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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 article 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, profits, value, sales 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.

Key words: Product market search, Customer base, Firm dynamics, Investment.

JEL Codes: E22, D83, D92, L11

1. INTRODUCTION

Firms spend substantial resources on marketing and selling: marketing expenditures have recently been estimated to make up as much as 8% of GDP, with advertising alone amounting to 2–3%.[1] Why are firms incurring these costs? In this article, we interpret this spending as evidence of frictions in product markets, which require firms to spend resources on customer acquisition, and study what other implications this has for firms: the level and volatility of firm investment, profits, value, sales and markups, the timing of firm responses to shocks, as well as the relationship between investment and Tobin's q. We then proceed to 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.

Our model builds on the Mortensen–Pissarides search and matching model, and nests the neoclassical adjustment cost model of investment. In the model, a continuum of firms produce and sell goods in a market hampered by informational frictions concerning product characteristics. Search frictions: (i) require firms to spend resources on customer acquisition, and (ii) render customer relationships long-term in nature, and the customer base 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.

1. Arkolakis (2010).

Examples of products motivating our model are newspaper subscriptions and cell phone services. Newspapers typically offer discounts to attract new customers, subsequently charging a price above the marginal cost of production for an extended period of time. Similarly, cell phone service providers offer initial discounts in the form of a free phone. In these industries, it is 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 our main insights to hold more broadly than this, however, also applying to markets without contractual long-term customer relationships.

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.[2]

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 lagged 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, the increase in production capacity leaves the firm short of customers to sell to, as the convex costs of customer acquisition slow down the expansion in sales. Investment rises on impact, but continues to rise further as the firm accumulates customers (and eventually finds itself short of production capacity), generating a lagged response. These changes in dynamics allow frictional product markets to provide a natural micro-foundation for the capital adjustment cost specification adopted recently by Christiano *et al.* (2005), as well as Eberly *et al.* (2012), as a means to limit/lag investment responses to shocks by penalizing the rate of change in investment.[3]

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 adjustment cost model, that Tobin's q be a sufficient statistic for firm investment, has little success empirically (Chirinko 1993, Caballero 1999). 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. The model also generates cash flow effects in an investment-q regression:[4] firm profits appear to have stronger explanatory power for investment than Tobin's q, because profits share the lagged 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. To sort markets according to the degree of friction, we use the model prediction that in markets with greater frictions, firms spend more on selling expenses.

2. The article is thus related to the literature emphasizing the importance of intangible capital (Ai *et al.*, 2013; Atkeson and Kehoe, 2005; Eisfeldt and Papanikolaou, 2013; Hall, 2001b; McGrattan and Prescott, 2010a,b). See also Belo *et al.* (2013).

3. We show that the investment lags generated by our model carry over to a general equilibrium setting with aggregate shocks in Gourio and Rudanko (2011). The complementarity of customer capital with physical capital plays a key role in generating lagged responses in investment. For example labour markets frictions, which generate both intangible capital and lagged responses in sales, do not generate strong investment lags, as we show in Section 3.

4. In the absence of financing constraints.

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.

Two features of the model are essential for the results we emphasize: the convex costs of customer acquisition (which limit firm expansion), and the long-term customer relationships (which turn the customer base into a state-variable for firms). It is easy to find evidence of long-term customer relationships in contexts with an explicit long-term contract between buyer and seller, such as banking, telephone and internet services, or in repeated business-to-business transactions.[5] But implicit long-term customer relationships appear prevalent in other contexts as well: for example Bronnenberg *et al.* (2012) provide striking evidence in the context of consumer packaged goods, showing that brand preferences are extremely persistent over the consumer life-cycle. Significant consumer inertia has been documented in preceding work as well (see Dubé *et al.*, 2010). As to customer acquisition constraining expansion, Foster *et al.* (2009) show that even in the context of relatively homogenous manufacturing goods, the gradual endogenous building up of demand-side capital limits expansion in sales. The marketing literature also emphasizes time-of-entry as a key determinant of market share, with early entrants capturing a larger share of the market (see Bronnenberg *et al.*, 2009; Kalyanaram *et al.*, 1995).

In all, we provide a novel micro-founded model of firm dynamics emphasizing the role of customer base concerns. Our theory offers tractability and relatively sharp characterizations, providing a benchmark model to facilitate exploring this under-researched area more thoroughly going forward. We show that adding customer capital to even the simplest quadratic capital adjustment cost model improves the fit of the model substantially relative to the data.[6] While more general model specifications may allow an even better fit, this particular micro-foundation goes a long way. We also show that our theory compares favourably against proposed alternatives in an empirical horse race. Our findings underscore the role of customer base concerns as an important determinant of firm dynamics, calling for further investigation of these ideas in the economics literature.

1.1. *Relation to literature: customer base in macroeconomics*

The notion of a customer base has a history in macroeconomics dating back at least to the seminal contribution of Phelps and Winter (1970). Despite important contributions by Bils (1989) and Rotemberg and Woodford (1991), work in this area has remained somewhat limited, likely due to the complexity of modelling these ideas in a tractable way.[7]

Recently, there has been a resurgence of interest in modelling the customer base in various contexts, however. In the context of dynamic stochastic macro-models, Ravn *et al.* (2006) explore aggregate dynamics in a model where goods-level habit preferences lead to persistence in demand[8] and Petrosky-Nadeau and Wasmer (2011) in a model with search frictions in credit, goods, and labour markets. Dinlersoz and Yorukoglu (2012) develop a model of informative advertising

5. See Section 3 and the evidence on long-term trade relationships in Eaton *et al.* (2010).

6. Although the quadratic adjustment cost model represents a very stylized view of firm behaviour, it serves to provide a well-understood benchmark for studying the impact of customer capital. Our results do not hinge on this specification, however, as customer capital would tend to generate investment lags even in the absence of capital adjustment costs (see section on robustness).

7. Note that long-term customer relationships are not part of the models of frictional product markets in the monetary search tradition following Kiyotaki and Wright (1989).

8. Nakamura and Steinsson (2011) extend this work to internal habits. Other recent work studying pricing decisions in a model where the customer base is explicitly a state variable for firms includes Kleshchelski and Vincent (2009), Menzio (2007), Paciello *et al.* (2013), and Shi (2011).

and industry equilibrium and use it to analyse the effects of a long-run decline in the costs of information dissemination on market structure. Perla (2013) uses these ideas to develop a model of firm growth and decline over the industry life cycle, and Luttmer (2006) a theory of the firm size distribution. Drozd and Nosal (2012) develop a quantitative theory of export and import prices, explicitly modelling the dynamic accumulation of market share in foreign markets, while Arkolakis (2010) uses these ideas to explain market penetration by exporters, and Fitzgerald and Haller (2012) price responses to exchange rate shocks. Our work provides a called-for micro-foundation for these and other applications emphasizing the importance of customer base concerns for a broad range of issues.

1.2. *Relation to literature: investment and Tobin's q*

The failure of the investment-q regression evidence to comply with the basic q-theory of investment has posed a puzzle a large amount of research has sought to resolve. One approach has been to acknowledge the measurement problems involved. These papers argue that the theory holds up better if Tobin's q is measured: (i) by a "fundamental q" rather than stock market values directly, (ii) using bond prices, or (iii) acknowledging measurement error.[9] A limitation of this approach is that it does not provide a theory of why stock market values represent poor measures of investment opportunities, however.

The alternative approach has been to relax assumptions of the basic model by introducing: (i) market power, (ii) financing constraints, (iii) non-convex capital adjustment costs, or (iv) inter-related demand between capital and labour into the model.[10] A limitation of this literature is that even though relaxing key assumptions breaks the direct theoretical relationship between investment and Tobin's q discussed by Hayashi (1982), this may not be enough to explain the evidence. For example, regressions of investment on Tobin's q can work well in a model with fixed costs of investing (Caballero and Leahy, 1996) or financing constraints (Gomes, 2001).

In general, reproducing the empirical findings in the context of a calibrated, simulated model is not trivial, and the question of what mechanism best explains the evidence appears open. Relative to this literature, our theory proposes a simple, new mechanism, which delivers quantitatively significant effects in a calibrated, simulated model. Our empirical work further offers a novel cross-industry test of the empirical explanatory power of this mechanism, which shows that it compares favourably against proposed alternatives.[11]

The article is organized as follows. Section 2 presents our model. Section 3 fleshes out the implications of the model with a combination of analytical and quantitative results, which we study empirically in Section 4. Section 5 concludes.

2. THE MODEL

This section introduces a model of an industry designed for analysing the effects of frictional product markets on firm investment, sales, profits, value, and their dynamic responses to shocks. We return to discuss our modelling choices at the end of the section.

9. See: (i) Abel and Blanchard (1986), Gilchrist and Himmelberg (1995), Cummins *et al.* (2006); (ii) Philippon (2009); (iii) Erickson and Whited (2000).

10. See: (i) Schiantarelli and Georgoutsos (1990), Cooper and Ejarque (2003), Abel and Eberly (2011); (ii) Bond and Meghir (1994), Gomes (2001), Lorenzoni and Walentin (2007), DeMarzo *et al.* (2013); (iii) Abel and Eberly (1994), Caballero and Leahy (1996), Barnett and Sakellaris (1998), Bayer (2006); (iv) Merz and Yashiv (2007).

11. We are not aware of other studies adopting a similar cross-industry approach to test the empirical success of alternative mechanisms.

2.1. *Buyers*

The model economy is populated by a continuum of potential buyers, who are risk neutral and discount the future at rate β. Potential buyers face a time cost of search, with the value of a unit of time normalized to one. The value of each additional unit of the good produced by the industry to these buyers is u, determined in equilibrium by the demand for the industry output (as discussed later). The measure of active buyers is endogenous, as buyers choose to search only if the value of a new customer relationship makes up for the cost of search.

2.2. *Producers*

Industry production is carried out by a continuum of measure one firms facing idiosyncratic shocks to their productivity. Each firm produces with a Cobb–Douglas production technology $y=f(k,l,z)$. The firms' capital stock k evolves according to a law of motion $k'=(1-\delta_k)k+i$, with existing capital depreciating at rate δ_k. New investment entails a cost $\phi(i,k)$, which includes both the purchase price of capital and a standard convex adjustment cost. Production also makes use of a variable input l. Finally, productivity z is independent across firms, and follows a Markovian stochastic process with a bounded support and a continuous and monotone transition function. Firms discount the future at rate β.

2.3. *Frictional product market*

The product market is frictional, and operates with price posting/competitive search (Moen, 1997). Buyers are aware of all firms producing goods, as well as their pricing, but in order for a new customer relationship to form, a buyer must meet with a firm's sales representative.[12] As a result, an essential part of firm operations involves hiring sales people to build and maintain the firm's customer base. We assume decreasing returns in hiring more sales people, so that s efficiency units of sales people require hiring $\kappa(s)$ actual units of sales people, where $\kappa(s)$ is an increasing and convex function.[13]

A firm-level matching function formalizes the idea that meetings between sales people and potential buyers are subject to coordination frictions: each period some sales locations go without potential buyers arriving, while others get more than the sales person can handle. If a firm hires s efficiency units of sales people, with b potential buyers arriving across sales locations, the measure of new customer relationships is given by $m(b,s)=\xi b^{\gamma}s^{1-\gamma}$, where $\xi>0$ and $\gamma\in(0,1)$. This measure can be viewed as the product of the measure of meetings taking place, and the (exogenous) probability of a meeting leading to a new customer relationship.[14] It is convenient to denote the (firm-specific) average queue-length of buyers per seller as $\theta=b/s$. This allows writing the probability a buyer succeeds in matching as a decreasing function of the queue length: $\mu(\theta)\equiv m(1,1/\theta)$, and the probability a sales person succeeds in matching as an increasing function of the queue length: $\eta(\theta)\equiv m(\theta,1)$.[15]

12. The "sales representatives" in the model are a stand-in for a broader notion of marketing and selling efforts, and will be interpreted as such later on.

13. The convexity plays a role in the firm dynamics we study later, and can be thought of as arising for example from sales people being placed in different sales locations, differing in centrality.

14. This randomness can be thought of as arising from idiosyncratic differences in tastes across buyers and product characteristics across producers, or randomness in the success of the selling process.

15. An increase in buyers per sales person increases matches, but at a diminishing rate because buyers are more likely to arrive in locations with sales people occupied. Stevens (2007) describes such a matching process, showing that it generates an approximately Cobb–Douglas matching function.

2.4. *Buyer problem*

Due to the frictions in the product market, customer relationships become long term in nature, with the firm supplying the customer one unit of the good each period. The firm's pricing thus refers to a sequence of prices specifying how much the customer must pay each period, as long as the relationship lasts. These relationships end for exogenous reasons with probability δ_n each period, but otherwise continue as long as the value of the relationship remains non-negative to both parties. The customer values the good at u, and is thus happy to continue the relationship as long as the present value of per-period prices does not exceed the present value of goods, $u/(1-\beta(1-\delta_n))$. We assume that the firm, when posting a sequence of prices, cannot commit to future prices. In these circumstances, to maximize profits on existing customers, the firm will set the per-period price p to equal u each period, thus extracting the entire value of the match from existing customers.

The market for new customer relationships is competitive, with firms using initial discounts to compete for customers. Potential buyers are aware of the discounts ε offered by all firms, together with corresponding queue lengths θ determining the probabilities of matching, and optimally choose the firm to visit by maximizing the expected value of search, $\mu(\theta)\varepsilon$, across firms. (Note that the value of a new customer relationship to the buyer is ε, because the firm extracts all of the subsequent value from the customer.) For any equilibrium discount, the queue length must be such that the returns to search equal the costs, i.e., $1=\mu(\theta)\varepsilon$. This equation can be viewed as implicitly defining an increasing equilibrium relation between the discount a firm offers, and the corresponding queue length of buyers faced by the firm's sales people.

Note that in this setting it is possible to simultaneously observe different firms offering different discounts in equilibrium, with buyers indifferent across firms, because greater discounts also attract longer queues. In practice, the firms in the industry will indeed offer different discounts at any given point in time, due to heterogeneity in their desire to acquire new customers.

2.5. *Producer problem*

With this, we can write the firm problem as

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

$$y\leq n+s\eta(\theta), \tag{2.1}$$

$$y\leq f(k,l,z), \tag{2.2}$$

$$n'\leq(1-\delta_n)y, \tag{2.3}$$

$$k'\leq(1-\delta_k)k+i, \tag{2.4}$$

$$p=u, \tag{2.5}$$

$$\mu(\theta)\varepsilon=1, \tag{2.6}$$

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. Spending $\kappa(s)$ on sales people, the firm attracts $s\eta(\theta)$ new customers this period, which results in a realized measure of customers of $n+s\eta(\theta)$. The constraints (2.1) and (2.2) 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, (2.2) must hold with equality, determining how much of the variable input $\ell(k,y,z)$ is needed to produce y units of output. Constraint (2.3) 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. Constraint (2.4) is the law of motion for capital. Equation (2.5) sets the per-period price to the customer valuation for the good. Finally, as part of competitive search, equation (2.6) imposes rational expectations regarding the queue length attracted by the choice of discount ε.

The firm's objective is to maximize the present discounted value of dividends, with current dividends given by sales revenue net of the costs of production and investment, and the present value of future dividends by $\beta E_z v(k',n',z'|u)$.

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 δ_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-looking, satisfying the envelope condition

$$v_n(k,n,z|u) = p - \ell_y(k,y,z) + \beta(1-\delta_n)E_z v_n(k',n',z'|u). \tag{2.7}$$

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

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 s:

$$\frac{\kappa'(s)}{\eta(\theta)} + \varepsilon = v_n(k,n,z|u). \tag{2.8}$$

Here the costs consist of both the resources spent on additional sales people, as well as the discounts given. These up-front costs of customer acquisition generally imply that existing customers are valuable assets to the firm (*i.e.* $v_n(k,n,z|u) > 0$). 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 the matching probability per sales person, but also reduces the profitability of those new customers to the firm. The firm raises the discount to a point where the percentage increase in new customer relationships just compensates for the percentage drop in profitability. This first-order condition for ε can be re-written as:

$$\varepsilon = \gamma v_n(k,n,z|u), \tag{2.9}$$

stating that the customer's share of the marginal value of an additional customer, $v_n(k,n,z|u)$, is given by the matching function elasticity γ. Here the matching function elasticity governs the extent to which it is profitable to offer low prices to attract more customers: a low value of γ implies that sales people cannot handle more customers per unit of time, and as a result competition does not lead to large discounts.

Combining the optimality conditions above implies that within a product market (with a given degree of friction), firms choosing to hire more sales people also offer bigger discounts. Because bigger discounts attract longer queues, these sales people are also more likely to match with buyers. Firms thus use both margins to expand: reducing prices as well as increasing their sales force. The formal result reads:

Proposition 1. *In equilibrium, we have* $\theta(k,n,z|u)=\gamma/(1-\gamma)\times\kappa'(s(k,n,z|u))$ *and* $\varepsilon(k,n,z|u)=\theta(k,n,z|u)^{1-\gamma}/\xi$.

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

$$\phi_i(i,k)=\beta E_z v_k(k',n',z'|u), \tag{2.10}$$

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.* $v(k',n',z'|u)/k'$), which implies a linear relationship between the investment rate and Tobin's q.[16] 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.

2.6. *Distribution of producers and industry output demand*

To simplify notation, we denote a firm's state by $x=(k,n,z)$. The cross-sectional distribution of firms across capital, customers and productivity can then be denoted by $\nu(x)$. The distribution evolves over time according to a law of motion $\nu'=T(\nu)$, determined by the productivity process and firm decision rules, but we focus on a stationary distribution where $\nu'=\nu$. Integrating over the stationary distribution yields total industry output $\overline{y}(\nu,u)=\int y(x|u)d\nu(x)$.[17] We assume a decreasing demand curve for industry output: $u=\overline{y}(\nu,u)^{-1/\sigma}$, where $1<\sigma<\infty$.[18] Integrating over the stationary distribution, we also arrive at an expression for the total measure of active buyers $\overline{b}=\int s(x|u)\theta(x|u)d\nu(x)$.[19]

Definition 1. *A stationary competitive search equilibrium specifies firm decision rules* $y(x|u)$, $i(x|u)$, $l(x|u)$, $s(x|u)$, $\theta(x|u)$, $\varepsilon(x|u)$, $p=u$, *and value function* $v(x|u)$, *the distribution of firms* ν, *and the total measure of output* $\overline{y}(\nu)$, *such that*

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

17. For this aggregation over goods procured across buyers to make sense, the goods can be assumed to be either literally identical, or effectively identical ex post (*e.g.*, shirts of different colors).

18. A macroeconomist might naturally think of the aggregate product market as featuring a continuum of different varieties of goods, each of which enters the representative household's preferences via a CES-aggregator over varieties, as in Dixit and Stiglitz (1977). Interpreting the industry modelled here as corresponding to one such variety, the representative household would aggregate up the total industry output, with the demand for the variety then based on the household's decisions regarding how much of each of the varieties to demand given prices across varieties. This would give rise to a downward-sloping demand curve between industry output $\overline{y}$ and the corresponding output price u of the form $\overline{y}=u^{-\sigma}$, with σ the elasticity of substitution across varieties.

19. We use this measure in parameterizing the model in the next section, together with the total measure of sales representatives $\int\kappa(s(x|u))d\nu(x)$. Note that these values represent total measures of man-hours spent in selling and buying activities within the industry.

1. *Firm decision rules and value function solve the problem* (F).
2. *Buying behaviour satisfies:* $\mu(\theta(x|u))\varepsilon(x|u)=1$ *whenever* $\theta(x|u)>0$*, for any equilibrium* $(\theta(x|u),\varepsilon(x|u))$*-pair.*
3. *Stationarity: the distribution of firms* ν *is stationary.*
4. *Industry demand:* $u=\bar{y}(\nu,u)^{-1/\sigma}$*, where* $1<\sigma<\infty$.

Equilibrium allocations are efficient, assuming the planner faces the same frictions in the product market:

Proposition 2. *The equilibrium allocation is efficient.*

Proof See Supplementary Appendix A. ||

This result—which may be anticipated in the context of competitive search—implies that not only is a competitive equilibrium constrained efficient, but that we can use the planning problem to understand equilibrium allocations. In particular, this means that the predictions of the theory for allocations do not depend on the particular pricing schedule we have chosen to focus on, but hold more generally.

2.7. *Discussion of modelling approach*

Before proceeding to study the model implications, we briefly discuss four key elements of our modelling approach. First, the buyers in our model spend time searching for products because of informational frictions concerning product characteristics. An alternative approach would be to assume search 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 analyse 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 (Pissarides, 2000). 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 labour) 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 analyse firm dynamics in frictional labour markets (Garibaldi and Moen, 2010; Kaas and Kircher, 2011), we too have adopted a convex cost function (κ) 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 activities 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 γ 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) the total measure of active buyers in equilibrium is low.[20]

20. In the limiting case with $\gamma=0$, discounts disappear altogether, and the total measure of active buyers goes to zero.

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. 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). This particular path of prices is not essential for our results, as shown below, but there is some intuitive appeal to the idea of simply using initial discounts to attract customers, instead of more complex pricing schemes.

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.[21]

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 with a combination of analytical and quantitative results, to be studied empirically in Section 4.

3.1. *Parametrization*

To illustrate the impact of frictions, as well as to get a rough idea of magnitudes, we parameterize and solve the model numerically. Supplementary Appendix A discusses our numerical approach.

We begin with a conventional parametrization of the neoclassical adjustment cost model.[22] 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.[23] Finally, the $AR(1)$ process for productivity z is estimated using indirect inference such that our model is consistent with the data, as described in Supplementary Appendix B. We arrive at an annualized $AR(1)$ coefficient of 0.88 and a standard deviation of the shock of 0.23.

The parameters governing the frictional product market require more thought: the customer depreciation rate δ_n, the matching function parameters ξ and γ, along with the function $\kappa(s)$. We use available evidence to set values for these parameters, returning to examine sensitivity later.

The customer depreciation rate δ_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

21. As most of the literature, we also abstract from inventories.

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

23. For example Gilchrist and Himmelberg (1995) estimate a value around 6, while Erickson and Whited (2000) a value around 20. In contrast, the direct investment-q regression evidence suggests a parameter around 30. Our results do not depend significantly on the value of the adjustment cost parameter, however.

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%, translating into annual rates of 11–26%. In online banking, the corresponding annual rates are in the 10–20% 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 (in addition to Bronnenberg *et al.* (2012) cited in the introduction), survey evidence on the frequency at which consumers switch their primary super market suggests annual customer turnover rates of 10–25%. Acknowledging that there exists significant heterogeneity on this dimension, we adopt an annual customer depreciation rate of $\delta_n = 0.15$.

Next, the parameters γ and ξ of the matching function $m(b,s) = \xi b^{\gamma} s^{1-\gamma}$ are determined based on evidence on the share of time spent in buying, selling and production activities at the aggregate level.[25] Our target for time spent in selling relative to production is 7.15%, and our target for time spent in buying relative to selling 25%. (Note that time devoted to production well exceeds that devoted to buying and selling.) To arrive at these targets, we use data on the share of the labour 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% of U.S. workers are employed in sales-related occupations.[26] Examples of such occupations include sales representatives, advertising agents, retail salespersons, cashiers, and real estate brokers. Because workers in other occupations are likely to spend a share of their time in selling activities also, we attribute 10% of their time to selling as well. Examples of other occupations with a significant selling component are advertising and promotions managers, marketing and sales managers, as well as waiters. Overall, this implies that 20% of working time is spent in selling activities.[27] 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. With 6.67% of market labour devoted to selling, time spent on selling relative to production amounts to 7.15%.

Turning to resources spent on buying, 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 0.56% of total time. With a third of total time spent on market labour (production and sales), buying relative to selling becomes 25%.

Finally, we adopt a quadratic specification for the function $\kappa(s) = \kappa_0 s^2/2$, where the value of κ_0 can be normalized to one, without loss of generality. With this, the targets for time spent on buying relative to selling and selling relative to production determine unique values for γ and ξ. Supplementary Appendix A shows these results.

The remaining parameter is the demand elasticity σ. It turns out that the variables we focus on in the subsequent analysis are unaffected by the specific value of σ, however, due to the calibration approach described above.[28]

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

24. See Raice (2010), Ackermann (2010), Food Marketing Institute (1994), Food Marketing Institute (2004).

25. Note that in the model agents are indifferent between spending their time in buying activities and market work (selling and production), as the opportunity cost is equal to the wage, normalized to one.

26. Data source: http://www.bls.gov/oes/tables.htm, accessed 4 April 2014.

27. 11% + 10% of 89% = 19.9%.

28. The value of σ does affect the scale of the industry for example, but not the ratios we focus on below, as shown in Supplementary Appendix A.

TABLE 1
Parametrization

Discount rate β	0.95
Persistence of productivity ρ_z	0.88
Standard deviation of productivity σ_z	0.23
Share of capital α	0.30
Depreciation of capital δ_k	0.10
Adjustment cost function coefficient φ_k	10
Depreciation of customers δ_n	0.15
Matching function elasticity γ	0.11
Matching function coefficient ξ	0.15

Notes: The table reports annual values.

3.2. *Comparing markets with differing degrees of friction*

In our empirical work, we seek to study whether the model predictions hold across product markets with differing degrees of friction. The first challenge in doing so is finding a way to measure the degree of friction based on available data. To this end, we use the following result, which states that in product markets with greater frictions, firms spend more on selling expenses relative to their sales.

Proposition 3. *Steady-state selling expenses relative to sales, $\kappa(s)/(py - s\eta(\theta)\varepsilon)$, are strictly decreasing in ξ.*

Proof See Supplementary Appendix A. ||

Differences in average selling expenses across markets are thus informative about differences in the degree of product market friction across these markets, ceteris paribus.

3.3. *Level effects*

The model then makes predictions about how various firm-level observables depend on the degree of friction. We begin with a theoretical result, stating that the greater the degree of friction in the product market, the greater are the average profit rate, Tobin's q, sales-to-capital ratio, and markup, for firms operating in that market.

Proposition 4. *(i) The steady-state firm profit rate π/k, Tobin's q v/k, sales-to-capital ratio $(py - s\eta(\theta)\varepsilon)/k$, and markup,* i.e., *sales per unit sold $(py - s\eta(\theta)\varepsilon)/y$ relative to marginal cost ℓ_y, are all strictly decreasing in ξ. (ii) The steady-state investment rate, $i/k = \delta_k$, is independent of ξ.*

Proof See Supplementary Appendix A. ||

Figure 1 illustrates these effects in the parameterized model. The top left panel shows that the greater the frictions, the more firms spend on customer acquisition, by plotting steady-state selling expenses as a function of $1/\xi$. In the frictionless limit (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 4–5% 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

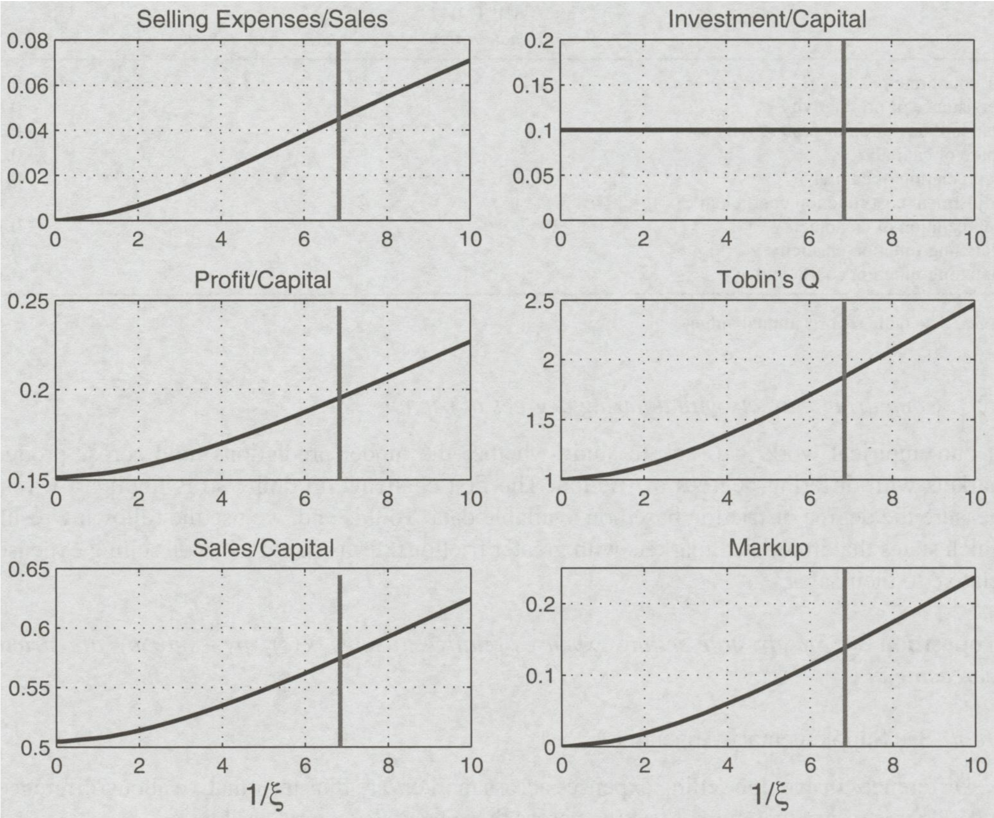

FIGURE 1

Impact of friction on steady state.

Notes: The figure plots the steady state as a function of the degree of friction, as measured by $1/\xi$, where ξ is the matching function coefficient. The frictionless limit is on the left, and the vertical line indicates our baseline parametrization. Selling expenses refer to $\kappa(s)$, sales to $py - s\eta(\theta)\varepsilon$, profit to sales net of labour costs of production and selling, and the markup to sales per unit sold $(py - s\eta(\theta)\varepsilon)/y$ over the marginal cost ℓ_y

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, firm value exceeds the value of physical capital because: (i) due to the up-front costs of customer acquisition, firms charge a positive markup on these customers later on, rendering existing customers valuable assets to the firm, and (ii) due to the convex costs of customer acquisition, even though competition for new customers drives the value of the marginal new customer to zero, the value of the average new customer exceeds that of the marginal. As a result, Tobin's q is as high as 1.9 in our benchmark parametrization, with an average markup of 14% (which translates into increased sales revenue per unit of capital as well). Similarly, averaging across new and existing customers leads to a firm profit rate of 20%, exceeding the cost of capital.[29] The steady-state investment rate remains unaffected, however, continuing to equal the depreciation rate of capital.

29. Recall that even if the present value of future profits the firm makes on 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.

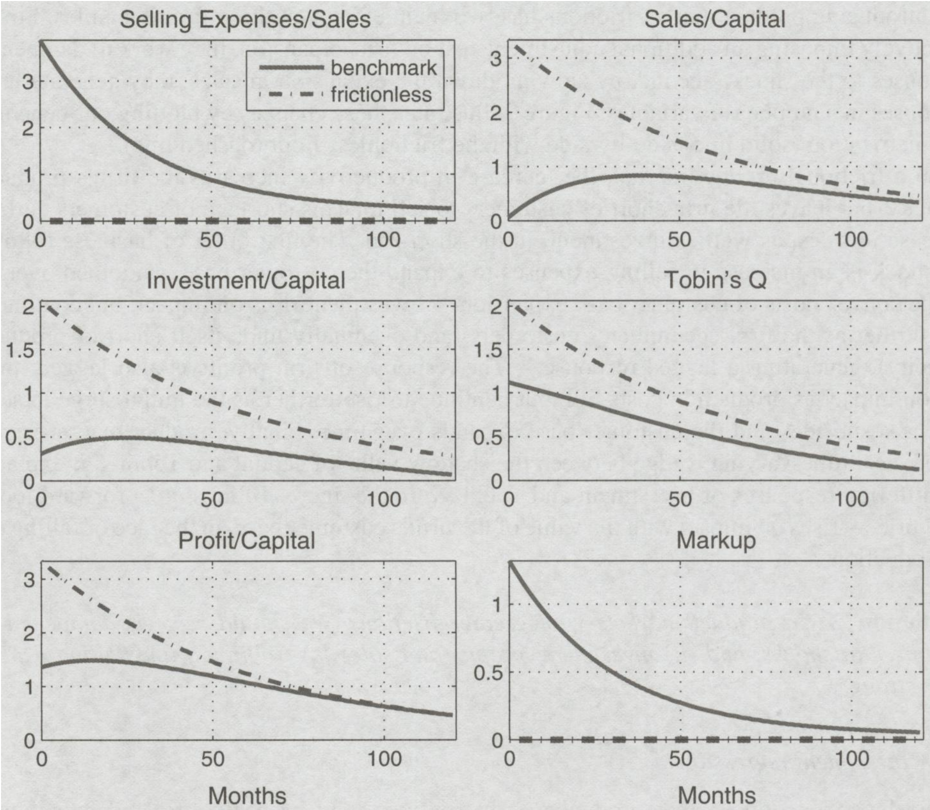

FIGURE 2

Impulse responses to firm-level productivity shock.

Notes: The responses are in percentage deviations from steady state. Selling expenses refer to $\kappa(s)$, sales to $py - s\eta(\theta)\varepsilon$, profit to sales net of labour costs of production and selling, and the markup to sales per unit sold $(py - s\eta(\theta)\varepsilon)/y$ over the marginal cost ℓ_y

Prediction 1. *In product markets with greater frictions, we should see greater average profit rates, Tobin's q, sales-to-capital ratios and markups, but identical investment rates, than in markets with lesser frictions.*

3.4. *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]

30. As shown by Hayashi (1982).

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 dampen firm responses to the shock. Second, by slowing down the expansion in sales, they generate lagged 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 lagged response.[32] The response of firm profits is also lagged: profits rise on impact as production costs fall, but continue to rise further as the initial surge in selling expenses subsides and the customer base expands over time. 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. Tobin's q—a forward looking asset price—rises on impact with the value of the firm's customer base, in the face of falling costs of production.

Prediction 2. *In product markets with greater 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.*

3.5. *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 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.

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

$$i_{jt}/k_{jt} = a_0 + a_1 q_{jt} + \varepsilon_{jt}, \text{ and} \tag{3.11}$$

$$i_{jt}/k_{jt} = a_0 + a_1 q_{jt} + a_2 \pi_{jt}/k_{jt} + \varepsilon_{jt}, \tag{3.12}$$

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

31. The convexity of $\kappa(s)$ 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 (2.8) for s is $\gamma^{-\gamma}(1-\gamma)^{\gamma-1}\kappa'(s)^{1-\gamma}/\xi$.

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 lagged, however, with Tobin's q rising on impact.

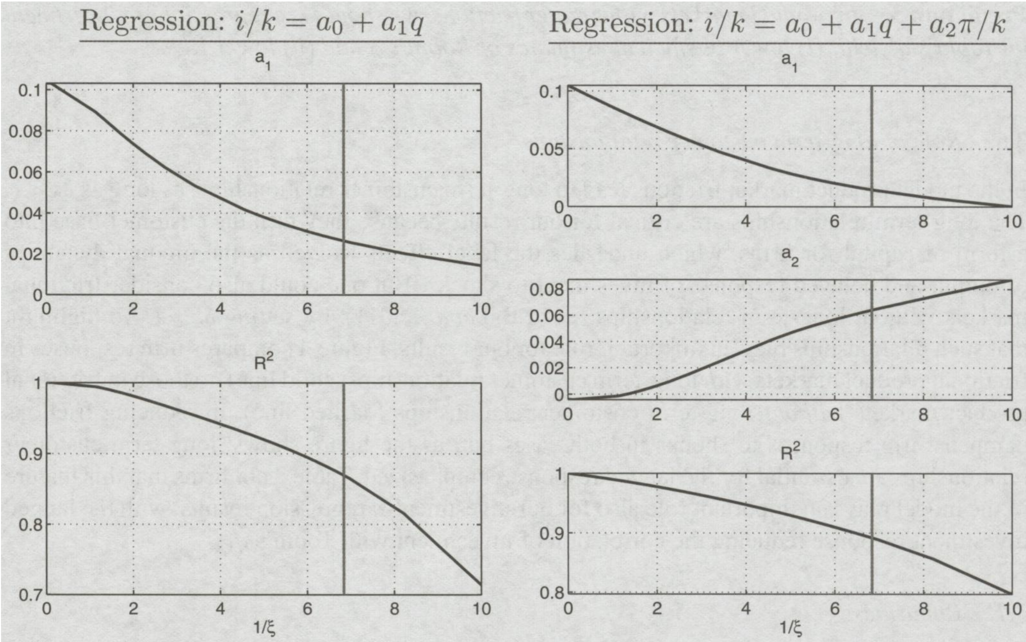

FIGURE 3

Impact of friction on investment-q regressions.

Notes: The figure plots the results from regressions (3.11) and (3.12) on model simulated data, as a function of the degree of friction, as measured by $1/\xi$, where ξ is the matching function coefficient. The frictionless limit is on the left, and the vertical line indicates our baseline parametrization

adjustment cost parameter, $1/\varphi_k = 0.10$, 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). Here the lower R^2 reflects the weaker correlation of investment with Tobin's q (as illustrated by the impulse responses), while the slope coefficient is attenuated further by the reduced volatility of investment relative to Tobin's q.[33]

Figure 3 also shows what happens 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, and the coefficient on cash flow 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 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. Figure 3 illustrates 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.

33. 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.

Prediction 3. *In product markets with greater 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.*

3.6. *Role of long-term customer relationships*

In the model product market frictions lead to long-term customer relationships, as long as $\delta_n < 1$. The long-term relationships are critical for our results because they turn the customer base into a form of capital for firms, which underlies the level effects as well as the gradual dynamics of output and delayed response of investment to shocks. But one could also consider frictional markets without long-term relationships (as in Bai *et al.*, 2011), by setting $\delta_n = 1$. To highlight that such relationships play an important role for our results, Figure 4 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 lagged responses emphasized. Table 2 confirms that this feature of the model plays an important role also for our investment-q regression results, with the lagged investment response reducing the correlation of investment with Tobin's q.

3.7. *Robustness*

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, Supplementary Appendix A considers the sensitivity of our results to lower targets for buying and selling activity, as well as higher customer depreciation rates. We find that our results are not strongly sensitive to the specifics of the parametrization used. We also show that the quadratic capital adjustment cost specification is not critical for our results, in that the model generates lagged investment responses even in the absence of capital adjustment costs, and that our regression results are not particularly sensitive to the magnitude of these costs.

Supplementary Appendix A also shows that our results would remain intact under an alternative pricing policy, where customers pay a constant price each period throughout the purchasing relationship, including the initial period. Even though we know that allocations remain unaffected by this change, some of our variables of interest involve prices, so it is useful to verify that the results are not driven by the front-loading of discounts in our baseline specification. As the results show, they are not. First, the customer base continues to be a valuable asset for firms due to the up-front costs of customer acquisition, despite the change in the timing of payments, so the steady-state predictions continue to hold. Second, the response of Tobin's q to a shock remains qualitatively identical: as a forward-looking asset price, it rises on impact with the value of the firm's customer base as costs decline. Hence, our basic investment-q regression results remain practically unaffected, as Table 2 shows. The main difference in the dynamics is that the lag in the response of profits to a shock becomes somewhat weaker, and this reduces slightly the cash flow coefficient in the cash flow augmented regression.

Further, we illustrate that a model with frictional labour (instead of product) markets will typically not produce our main results on the dynamics of firm investment. Introducing frictions in the labour market does introduce a form of intangible worker capital into the model, but does not lead to the clearly delayed investment responses customer capital does—the complementarity of customer capital with productive capacity plays a key role in generating these.[34]

34. As explained in the context of the impulse responses in Figure 2.

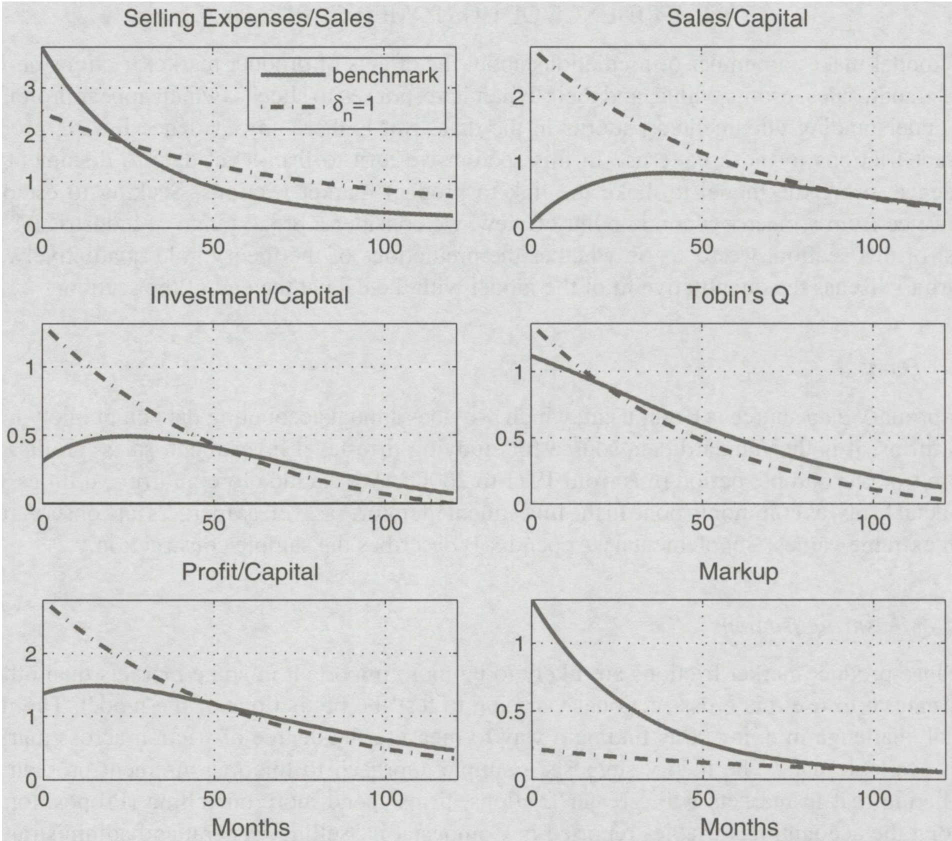

FIGURE 4

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 activity as the benchmark model. Selling expenses refer to $\kappa(s)$, sales to $py - s\eta(\theta)\varepsilon$, profit to sales net of labour costs of production and selling, and the markup to sales per unit sold $(py - s\eta(\theta)\varepsilon)/y$ over the marginal cost ℓ_y

TABLE 2

Investment-q regressions in alternative models

	Frictionless	$\delta_n = 1$	Benchmark	Constant Price	Labour friction
a_1	0.10	0.07	0.03	0.03	0.08
R^2	1.00	1.00	0.87	0.85	1.00

Notes: The table reports results from regression (3.11) 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. The model with alternative pricing is parameterized the same as the benchmark, the parametrization of the labour market model is described in Supplementary Appendix A, which also describes both of the latter specifications.

The investment-q regression results in Table 2 reflect this, with labour market frictions leading to much smaller departures from the frictionless model than product market frictions.[35]

35. Merz and Yashiv (2007) argue that a model with capital and labour adjustment costs, including interaction effects between the two, does well in explaining the relationship between investment and Tobin's q. Note that the spirit

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.[36] For most of this section, we focus on whether the predictions of the theory hold qualitatively, but return to discuss the quantitative fit of the model with the data at the end of the section.

4.1. *Data*

Our primary data source is Compustat, which provides annual accounting data on publicly listed U.S. firms. It is the standard data source for studying firm-level investment, sales, profits, and Tobin's q. Our sample period runs from 1971 to 2006.[37] We exclude foreign firms, utilities, and financial firms, as commonly done in the investment literature, as well as mergers and observations with extreme values. Supplementary Appendix B describes the sample construction.

4.2. *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 by predicting that in markets with greater frictions, firms spend more on selling (Proposition 3). 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 subsamples on the Predictions 1–3 discussed in Section 3.

Our sorting variable, SGA expenses, includes selling expenses such as advertising and marketing expenses, sales people's salaries, commissions and travel 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/sales and SGA expenses/sales is 0.32, while the firm-level time-series correlation between the two is 0.36. The industries falling into our

of their exercise differs from ours in that while we generate moments from calibrated, simulated models, and focus on firm-level data, they estimate a structural model using GMM on aggregate data, without needing to fully specify the data-generating process. Intuitively, it is not obvious that the negative interaction effects they find (between investment and hiring) would help generate lagged investment responses: if investing becomes less costly when the firm expands hiring, that should reinforce the on-impact response of investment rather than delaying it.

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

37. Our data on investment prices and depreciation rates end in 2008, and to avoid having our results be affected by the Great Recession period, we end the sample in 2006.

TABLE 3
Summary statistics

Medians	Low SE	High SE
Selling expenses/Sales	0.168	0.269
	(0.003)	(0.005)
Advertising/Sales	0.013	0.018
	(0.000)	(0.001)
Sales	233.62	198.34
	(9.74)	(9.89)
Growth rate of sales	0.037	0.035
	(0.002)	(0.002)
Assets	198.87	153.91
	(8.83)	(6.68)
Growth rate of assets	0.021	0.024
	(0.002)	(0.003)
Debt/Assets	0.195	0.138
	(0.004)	(0.004)
Dividends/Assets	0.002	0.001
	(0.000)	(0.000)
Number of firms	2209	1551
Number of observations	40856	28686
Share of observations in manufacturing	29%	31%
Share of total sales	68%	32%
Share of total assets	69%	31%

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

high and low SGA expense samples are given in Tables A2 and A1 in Appendix. 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, with median annual sales above 200 million of 2005 dollars. More than two-thirds of observations are outside of manufacturing. The high selling expense sample is slightly smaller, both in terms of numbers of firms, and share of total sales or assets.[38] Perhaps surprisingly, the samples are equally 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 smaller. There are substantial differences in selling expenses across samples, with firms in the high selling expense sample also spending significantly more on advertising.[39]

Next, we turn to study Predictions 1–3 of the model in this data.

4.3. *Prediction 1: Level effects*

Themodel predicts a positive relationship between the degree of product market friction and the levels of Tobin's q, profits/capital, sales/capital, and markups. To study this prediction, we first

38. The low and high selling expense samples are not equal in size because the largest industry in our sample (sic=36, Electronic and other electric equipment) in number of firms is the median industry. Here it is assigned to the low selling expense sample, making it larger in size, but the results would not be substantially affected by assigning it to the high selling expense sample instead.

39. The advertising figure is calculated for the subset of firms with separate data on advertising.

TABLE 4
Medians

	Low SE	High SE
Investment/Capital	0.137	0.136
	(0.002)	(0.002)
Profit/Capital	0.250	0.338
	(0.005)	(0.009)
Sales/Capital	2.409	3.201
	(0.047)	(0.062)
Markup	0.142	0.305
	(0.006)	(0.013)
Tobin's q	1.311	1.954
	(0.029)	(0.051)

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, except the investment rate.

compute time-series medians of Tobin's q, profits/capital, sales/capital, and markups for each firm. We then compute medians across firms of these time-series medians, for each subsample. The results line up with the model: Table 4 reveals a significant increase in each of these variables from the low to the high selling expense sample. Also consistent with the model, the investment rate remains similar across the subsamples.

Note that although the proper measurement of markups is a non-trivial problem beyond the scope of this article, the empirical measures provided in the table nevertheless allow a comparison across samples. We do not have data on marginal costs, but instead use the accounting variable "cost of goods sold," which covers most of labour and intermediate input costs, and adjust to account for the difference between average and marginal cost.[40]

While sorting industries into these two broad groups has the advantage of leaving two relatively large samples to study, it is useful to examine the evidence on a less aggregated level as well, even if sample sizes diminish in doing so. Turning thus to an industry-by-industry comparison, we compute medians across firms of the above time-series medians *for each industry separately.* The top panels in Figure 5 illustrate the results by plotting these measures of industry Tobin's q and profit rate against industry selling expenses. The results are consistent with the model, displaying a clear positive relationship in both cases, as well as significant variation across industries.

4.4. *Prediction 2: Firm dynamics*

The model predicts a negative relationship between the degree of product market friction and firm-level volatility. To study this prediction, we first compute time-series standard deviations of investment/capital, sales/capital, profits/capital, Tobin's q and markups for each firm. The left column of Table 5 then reports medians across firms of these time-series standard deviations, for each subsample. It turns out that with the exception of the investment rate, instead of a decrease in volatility, the table displays an increase in firm volatility from the low to the high selling expense sample.

40. With a Cobb–Douglas production function over capital, labour and intermediate inputs, the marginal cost can be written as (average cost of labour and intermediates)/(1 − capital share). We thus adjust our cost measure by dividing by 1 − capital share = 0.82. We arrive at this number as follows: First, the share of intermediate inputs in gross output is 0.45 (source: BEA industry tables). Then, if value added is attributed 2/3 to labour and 1/3 to capital, gross output is divided: 0.45 to intermediates, $0.55 \times 1/3 = 0.18$ to capital and $0.55 \times 2/3 = 0.37$ to labour.

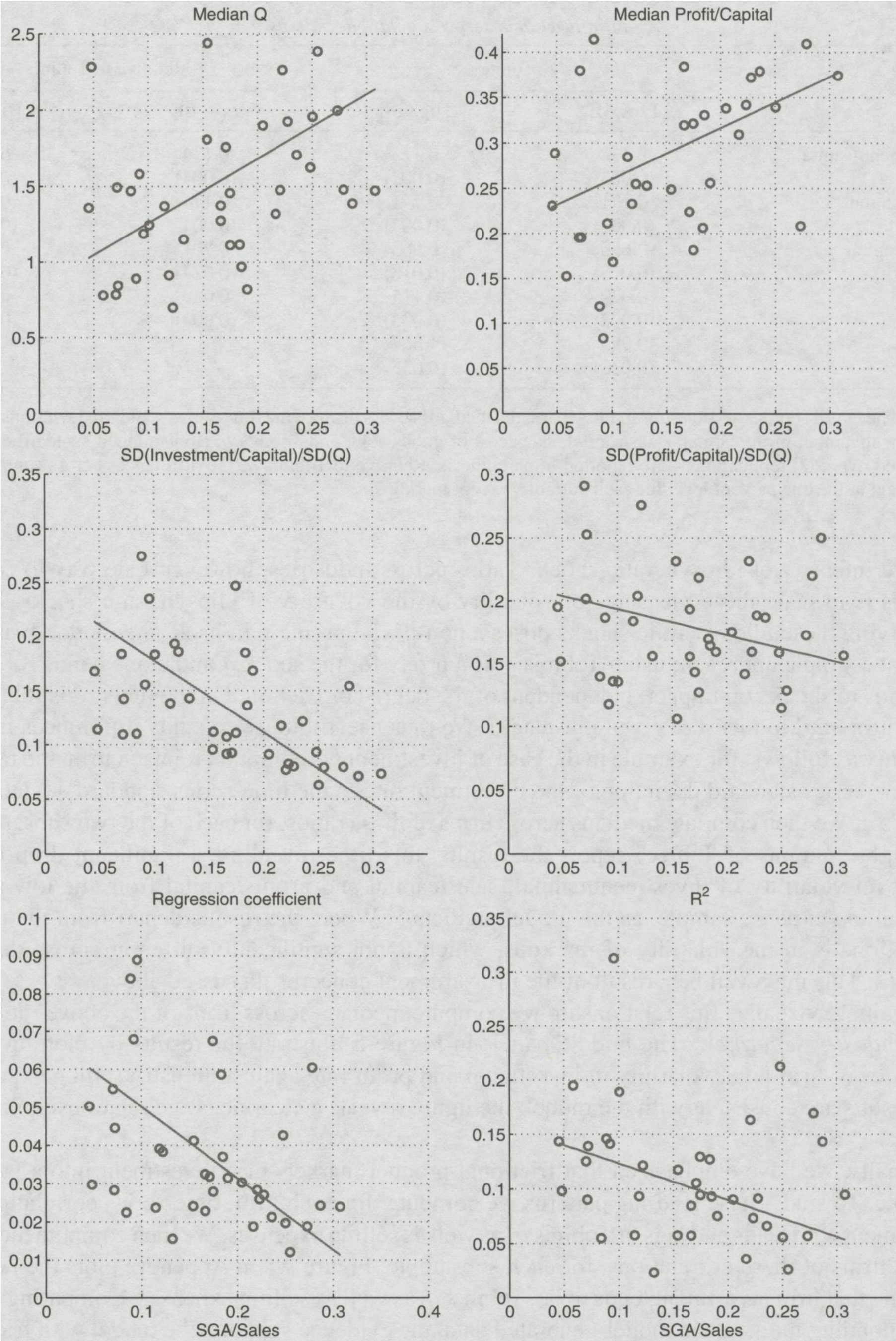

FIGURE 5

Industry selling expenses versus firm-level evidence: levels, volatilities, regressions.

Notes: Each circle corresponds to a two-digit SIC industry with 300 or more firm-year observations. 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 profit/capital (normalized by that of Tobin's q). The bottom two panels plot, for each industry, the slope coefficient and R^2 from regression (4.13) (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	0.132	0.125	0.134	0.080
	(0.003)	(0.003)	(0.004)	(0.003)
Profit/Capital	0.171	0.241	0.174	0.154
	(0.005)	(0.007)	(0.004)	(0.005)
Sales/Capital	0.690	0.963	0.701	0.615
	(0.018)	(0.018)	(0.024)	(0.019)
Markup	0.079	0.115	0.080	0.073
	(0.002)	(0.003)	(0.003)	(0.003)
Tobin's q	0.985	1.567	-	-
	(0.030)	(0.035)	-	-

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, except markups.

The intensity of idiosyncratic shocks varies across industries, however. One way to control 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.[41] We thus use Tobin's q to study differences 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 medians across firms of these ratios, for each of the two subsamples. The right columns of Table 5 report the results, this time revealing a significant drop in the firm-level volatility of investment/capital, sales/capital and profits/capital from the low to the high selling expense sample, as the model predicts.[42] Where the results depart from the model predictions is in the volatility of markups, which is not significantly different across the two samples. This may well be a result of the measurement concerns discussed above.

Again, to visualize this relationship we compute medians across firms of the above ratios *for each industry separately.* The middle panels in Figure 5 illustrate the results by plotting these measures of firm-level volatility in investment and profit rate against industry selling expenses. The results are consistent with the model: the figure reveals a clear negative relationship in both cases.

Finally, we have emphasized that frictional product markets turn investment into a lagging variable. To study these lead-lag patterns we compute, for each firm, time-series correlations of investment with leads and lags of Tobin's q, as well as selling expenses. We then compute medians across firms of these correlations, for each subsample. Figure A1 in Appendix plots the results, showing that firm investment tends to lag Tobin's q, as well as selling expenses. Comparing to the corresponding moments in model-generated data, the evidence supports the model with frictions

41. 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.

42. For reference, Figure 1 in Supplementary Appendix A plots these relationships in model-generated data. 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.

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	0.036	0.023	0.040	0.027	0.046	0.030	0.050	0.034
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
R^2	0.094	0.069	0.092	0.066	0.085	0.062	0.078	0.054

Notes: The table reports results from panel regression (4.13) 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.

(generating these lags) over the frictionless model (which predicts a contemporaneous relationship between investment and Tobin's q, and makes no predictions about selling expenses).[43]

4.5. *Prediction 3: Investment regressions*

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

$$i_{j,t}/k_{j,t-1} = a_0 + a_1 q_{j,t-1} + d_t + f_j + \varepsilon_{j,t}, \tag{4.13}$$

in both subsamples.[44] Here d_t controls for time effects and f_j firm fixed effects. The results in Table 6 are consistent with the literature, replicating the low slope coefficients and R^2's documented. But more importantly, comparing the two subsamples reveals that the empirical evidence lines 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.[45]

This cross-sample support for our theory only becomes more convincing when we turn to the industry-by-industry evidence: running these panel regressions for each industry separately confirms the negative relationship between industry selling expenses and both coefficient estimates and R^2's in these regressions. The bottom panels of Figure 5 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

$$i_{j,t}/k_{j,t-1} = a_0 + a_1 q_{j,t-1} + a_2 \pi_{j,t-1}/k_{j,t-1} + f_j + d_t + \varepsilon_{j,t}, \tag{4.14}$$

in both subsamples. Comparing samples in Table 7, we again see a significant drop in the slope coefficient on Tobin's q from the low to high selling expense sample. The coefficient estimates on cash flow are clearly significant and non-trivial in magnitude across the board, and show a significant increase from the low to high selling expense sample. These patterns are consistent with the predictions of the model, illustrated in Figure 3. Where the empirical results depart somewhat from the model predictions is in the R^2's of these cash-flow augmented regressions, which do not decrease from the low to high selling expense sample.

43. The model also produces the so-called lagged-investment effect emphasized by Eberly *et al.* (2012), *i.e.* the pattern where past investment has predictive power over current investment.

44. The model regressions were run with the timing which is correct in the model, while we follow the standard timing of investment regressions in the empirical literature, by using lagged values of Tobin's q. The empirical results would hold with the model-consistent timing also, however.

45. Because there is no strong theoretical motivation for including time and/or fixed effects, we report results with and without them. As Table 6 shows, our results do not depend on the specification. In addition, these results appear robust to changes in the definition of Tobin's q, as well as changes in the specification of the regressions (levels versus logs).

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	0.027	0.015	0.032	0.020	0.037	0.021	0.042	0.026
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
a_2	0.081	0.103	0.066	0.087	0.099	0.101	0.078	0.082
	(0.005)	(0.004)	(0.005)	(0.004)	(0.007)	(0.005)	(0.007)	(0.004)
R^2	0.115	0.137	0.114	0.134	0.105	0.132	0.100	0.123

Notes: The table reports results from panel regression (4.14) 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.

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 analysing a broader set of industries than manufacturing alone. To relate our findings to studies focusing on manufacturing, Tables A5 and A6 in Appendix report the corresponding results restricting the sample to manufacturing only. The conclusions continue to hold in this subsample.

4.6. *Industry-level shocks*

The above analysis focuses on firm-level shocks, but we could consider industry-level shocks as well by aggregating up the firm-level data. To this end we first compute, for each two-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 use these aggregated data to compute industry-level time-series standard deviations, as well as running time-series investment-q regressions. The results are consistent with the predictions of the model, with Figure 6 illustrating the results: a negative relationship between industry selling expenses and volatility, as well as industry selling expenses and investment-q regression results.

4.7. *Alternative explanations*

As discussed in the Introduction, a number of alternative theories have been proposed for the investment-q regression evidence, the main ones relaxing key assumptions of the neoclassical model by introducing market power, financing constraints, or non-convex capital adjustment costs. The results of the cross-industry comparisons are particularly valuable for distinguishing our theory from these alternatives, but a concern that remains is the possibility of a systematic relationship between these alternative theories and selling expenses, potentially explaining our regression results.[46]

To alleviate concerns that the cross-sectional support we have documented for the customer capital mechanism stems from an empirical correlation between measures of selling expenses and proxies for market power, financing constraints, or fixed costs, Figure 7 turns to the evidence on these relationships. The three cross-industry plots display the relationships between industry selling expenses and measures of industry concentration, dividend payout and firm size—all of which are rather weak. There is perhaps a marginally positive relationship between selling

46. We do not consider the interrelated factor demand story in this comparison, for lack of simple proxies to quantify differences across industries in that case.

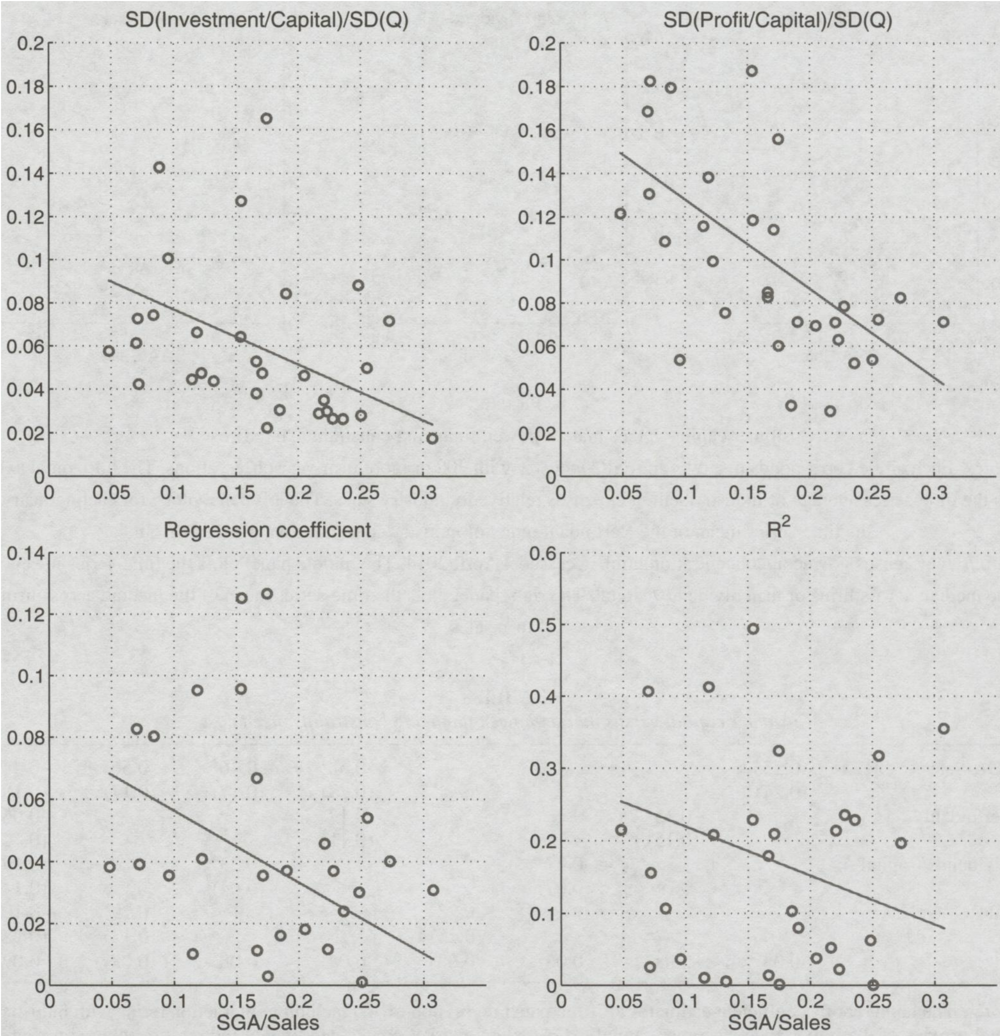

FIGURE 6

Industry selling expenses versus industry-level evidence: volatility, regressions.

Notes: Each circle corresponds to a 2-digit SIC industry with 300 or more firm-year observations. The horizontal axis is the time-series average of industry selling expenses relative to sales. The top two panels plot the time-series standard deviations of industry investment/capital and industry profits/capital (normalized by that of Tobin's q), and the bottom two results from the time-series regression of industry investment/capital on industry Tobin's q. We include a fitted line for reference

expenses and dividend payout, but it is not clear it would help explain our evidence: if financing constraints were causing our q-theory results, we might expect these regressions to work less well in industries with lower dividend payout,[47] and therefore lower selling expenses, rather than the opposite.

47. It is natural to assume that financing constraints are associated with reduced dividend payout. Note, however, that Kaplan and Zingales (1997) argue that investment-q regressions may work better in financially constrained industries.

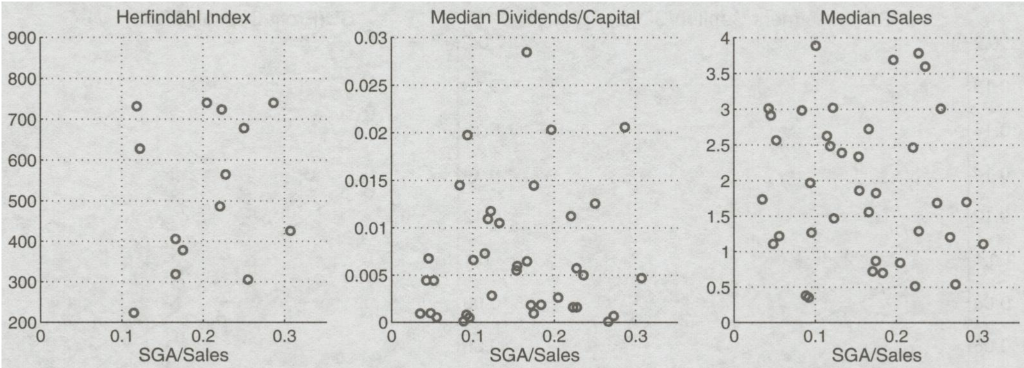

FIGURE 7

Customer capital versus market power, financing constraints, fixed costs.

Notes: Each circle corresponds to a two-digit SIC industry with 300 or more firm-year observations. The horizontal axis is the time-series average of industry selling expenses relative to industry sales. The left panel plots, for each industry, the time-series mean of the Herfindahl index of industry concentration, available from http://www.census.gov/econ/concentration.html, accessed 4 April 2014. The middle panel plots the time-series mean of the median across firms of firm dividends/capital. The right panel plots the time-series mean of the median across firms of firm sales

TABLE 8
Customer capital versus market power, financing constraints, fixed costs

SGA/Sales	−0.55*				−0.58*	−0.46*	−0.56*	−0.44*
	(0.24)				(0.23)	(0.17)	(0.17)	(0.15)
Herfindahl		0.15			0.17			−0.06
		(0.15)			(0.11)			(0.12)
Dividends/Capital			−0.27*			−0.23*		−0.19
			(0.07)			(0.04)		(0.14)
Sales				−0.28			−0.29*	−0.10
				(0.15)			(0.12)	(0.28)
R^2	0.08	0.08	0.08	0.08	0.08	0.08	0.08	0.09

Notes: The table reports coefficient estimates c_1^m from panel regression (4.15) including interaction terms with industry-level proxies of the importance customer capital (SGA/Sales), market power (Herfindahl index), financing constraints (Dividends/Capital), and fixed costs (Sales). Standard errors, in parenthesis, are clustered by industry. The sample is manufacturing only to allow including the Herfindahl index, while Table A7 in Appendix reports the corresponding results for the full sample.

The above evidence supports our mechanism as more-or-less orthogonal to these proposed alternatives. But how does it compare in terms of explanatory power? To address this, we run a horse race between these alternatives, with results reported in Table 8. The table displays results from the regression

$$i_{j,t}/k_{j,t-1}=a_0+a_1q_{j,t-1}+\sum_{m=1}^{4}c_0^m x_j^m+\sum_{m=1}^{4}c_1^m x_j^m q_{j,t-1}+f_j+d_t+\varepsilon_{j,t}, \tag{4.15}$$

where $\{x^m\}_{m=1}^4=$ {industry selling expenses, concentration, dividend payout and firm size}. To allow comparing the magnitudes of the coefficients to each other, we have normalized these industry variables $\{x^m\}$ such that the coefficient measures the effect of a one standard deviation change in the variable on the coefficient estimate on Tobin's q. (A coefficient of one would mean that a one standard deviation increase in the variable increases the coefficient estimate on q by 0.01.)

Including each variable in turn, we find that only selling expenses and dividend payout appear significant, with selling expenses having a clearly stronger effect. The effect of selling expenses remains significant and relatively stable across specifications, and when we include all the variables at the same time, it is the only one to remain significant.[48] Finally, note that while this table reports results restricting to manufacturing alone (to allow including the market concentration index in the horse race), Table A7 in Appendix reports the corresponding results on the broader sample. Our conclusions continue to hold there, with the impact of selling expenses even greater. We have also tried alternative measures of market power, financing constraints and fixed costs, and the results are robust.[49] We conclude that not only does customer capital provide an independent explanation for the empirical evidence, it appears at least comparable, if not stronger, in explanatory power than these alternatives.

4.8. *Explaining differences across markets quantitatively*

So far we have focused in the comparison on whether the differences across samples are economically and statistically significant, and line up with the theory qualitatively. A more demanding test is whether a plausibly calibrated version of our model can account for the observed variation across industries also quantitatively. To facilitate this assessment, Table 9 collects moments from the model and data, comparing the two side by side. Starting with the level of Tobin's q, note that the empirical measures vary from 1.37 in the low selling expense sample to 2.07 in the high selling expense sample. In the model, such an increase in q would correspond to our measure of frictions, $1/\xi$, increasing from roughly 4 to 8 (with our benchmark parametrization in between). The table proceeds to provide moments from the model for these two alternative parametrizations, to allow a comparison of low versus high friction markets.

As the table shows, this increase in frictions implies a drop in the model-generated regression coefficient on q from 0.05 to 0.02, which compares favourably with the evidence, and in the process the model-implied R^2 also falls quite significantly relative to the difference across samples in the data. The overall levels of R^2 in the model clearly exceed those in the data, but then even classical measurement error in investment would reduce these R^2's. The model does seem to generate roughly the right amount of cross-sectional variation in profit rates and markups, although the levels of both fall short of their empirical counterparts. This level difference may be reasonable given that the model abstracts from market power and decreasing returns in production. Finally, the model under-predicts the volatility of Tobin's q and over-predicts the volatility of profits, suggesting that there may be other shocks than those in the model that cause significant variation in stock market values, without corresponding effects on profits. Overall, we view the model's quantitative implications as reasonably in line with the data, given its stylized nature.

4.9. *Summing up*

The model makes a number of predictions which depend on the degree of friction in the product market, and the goal of this section has been to document the evidence on these predictions across a

48. A concern one might have in reading the table is that including both Sales and SGA/Sales simultaneously gives rise to a multicollinearity problem. The correlation between these variables is only weakly negative (-0.12), however, as both are constructed as time-series averages of industry medians.

49. Other indexes of market concentration than the Herfindahl, number of firms paying dividends, debt/asset ratio, external finance dependence, log sales, employment, log employment.

TABLE 9
Quantitative comparison: model versus data

	Model			Data		
	Low Frict.	High Frict.	*Diff.*	Low SE	High SE	*Diff.*
Level						
Tobin's q	1.37	2.07	*0.70*	1.31	1.95	*0.64*
Profit/Capital	0.17	0.21	*0.04*	0.25	0.34	*0.09*
Markup	0.06	0.17	*0.11*	0.14	0.30	*0.16*
Volatility						
Investment/Capital	0.04	0.02	*−0.02*	0.13	0.08	*−0.05*
Profit/Capital	0.39	0.25	*−0.13*	0.17	0.15	*−0.02*
Regression of i/k on q						
a_1	0.05	0.02	*−0.02*	0.05	0.03	*−0.02*
R^2	0.95	0.81	*−0.14*	0.08	0.05	*−0.02*
Regression of i/k on q and π/k						
a_1	0.04	0.01	*−0.03*	0.04	0.03	*−0.02*
a_2	0.03	0.07	*0.04*	0.08	0.08	*0.00*
R^2	0.96	0.84	*−0.11*	0.10	0.12	*0.02*

Notes: The table collects moments from the model and data (Figures 1 and 3, Tables 4, 6, and 7). For the model, low friction refers to $1/\xi = 4$ and high friction to $1/\xi = 8$.

range of markets. We find support for many of these predictions, although the evidence is arguably stronger for some predictions than others. The differences across samples and industries are clearly significant for the level effects, the relative volatilities, and regressions of investment on Tobin's q. A horse race between alternative explanations for the investment-q regression evidence also shows customer capital to provide an independent and at-least-equally (if not more) powerful explanation as proposed alternatives. Where the theory does less well is in the direct comparisons of the lead-lag patterns and levels of volatility across samples. These limitations may be driven in part by our approach—aimed at illustrating the mechanism by keeping the model relatively simple—which could be relaxed to allow matching the data more closely.[50] We discuss some natural directions to extend the model in the concluding section.

5. CONCLUDING REMARKS

This article studies, both theoretically and empirically, the implications of frictional product markets and long-term customer relationships for firm dynamics. To understand the 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.

On the theoretical side, we have abstracted from a number of elements which could be viewed as relevant here, such as endogenous customer turnover, customer poaching, an intensive margin of demand, inventories, intermediate inputs, all left for future work. On the empirical side, our exercise would clearly benefit from better measures of the customer base, including customer acquisition and turnover rates, calling for developing the evidence on these. It would also be interesting to consider a structural estimation approach, perhaps focusing on industries with more detailed evidence available.

50. We assume, for example, that all firms face the same shock structure, constant-returns technology and capital adjustment costs.

Finally, although we have focused on firm-level dynamics in the article, the theory provides a natural framework for studying the role of customer base concerns for business cycle dynamics as well. Introducing customer capital into a standard general equilibrium macroeconomic model not only generates hump-shaped responses to aggregate shocks, in line with the evidence in Blanchard and Quah (1989), but also for example a counter-cyclical labour wedge, in line with the evidence in Shimer (2009).

APPENDIX: ADDITIONAL EMPIRICAL RESULTS

TABLE A1
Low SGA industries

Division A: Agriculture, forestry, and fishing	
	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

TABLE A2
High SGA industries

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, analysing, 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
	82: Educational services

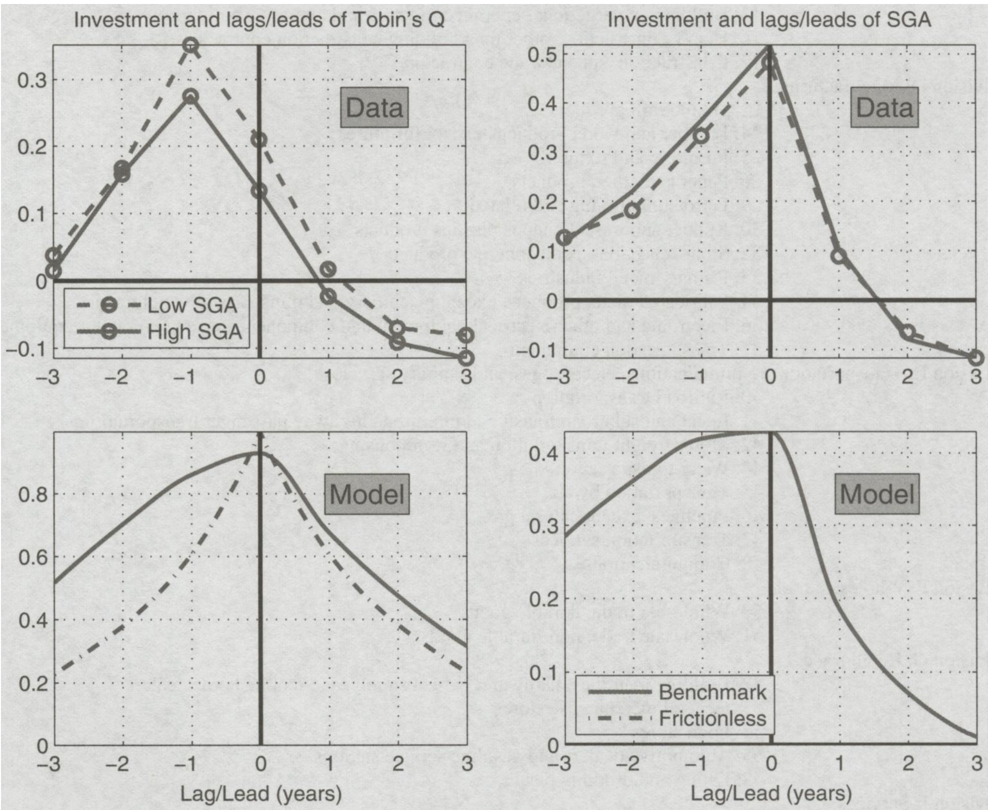

FIGURE A1

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 with and without frictions. Tables A3 and A4 in Appendix report the numbers, including standard errors.

TABLE A3
Firm-level cross-correlations of i_t/k_t with q_{t+j}

j	−3	−2	−1	0	1	2	3
Low SE	0.039	0.170	0.353	0.213	0.020	−0.063	−0.081
	(0.004)	(0.004)	(0.005)	(0.004)	(0.005)	(0.004)	(0.002)
High SE	0.015	0.152	0.269	0.134	−0.026	−0.093	−0.122
	(0.004)	(0.006)	(0.007)	(0.005)	(0.004)	(0.004)	(0.004)

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 A4
Firm-level cross-correlations of i_t/k_t with SE_{t+j}/k_{t+j}

j	−3	−2	−1	0	1	2	3
Low SE	0.126	0.182	0.333	0.482	0.089	−0.064	−0.116
	(0.005)	(0.003)	(0.003)	(0.005)	(0.003)	(0.004)	(0.004)
High SE	0.116	0.220	0.364	0.518	0.103	−0.079	−0.116
	0.006)	(0.005)	(0.004)	(0.004)	(0.004)	(0.008)	(0.004)

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 A5
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	0.031	0.023	0.036	0.028	0.037	0.028	0.042	0.033
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
R^2	0.095	0.070	0.091	0.067	0.091	0.067	0.081	0.056

Notes: The table reports results from panel regression (4.13) on the subset of industries in manufacturing, with and without firm fixed effects and time effects. Robust standard errors are reported in parenthesis.

TABLE A6
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	0.020	0.015	0.026	0.020	0.026	0.018	0.033	0.025
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.002)	(0.001)
a_2	0.104	0.097	0.088	0.082	0.111	0.106	0.084	0.088
	(0.007)	(0.004)	(0.007)	(0.004)	(0.009)	(0.006)	(0.009)	(0.005)
R^2	0.138	0.127	0.135	0.123	0.134	0.124	0.125	0.116

Notes: The table reports results from panel regression (4.14) on the subset of industries in manufacturing, with and without firm fixed effects and time effects. Robust standard errors are reported in parenthesis.

TABLE A7
Customer capital versus financing constraints, fixed costs

SGA/Sales	−0.86**			−0.94**	−0.84**	−0.93**
	(0.29)			(0.31)	(0.29)	(0.32)
Dividends/Capital		−0.30*			−0.24*	−0.04
		(0.15)			(0.09)	(0.14)
Sales			−0.13	−0.35*		−0.31
			(0.20)	(0.16)		(0.23)
R^2	0.09	0.08	0.08	0.09	0.09	0.09

Notes: The table reports coefficient estimates c_1^m from panel regression (4.15) including interaction terms with industry-level proxies of the importance customer capital (SGA/Sales), financing constraints (Dividends/Capital), and fixed costs (Sales). Standard errors, in parenthesis, are clustered by industry.

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Supplementary Data

Supplementary data are available at *Review of Economic Studies* online.

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