital | 0.122 | 0.087 | 1.569 | 0.855 |
| | (0.011) | (0.007) | (0.180) | (0.087) |
| Profit/Capital | 0.128 | 0.062 | 1.650 | 0.614 |
| | (0.023) | (0.005) | (0.176) | (0.062) |
| Sales/Capital | 0.082 | 0.042 | 1.059 | 0.415 |
| | (0.011) | (0.004) | (0.100) | (0.042) |
| Markup | 0.020 | 0.021 | 0.252 | 0.205 |
| | (0.002) | (0.002) | (0.024) | (0.016) |
| Tobin's $q$ | 0.078 | 0.101 | - | - |
| | (0.009) | (0.008) | - | - |

*Notes:* The table reports the aggregate-level time-series standard deviations of investment/capital, profit/capital, sales/capital, sales/cost of goods sold, and tobin's $q$. Standard errors – computed using Newey-West and the delta method – are reported in parenthesis. The differences across samples are significant at the one percent level for each variable, except the markup, both in absolute terms and relative to Tobin's $q$. For the markup, the difference is significant at the five percent level relative to Tobin's $q$.

gregate data, we begin by taking logs, seasonally adjusting,[50] and $HP(1600)$-filtering before computing moments.[51]

We first return to examine the effects of product market frictions on volatility, now in response to more aggregate-level shocks. To this end we compute, for each subsample, time-series standard deviations of our aggregate time series. Table 8 reports the results, revealing a significant drop in volatility from the low to high selling expense sample for investment, sales and profits. Tobin's $q$, on the other hand, is again significantly more volatile in the high selling expense sample. As a result, if we again examined changes in volatility relative to that of Tobin's $q$, the drop in the volatility of investment, sales and profits would only become more striking.[52]

We then return to examine the effect of product market frictions on investment-$q$ regres-

[50]The seasonal adjustment is done by regressing variables on quarter dummies and removing this seasonal component.

[51]Note that we follow convention in analyzing firm-level data in levels and aggregate data in logs. While aggregate data are typically analyzed in logs, taking logs becomes problematic with firm-level data due to negative observations (e.g. in profits).

[52]It may seem surprising that these numbers are larger than the standard deviations for firm-level shocks in Table 5. Recall, however, that these numbers represent percentage variation (the data is logged first), while the firm-level numbers represent absolute variation.

sion results. We run, in each subsample, time-series regressions of aggregate investment on Tobin's $q$ and cash flow. The results, reported in Table 9, are qualitatively similar to those at the firm-level: Both the slope coefficient and $R^2$ fall as we move from the low to high selling expense sample, and cash flow is significant throughout. In this case the samples are harder to distinguish statistically, however, because the number of observations in these time-series regressions is small.[53]

Table 9: Time-Series Regression of Investment on Tobin's $q$ and Cash Flow

| | Low SE | High SE | Low SE | High SE |
|---|---|---|---|---|
| $a_1$ | 0.449 | 0.218 | 0.136 | 0.107 |
| | (0.176) | (0.136) | (0.110) | (0.137) |
| $a_2$ | - | - | 0.489 | 0.521 |
| | - | - | (0.101) | (0.155) |
| $R^2$ | 0.082 | 0.065 | 0.307 | 0.188 |

*Notes:* The table reports results from time-series regressions of investment on Tobin's $q$ and cash flow in quarterly data. Standard errors – computed using Newey-West – are reported in parenthesis. The P-values for a decrease in the slope coefficient $a_1$ moving from the low to the high selling expense sample are 0.15 and 0.45, respectively.

**Industry shocks** Finally, we also consider responses to industry-level shocks. We first compute, for each 2-digit SIC industry, aggregate time series of our variables of interest by adding up the firm-level observations at each point in time. We then compute, for each industry, time-series standard deviations, as well as running time-series investment-$q$ regressions. Figure 9 illustrates the results: a negative relationship between industry selling expenses and volatility (top panels), as well as industry selling expenses and investment-$q$ regression results (bottom panels).

**Summing up** The model makes a number of predictions which depend on the degree of friction in the product market. The goal of this section has been to document the evidence on these predictions, across a broad range of markets and levels of aggregation. Our measure of selling expenses plays an important role in this by providing a way of quantifying the degree of friction in a market, in order to link product market frictions to the various predictions we

[53]Note that the coefficient estimates are not directly comparable to those of the panel regressions, both because the frequency is different, and because these regressions are in logs rather than levels.

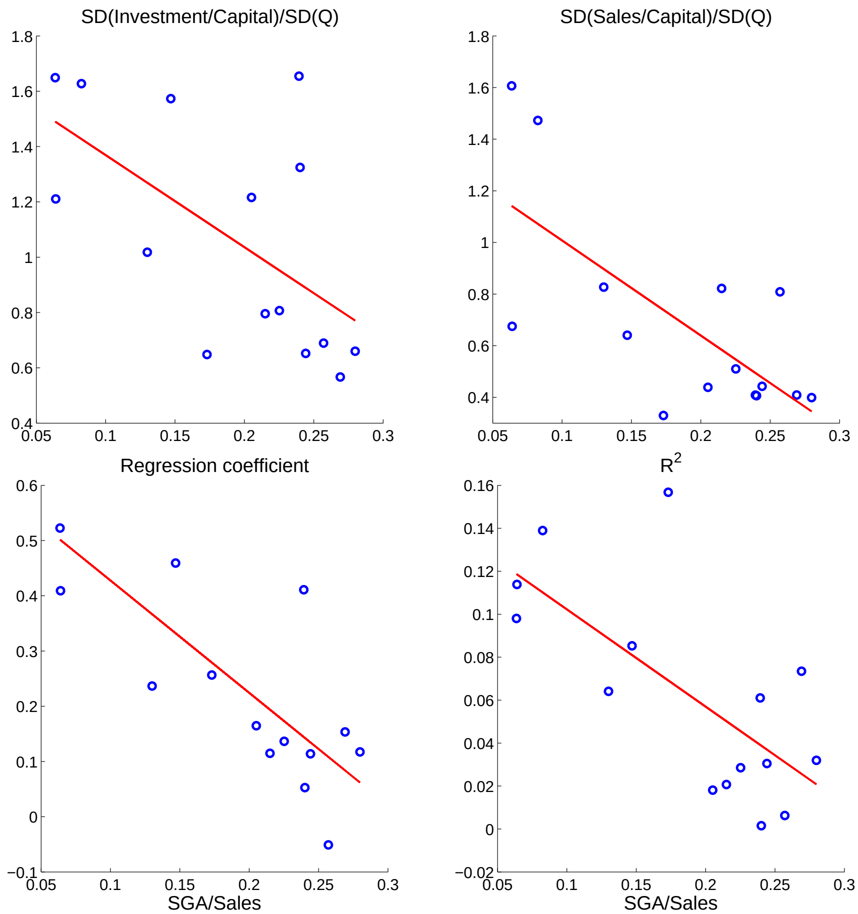


Figure 9: Industry Selling Expenses vs Industry-Level Evidence: Volatility, Regressions
*Notes:* Each circle corresponds to a 2-digit SIC industry with ten or more firms. The horizontal axis shows the time-series average of industry selling expenses relative to sales. The top two panels plot the time-series standard deviations of industry investment and industry sales, and the bottom two results from the time-series regression of industry investment on industry Tobin's $q$. We include a fitted line for reference. For expositional reasons, the axis scaling leaves two industries with low selling expenses and particularly high investment volatility outside the top-left panel.

examine. We find support for a broad range of these predictions, although the evidence is arguably stronger for some predictions than others. The differences across samples are clearly significant for the level effects, the relative volatilities, and regressions of investment on Tobin's $q$. Where the samples are harder to distinguish are the cross-correlations measuring lagged responses, where the standard errors are larger.

# 5 Related Literature

The notion of a customer base has a history in macroeconomics dating back at least to the seminal contribution of Phelps and Winter (1970). Well-know applications include Bils (1989) and Rotemberg and Woodford (1991), who study the cyclical behavior of markups. Work in this area has been somewhat limited, however, likely due to the complexity of modeling these ideas in a general equilibrium setting, leading researchers to turn to the Dixit and Stiglitz (1977) framework of monopolistic competition instead.

Recently, there has been a resurgence of interest in modeling the customer base in various contexts, however. Building on Fishman and Rob (2003), Dinlersoz and Yorukoglu (Forthcoming) develop a model of informative advertising and industry equilibrium and use it to analyze the effects of a long-run decline in the costs of information dissemination on market structure. Their framework is similar to ours in incorporating the customer base as a state variable for firm decision-making, but unlike us, they abstract from firm investment decisions, focusing on entry and exit instead.[54] Their empirical evidence is based on time-series variation in advertising costs, whereas we focus on cross-industry variation in a broader measure of selling costs. Recent empirical work by Foster, Haltiwanger, and Syverson (2009) emphasizes the role of customer base concerns for firm/establishment expansion in US manufacturing, showing that new establishments face a demand gap relative to existing ones which closes only slowly over time. Entry and exit are central also in the work of Arkolakis (Forthcoming, 2010), who argues that the marketing costs of penetrating foreign markets play an important role in firms' export decisions. While Arkolakis abstracts from long-term trade relationships, on-going work by Eaton, Eslava, Kugler, Krizan, and Tybout (2010) explicitly focuses on the dynamics of such relationships. Also in the international setting, Drozd and Nosal (Forthcoming) develop a quantitative theory of export and import prices, explicitly modeling the dynamic accumulation of market share in foreign markets. While they emphasize the importance of product market frictions for understanding the dynamics of prices (with quantities more or less unaffected), our goal has instead been to argue

[54] Note that while search models of frictional product markets are common in the literature, appearing for example in the seminal work of Kiyotaki and Wright (1989), models with long-term customer relationships are not.

that frictions *are* important for understanding the dynamics of quantities. Finally, Ravn, Schmitt-Grohe, and Uribe (2006) study models where goods-level habit preferences lead to persistence in demand, generating counter-cyclical markups, but their model abstracts from the costs of selling and long-term customer relationships which are central in ours.[55]

# 6 Concluding Remarks

This paper studies, both theoretically and empirically, the implications of frictional product markets and long-term customer relationships for firm dynamics. To understand their implications for firms, we first develop a tractable model framework, which builds on recent developments in the search literature. The model makes a number of predictions which appear promising for understanding documented patterns in the data. To establish the empirical relevance of the model mechanism, we then use firm-level data to study these predictions, documenting broad support across a range of markets and degrees of aggregation. In addition to developing our understanding of the demand-side determinants of firm dynamics, the findings are likely to have important implications for macroeconomic measurement and policy, calling for further work.

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[55] Nakamura and Steinsson (Forthcoming) relax their assumption that habits are external, and show that this can create an incentive for rigid prices when firms cannot commit. Another recent paper studying pricing decisions in a model where the customer base is explicitly a state variable for firms is Kleshchelski and Vincent (2009), who study cost pass-through in the face of industry-level shocks. Within the search framework, Menzio (2007) and Shi (2011) study price dynamics in models of directed search in the product market with long-term customer relationships.

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## Supplementary Appendixes: Not for Publication

# A Planning Problem

This section shows that the optimality conditions of the planning problem in Section 3 coincide with those of the market equilibrium. We focus on the first order conditions, due to the strict concavity of the planning problem.

The envelope conditions of the planning problem read, for a given $x = (k, n, z)$,

$$V_n(\lambda) = u_c(c,l) - u_l(c,l)\ell_y^p(k, y(x), z) + \beta(1-\delta_n)E_z V_n(\lambda'), \tag{23}$$

$$V_k(\lambda) = -u_c(c,l)\phi_k(i(x), k) - u_l(c,l)\ell_k^p(k, y(x), z) + \beta(1-\delta_k)E_z V_k(\lambda'). \tag{24}$$

The FOC for $l^s(x)$ reads

$$\kappa'(l^s(x)) = m_s(l^b(x), l^s(x))\frac{V_n(\lambda)}{u_l(c,l)}, \tag{25}$$

the FOC for $l^b(x)$

$$1 = m_b(l^b(x), l^s(x))\frac{V_n(\lambda)}{u_l(c,l)}, \tag{26}$$

and the FOC for $i(x)$

$$\phi_i(i(x), k) = \beta E_z \frac{V_k(\lambda')}{u_c(c,l)}. \tag{27}$$

Defining $w := u_l(c,l)/u_c(c,l)$, $v_n(\lambda) := V_n(\lambda)/u_c(c,l)$ and $v_k(\lambda) := V_k(\lambda)/u_c(c,l)$, the envelope conditions can be written as

$$v_n(\lambda) = 1 - w\ell_y^p(k, y(x), z) + \beta(1-\delta_n)E_z\frac{u_c(c',l')}{u_c(c,l)}v_n(\lambda'), \tag{28}$$

$$v_k(\lambda) = -\phi_k(i(x), k) - w\ell_k^p(k, y(x), z) + \beta(1-\delta_k)E_z\frac{u_c(c',l')}{u_c(c,l)}v_k(\lambda'). \tag{29}$$

Restricting attention to a stationary environment implies that consumption and leisure remain constant, so $u_c(c', l')/u_c(c, l) = 1$. The envelope conditions thus reduce to those of the market equilibrium. Similarly, equation (27) reduces to the market condition (12).

Combining equations (25) and (26) implies: $\theta(x) = \gamma/(1-\gamma) \times \kappa'(l^s(x))$ i.e. equation (3) characterizing market equilibrium. Moreover, equation (25) implies that

$$w\frac{\kappa'(l^s(x))}{\eta(\theta(x))} + \frac{\theta(x)\eta'(\theta(x))}{\eta(\theta(x))}v_n(\lambda) = v_n(\lambda). \tag{30}$$

If we define $\varepsilon(x) := \theta(x)\eta'(\theta(x))/\eta(\theta(x)) \times v_n(\lambda)$, this equation reduces to equation (10) characterizing the market equilibrium, with $\varepsilon(x)$ playing the role of the discount. Defining the discount in this way also implies that the market condition (11) holds. Finally, equation (26) reduces to $w = \eta'(\theta(x))v_n(\lambda)$, or $w = \mu(\theta(x))\varepsilon(x)$. This implies equation (4).

# B Parametrization, Solution Method and Sensitivity

**Solution method** We solve the model numerically, using a log-linear approximation around the non-stochastic steady state. More precisely, we first solve for the non-stochastic steady state, and then log-linearize the model around this steady state. This solution method has the advantage that, by abstracting from non-linearities in firm dynamics, it underlines the fact that *the key mechanism in our model does not rely on non-linearities.* The system of equations is available in an online appendix.[56] We use the same approach also for the model aggregate shocks.

**Parametrization of $\gamma$ and $\xi$** These parameters are determined by targets for total buying and selling time. In the non-stochastic steady state of the model, integrating over measure one identical firms gives total buying time $l^b$, and total selling time $\kappa(l^s)$. Given our targets for $l^b$ and $\kappa(l^s)$, and the assumption that $\kappa(l^s) = (l^s)^2/2$, Proposition 1 directly implies that $\gamma = l^b/(l^b + (l^s)^2)$. The value of $\gamma$ is thus determined by the relative shares of time in buying and selling activities. Given these shares, the overall scale of buying and selling time is

[56] See: `http://people.bu.edu/rudanko/papers/customer_capital_onlineapp.pdf`

increasing in the degree of friction, and thus the targets for buying and selling time also pin down $\xi$.

**Moments in the model** As illustrated by Figure 10, the model predicts a dampening in firm investment, sales, profits and Tobin's $q$ as frictions increase. Observing higher volatility in the high selling expense subsample thus suggests that firms in that sample may face a more variable shock process. This means that testing for the reduction in volatility due to product market frictions requires controlling for the shock process. To this end, we scale the standard deviations of investment, sales and profits by that of Tobin's $q$. As the figure confirms, the model predicts that also these scaled moments decrease in the friction.

**Sensitivity** To assess the sensitivity of our results to the parametrization, we vary the targets for buying time, selling time, and customer depreciation. Figure 11 shows how the dynamics change when steady-state buying time is reduced by 50 percent to 0.265, Figure 12 when steady-state selling time is reduced by 50 percent to 1.15, and Figure 13 when the customer depreciation rate is increased by 50 percent to 22.5. Table 10 shows how these changes affect the various simulated moments of the model.

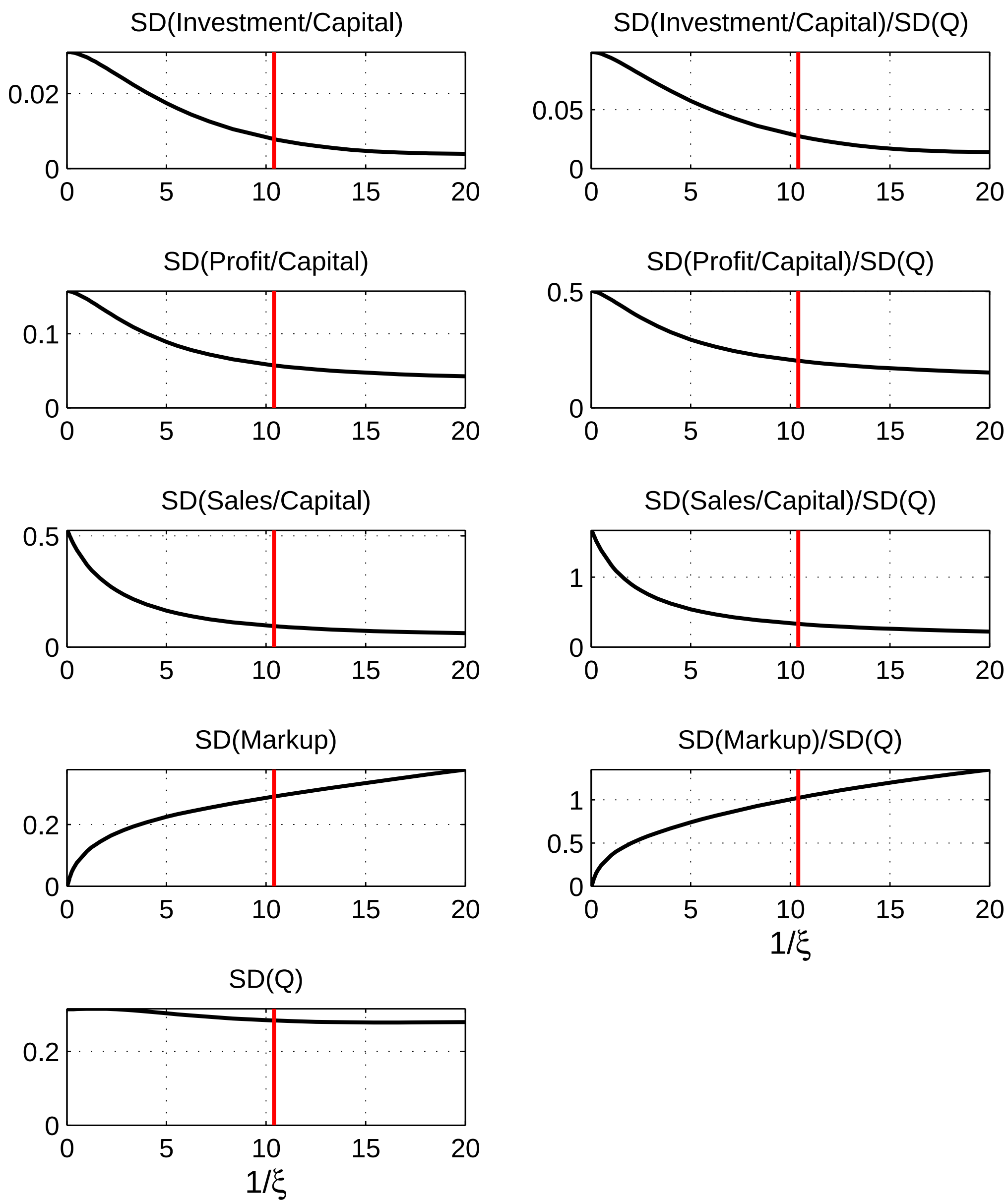


Figure 10: Impact of Friction on Volatility

*Notes:* The figure plots standard deviations of model variables both in absolute terms and relative to the standard deviation of Tobin's $q$. The moments are based on simulated data from the model. Note that these moments measure absolute variation – consistent with our empirical work – while the impulse responses in Figure 2 are in percentage terms. The differences are explained by the effect of frictions on the means.

Table 10: Sensitivity of Model Moments

| | Frictionless | Benchmark | Low $l^b$ | Low $\kappa(l^s)$ | High $\delta_n$ |
|---|---|---|---|---|---|
| Median | | | | | |
| Selling expenses/Sales | 0.000 | 0.047 | 0.047 | 0.024 | 0.047 |
| Profit/Capital | 0.151 | 0.198 | 0.197 | 0.175 | 0.191 |
| Sales/Capital | 0.505 | 0.579 | 0.577 | 0.541 | 0.572 |
| Markup | 0.000 | 0.147 | 0.144 | 0.073 | 0.133 |
| Tobin's $q$ | 1.000 | 1.910 | 1.881 | 1.458 | 1.773 |
| Standard deviation | | | | | |
| Investment/Capital | 0.031 | 0.008 | 0.008 | 0.015 | 0.012 |
| Profit/Capital | 0.158 | 0.058 | 0.059 | 0.075 | 0.061 |
| Sales/Capital | 0.526 | 0.095 | 0.093 | 0.139 | 0.140 |
| Markup | 0.000 | 0.289 | 0.297 | 0.233 | 0.252 |
| Tobin's $q$ | 0.314 | 0.284 | 0.279 | 0.304 | 0.276 |
| Standard deviation relative to $q$ | | | | | |
| Investment/Capital | 0.099 | 0.028 | 0.028 | 0.048 | 0.042 |
| Profit/Capital | 0.502 | 0.203 | 0.211 | 0.246 | 0.222 |
| Sales/Capital | 1.674 | 0.333 | 0.333 | 0.458 | 0.507 |
| Markup | 0.000 | 1.017 | 1.065 | 0.765 | 0.914 |
| Regression (19): investment on $q$ | | | | | |
| $a_1$ | 0.099 | 0.024 | 0.023 | 0.046 | 0.041 |
| $R^2$ | 1.000 | 0.758 | 0.732 | 0.931 | 0.942 |
| Regression (20): investment on $q$ and cash flow | | | | | |
| $a_1$ | 0.100 | -0.007 | -0.013 | 0.016 | 0.026 |
| $a_2$ | -0.002 | 0.178 | 0.196 | 0.147 | 0.087 |
| $R^2$ | 1.000 | 0.964 | 0.952 | 0.989 | 0.996 |

*Notes:* The table reports moments based on model simulated data. The first column is the frictionless limit, the second our benchmark parametrization, the third a parametrization with 50% lower buying time, the fourth with 50% lower selling time, and the fifth with 50% higher customer depreciation.

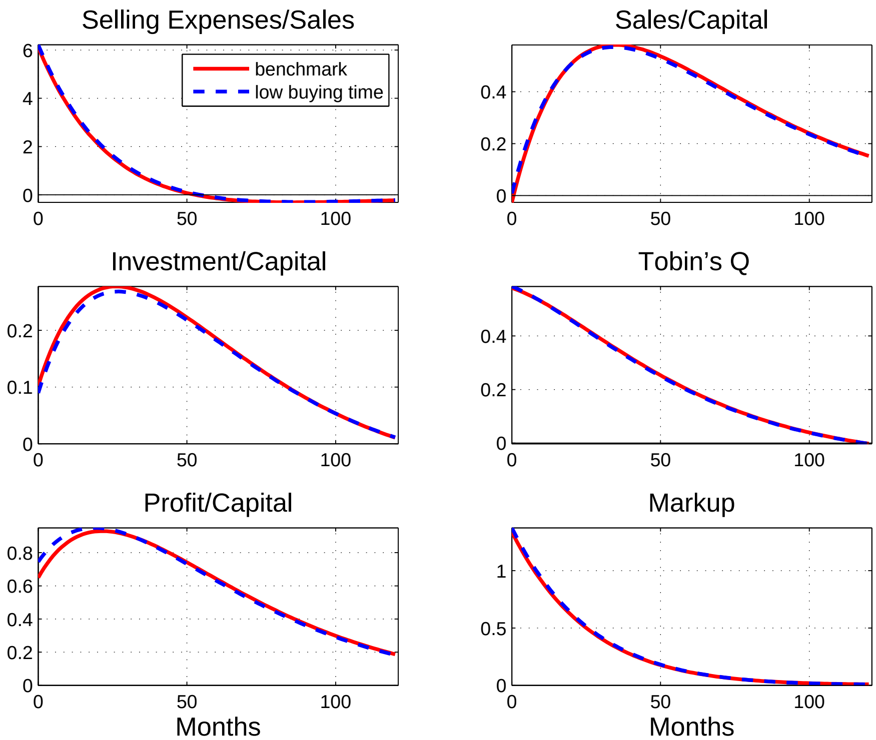


Figure 11: Impulse Responses: Benchmark versus Low Buying Time

*Notes:* The responses are in percentage deviations from steady state.

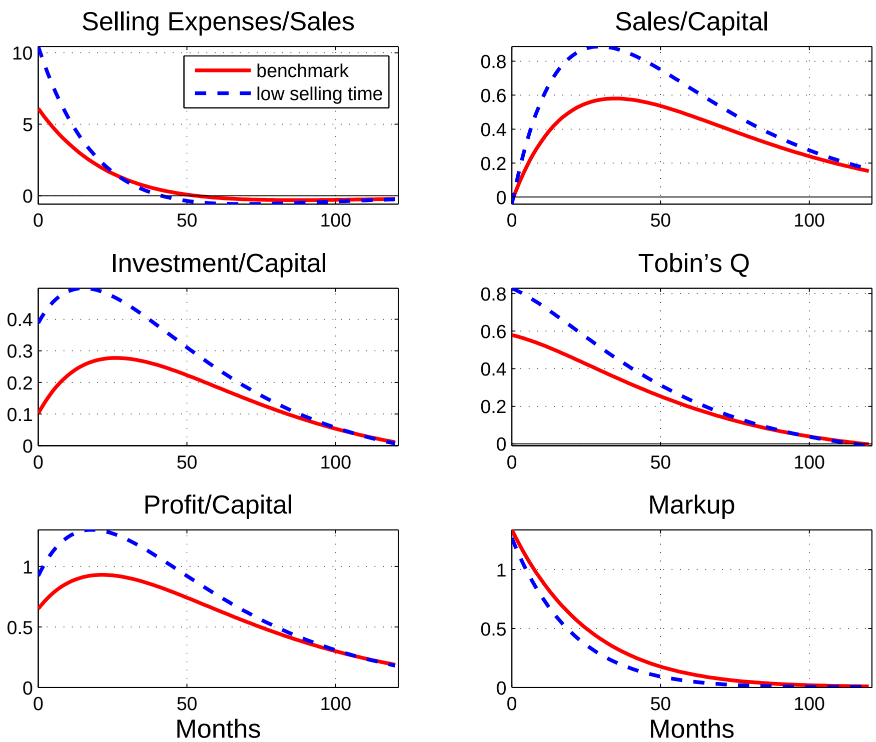


Figure 12: Impulse Responses: Benchmark versus Low Selling Time

*Notes:* The responses are in percentage deviations from steady state.

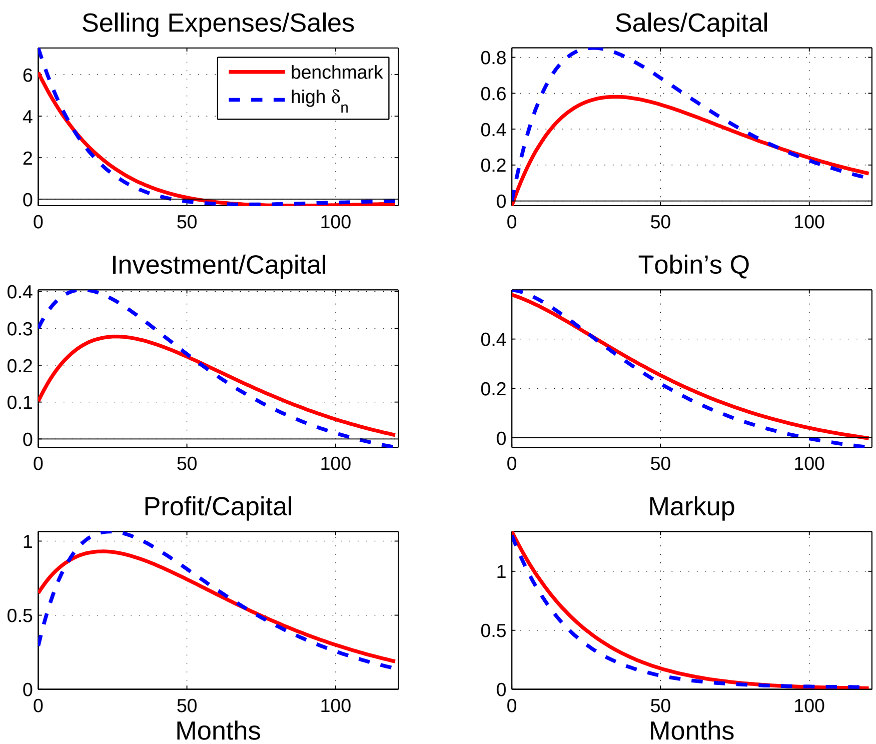

Figure 13: Impulse Responses: Benchmark versus High Depreciation
*Notes:* The responses are in percentage deviations from steady state.

# C Model with Aggregate Shocks

This section adapts the model to a setting with aggregate fluctuations in productivity. Suppose we alter the economy such that all firms have the same productivity each period, which fluctuates over time according to a Markov process. In those circumstances all firms will (eventually) be identical in size, but the size will fluctuate over time response to aggregate shocks. Aggregate shocks lead to fluctuations in the price of consumption, which must be taken into account in discounting firm profits, as well as evaluating the returns to search.

The household problem now reads

$$\begin{aligned}
&\max E_0 \sum_{t=0}^{\infty} \beta^t u(c_t, 1 - l_t^m - l_t^b) \\
&\text{s.t. } c_t \leq w_t l_t^m + w_t^b l_t^b + \Pi_t, \quad \forall t \geq 0.
\end{aligned}$$

This problem differs from the previous household problem because here the wage $w_t$, return to search $w_t^b$ and dividends $\Pi_t$ fluctuate over time in response to aggregate shocks. The household now maximizes expected utility over this uncertainty about the future. As before, the return to search satisfies $w_t^b = \mu(\theta_t)\varepsilon_t$, with $w_t = w_t^b$ for all $t$ in any equilibrium where the household spends time in both market work and search.

Firms choose output $y_t$, investment $i_t$, production labor $l_t^p$, sales labor $l_t^s$, queues $\theta_t$, and discounts $\varepsilon_t$, for all $t$, conditional on the realization of the aggregate shock history up to time $t$, to

$$\begin{aligned}
&\max E_0 \sum_{t=0}^{\infty} \tilde{\beta}_t [y_t - l_t^s \eta(\theta_t)\varepsilon_t - w_t l_t^p - w_t \kappa(l_t^s) - \phi(i_t, k_t)] \\
&\text{s.t. } y_t \leq n_t + l_t^s \eta(\theta_t), \\
&\qquad y_t \leq f(k_t, l_t^p, z_t), \\
&\qquad n_{t+1} \leq (1 - \delta_n) y_t, \\
&\qquad k_{t+1} \leq (1 - \delta_k) k_t + i_t, \\
&\qquad w_t^b = \mu(\theta_t)\varepsilon_t.
\end{aligned}$$

This firm problem differs from the previous one in three ways: i) all firms face the same productivity realization, ii) the wage (and return to search) fluctuate over time, and iii) firms discount future profits with the probability-normalized prices $\tilde{\beta}_t$ instead of $\beta^t$. Starting all firms with the same initial conditions implies that they remain identical forever. Aggregate variables are thus just a multiples of firm level variables and the measure of firms, one. The firm optimality conditions now imply that: i) all firms offer the same discount and have identical queues, and ii) in times when firms hire more sales people, queues are longer and discounts (relative to wages) higher:

**PROPOSITION 2.** *Queues and discounts are increasing in the choice of sales personnel* $l_t^s$*:* $\theta_t = \gamma/(1-\gamma) \times \kappa'(l_t^s)$ *and* $\varepsilon_t = w_t \theta_t^{1-\gamma}/\xi$.

The definition of equilibrium extends with straightforward changes from the text.

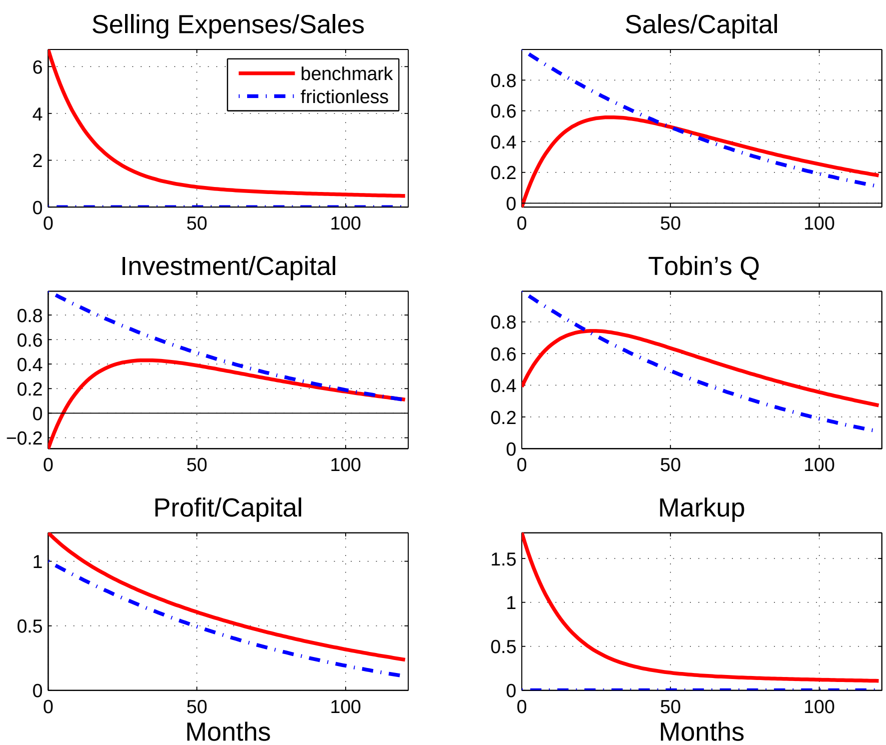


Figure 14: Impulse Responses to Aggregate Productivity Shock

*Notes:* The responses are in percentage deviations from steady state. Selling expenses refer to $w\kappa(l^s)$, sales to $(1 - l^s\eta(\theta)\varepsilon)y$, profit to sales net of labor costs of production and sales, and the markup to sales per unit sold $1 - l^s\eta(\theta)\varepsilon/y$ over the marginal cost $wl^p/y \times 1/(1-\alpha)$.

# D Data

For comparability with existing literature, we use the Compustat industrial annual data from 1983 to 1999, with the following standard exclusions: First, we drop firms with primary SIC classification between 6000 and 6999 and between 4900 and 4999, representing utilities and financial firms. We also drop foreign firms. Second, we drop firms with negative or zero book value of capital (Items 7 and 8), sales (Item 12), assets (Item 6), selling, general and administrative expenses (Item 189), cost of goods sold (Item 41). We also drop firms with negative advertising (Item 45) or R&D (Item 46). Observations with a merger flag in year $t$ are dropped from the sample in years $t-1$, $t$ and $t+1$. To minimize the impact of extreme observations, we drop as outliers firms which have in a given year a profit rate above 10 or less than $-4$, an investment rate above 3, or Tobin's $q$ above 10.

Investment is measured as Item 30, but netting out capital sales (Item 107) would not affect the results significantly. Earnings are measured as operating income (Item 13). The investment rate is measured as (Item 30)/(Item 7 lagged) and the profit rate as (Item 13)/(Item 7 lagged). Debt is measured as Item 9, dividends as Item 21+Item 19.

Finally, we balance the panel, keeping only firms with observations for all of the above variables between 1983 and 1999. This leaves 648 firms, with $11,016$ firm-year observations. Balancing facilitates studying time-series dynamics at the firm level, which requires repeated observations for each firm over time. Our Stata code is available on request.

Table 11: High SGA Industries

| |
|---|
| Division A: Agriculture, forestry, and fishing |
| 07: Agricultural services |
| Division D: Manufacturing |
| 20: Food and kindred products |
| 21: Tobacco products |
| 23: Apparel and other finished products from fabrics |
| 27: Printing, publishing, and allied industries |
| 28: Chemicals and allied products |
| 31: Leather and leather products |
| 35: Industrial and commercial machinery and computer equipment |
| 38: Measuring, analyzing, and controlling instruments |
| 39: Miscellaneous manufacturing industries |
| Division G: Retail trade |
| 56: Apparel and accessory stores |
| 57: Home furniture, furnishings, and equipment stores |
| 59: Miscellaneous retail |
| Division I: Services |
| 73: Business services |
| 75: Automotive repair, services, and parking |
| 76: Miscellaneous repair services |
| 81: Legal services |
| 82: Educational services |
| 84: Museums, art galleries, and gardens |
| 86: Membership organizations |
| 89: Miscellaneous services |

Table 12: Low SGA Industries

| |
|---|
| Division A: Agriculture, forestry, and fishing |
| 01: Agricultural production crops |
| 02: Agriculture production livestock and animal specialties |
| 08: Forestry |
| 09: Fishing, hunting, and trapping |
| Division B: Mining |
| 10: Metal mining |
| 12: Coal mining |
| 13: Oil and gas extraction |
| 14: Mining and quarrying of nonmetallic minerals |
| Division C: Construction |
| 15: Building construction: general contractors and operative builders |
| 16: Heavy construction: other than building construction contractors |
| 17: Construction: special trade contractors |
| Division D: Manufacturing |
| 22: Textile mill products |
| 24: Lumber and wood products, except furniture |
| 25: Furniture and fixtures |
| 26: Paper and allied products |
| 29: Petroleum refining and related |
| 30: Rubber and miscellaneous plastics products |
| 32: Stone, clay, glass, and concrete products |
| 33: Primary metal industries |
| 34: Fabricated metal products, except machinery and transportation equipment |
| 36: Electronic and other electrical equipment and components, except computer equipment |
| 37: Transportation equipment |
| Division E: Transportation, communications, electric, gas, and sanitary services |
| 40: Railroad transportation |
| 41: Local and suburban transit and interurban highway passenger transportation |
| 42: Motor freight transportation and warehousing |
| 44: Water transportation |
| 45: Transportation by air |
| 46: Pipelines, except natural gas |
| 47: Transportation services |
| 48: Communications |
| Division F: Wholesale trade |
| 50: Wholesale trade: durable goods |
| 51: Wholesale trade: non-durable goods |
| Division G: Retail trade |
| 52: Building materials, hardware, garden supply, and mobile home dealers |
| 53: General merchandise stores |
| 54: Food stores |
| 55: Automotive dealers and gasoline service stations |
| 58: Eating and drinking places |
| Division I: Services |
| 70: Hotels, rooming houses, camps, and other lodging |
| 72: Personal services |
| 78: Motion pictures |
| 79: Amusement and recreation services |
| 80: Health services |
| 83: Social services |
| 87: Engineering, accounting, research, management, and related services |
| Division J: Public administration |
| 99: Non-classifiable establishments |

Table 13: Firm-Level Cross-Correlations of $i_t/k_t$ with $q_{t+j}$

| $j$ | -3 | -2 | -1 | 0 | 1 | 2 | 3 |
|---|---|---|---|---|---|---|---|
| High SE | 0.126 | 0.211 | 0.301 | 0.124 | 0.042 | -0.026 | -0.041 |
| | (0.031) | (0.034) | (0.031) | (0.033) | (0.026) | (0.024) | (0.033) |
| Low SE | 0.072 | 0.190 | 0.372 | 0.248 | 0.085 | 0.009 | -0.035 |
| | (0.024) | (0.029) | (0.024) | (0.026) | (0.024) | (0.024) | (0.027) |

*Notes:* The table reports medians across firms of the time-series cross-correlations of the firm-level investment rate with lags and leads of firm-level Tobin's $q$. Bootstrapped standard errors – computed over 200 replications – are reported in parenthesis.

Table 14: Firm-Level Cross-Correlations of $i_t/k_t$ with $SE_{t+j}/k_{t+j}$

| $j$ | -3 | -2 | -1 | 0 | 1 | 2 | 3 |
|---|---|---|---|---|---|---|---|
| High SE | 0.161 | 0.252 | 0.366 | 0.521 | 0.195 | 0.049 | -0.042 |
| | (0.031) | (0.038) | (0.031) | (0.024) | (0.036) | (0.036) | (0.035) |
| Low SE | 0.098 | 0.184 | 0.315 | 0.466 | 0.149 | 0.003 | -0.012 |
| | (0.026) | (0.027) | (0.024) | (0.019) | (0.027) | (0.032) | (0.028) |

*Notes:* The table reports medians across firms of the time-series cross-correlations of the firm-level investment rate with lags and leads of firm-level $SE$. Bootstrapped standard errors – computed over 200 replications – are reported in parenthesis.

Table 15: Firm-Level Regression of Investment on Tobin's $q$ in Manufacturing

| | Simple regression | | Time effects | | Fixed effects | | Both effects | |
|---|---|---|---|---|---|---|---|---|
| | Low SE | High SE | Low SE | High SE | Low SE | High SE | Low SE | High SE |
| $a_1$ | 0.032 | 0.016 | 0.032 | 0.017 | 0.040 | 0.021 | 0.042 | 0.025 |
| | (0.004) | (0.002) | (0.004) | (0.002) | (0.004) | (0.003) | (0.004) | (0.003) |
| $R^2$ | 0.087 | 0.053 | 0.087 | 0.053 | 0.080 | 0.047 | 0.078 | 0.036 |

*Notes:* The table reports results from panel regression (21) on the subset of industries in manufacturing, with and without firm fixed effects and time effects. Robust standard errors are reported in parenthesis.

Table 16: Firm-Level Regression of Investment on Tobin's $q$ and Cash Flow in Manufacturing

| | Simple regression | | Time effects | | Fixed effects | | Both effects | |
|---|---|---|---|---|---|---|---|---|
| | Low SE | High SE | Low SE | High SE | Low SE | High SE | Low SE | High SE |
| $a_1$ | 0.012 | 0.006 | 0.016 | 0.009 | 0.024 | 0.011 | 0.029 | 0.017 |
| | (0.005) | (0.003) | (0.005) | (0.003) | (0.005) | (0.003) | (0.005) | (0.003) |
| $a_2$ | 0.171 | 0.110 | 0.141 | 0.087 | 0.171 | 0.123 | 0.130 | 0.085 |
| | (0.034) | (0.020) | (0.033) | (0.020) | (0.029) | (0.026) | (0.026) | (0.024) |
| $R^2$ | 0.127 | 0.084 | 0.126 | 0.082 | 0.115 | 0.075 | 0.112 | 0.064 |

*Notes:* The table reports results from panel regression (22) on the subset of industries in manufacturing, with and without firm fixed effects and time effects. Robust standard errors are reported in parenthesis.