Production Outsourcing and Demand Variability

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Abstract:
We examine the relation between demand variability and firms’ production outsourcing decisions. Contrary to the traditional intuition, we predict that demand variability has a negative impact on outsourcing by a manufacturer from a supplier. The analytical intuition is that the manufacturer does not smooth its production orders from the supplier under outsourcing, increasing supply chain costs. When demand variability is high, this is likely to outweigh the supplier’s cost advantage, leading to a negative relation between demand variability and outsourcing. We test this prediction using a large sample of manufacturing firms in Turkey. As predicted, we find that firms facing a more variable demand outsource a smaller proportion of their manufacturing costs on average, and are less likely to engage in outsourcing. The results are significant both statistically and economically and are robust to alternative specifications.

Key words: outsourcing, demand variability, production smoothing in supply chain.
1. Introduction

We examine the relation between firms’ production outsourcing decisions and demand variability, a key risk factor in the supply chain. Following prior literature (e.g., Lee et al. 1997; Randall et al. 2006; Netessine and Rumyantsev 2007; Gaur et al. 2007; Bray and Mendelson 2012), we interpret demand variability in terms of the variance of demand. The traditional intuition suggests that firms facing a more variable demand benefit more from outsourcing. However, we argue that outsourcing of production by a manufacturer from a supplier can increase production variability, because the manufacturer does not have an incentive to smooth her production orders from the supplier (but does have an incentive to smooth her own production in the case of insourcing). Higher production variability increases the supplier’s costs, and is likely to outweigh the savings from his cost advantage when demand variability is high. The resulting cost increase for the supplier is passed on to the manufacturer in the form of a higher equilibrium wholesale price. Therefore, when demand variability is sufficiently high, the wholesale price under outsourcing is likely to exceed the manufacturer’s internal production costs in the case of insourcing. This leads to a negative relation between demand variability and outsourcing, contrary to the traditional intuition. Empirical estimates for a large representative sample of manufacturing firms in Turkey support our argument.

To develop the intuition behind this apparently surprising result in a simple model, we incorporate the sourcing decision into the demand signal processing model of Lee et al. (1997). Lee et al. consider a firm (a “manufacturer” in our context) that faces stochastic demand over multiple periods, and show that optimal inventory management by the firm can increase the variance of its orders from the supplier relative to the variance of its downstream demand, a phenomenon known as the “bullwhip effect.” We extend the model in two ways. First, we assume that in the initial period the manufacturer can make a long-term choice

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1 For example, in a recent survey by the Economist magazine of executives responsible for risk management, 62% cited inability to predict future demand as a major risk factor (The Economist Intelligence Unit 2009).
2 Bray and Mendelson (2012) show empirically that the bullwhip effect is prevalent for a majority of firms. Chen and Lee (2012) point out that empirical estimates can understate the bullwhip effect because of temporal aggregation in the data, i.e., the actual prevalence of the bullwhip effect is likely to be even higher. Our predictions do not require the existence of a bullwhip effect but are stronger when it is present.
between insourcing (internal production) and outsourcing (purchasing finished units from a supplier at a given wholesale price, as in Lee et al.\textsuperscript{3}).\textsuperscript{3} Second, we model how the equilibrium wholesale price under outsourcing arises from competition among the potential suppliers, who have a cost advantage over the manufacturer. We examine how demand variability affects the manufacturer’s internal production costs under insourcing and the equilibrium wholesale price under outsourcing, the two main determinants of the manufacturer’s sourcing choice.

We assume that the manufacturer’s and the supplier’s production cost functions are convex, i.e., production variability is costly (e.g., Anand and Mendelson 1997; Aviv 2007; Chen and Lee 2009). Due to convexity, in the insourcing scenario the manufacturer will smooth her own production to reduce the expected costs, using inventory to absorb demand fluctuations (Kahn 1987; Graves et al. 1998; Balakrishnan et al. 2004). In contrast, in the outsourcing scenario the marginal cost of the manufacturer is equal to the equilibrium wholesale price. Therefore, the manufacturer does not have an incentive to smooth her production orders from the supplier. This causes incremental production variability for the supplier (relative to the manufacturer’s production variability under insourcing), which increases the supplier’s costs.

The supplier’s expected costs determine the equilibrium wholesale price in the case of outsourcing. Variability in the supplier’s production increases the wholesale price, whereas his cost advantage reduces the wholesale price. The manufacturer weighs the equilibrium wholesale price under outsourcing against her own production costs in the case of insourcing.\textsuperscript{4} If demand variability is low, the supplier’s cost advantage dominates, reducing the wholesale price below the manufacturer’s internal production costs.

\textsuperscript{3} Bullwhip effect models are typically formulated in terms of the relationship between a retailer and a supplier, in which insourcing is impractical. Lee et al. (1997) point out that the bullwhip effect can arise not only at the retail level but also further upstream in the supply chain, such as between the manufacturer and the manufacturer’s supplier in our analysis.

\textsuperscript{4} To maintain a clear focus on the effects of demand variability in a simple model, we eliminate other factors that could potentially deter outsourcing, such as supply chain delays (e.g., Jain et al. 2014), information asymmetry (Wang et al. 1997; Lee et al. 2000; Chen and Lee 2009), supplier’s bargaining power (Van Mieghem 1999), double-marginalization (Cachon 2003), hold-up problems (Klein et al. 1978; Grossman and Hart 1986; Shelanski and Klein 1995), and suboptimal capacity choices by the supplier (Cachon and Lariviere 2002; Bernstein and DeCroix 2004). We also abstract from the impact of demand variability on production technology choices (e.g., Randall and Ulrich 2001; Netessine et al. 2002; Randall et al. 2003; Goyal and Netessine 2007). In addition to production costs, the sourcing decision likely affects the manufacturer’s inventory-related costs; we capture this effect in our model.
Therefore, the manufacturer will outsource. However, if demand variability is sufficiently high, the supplier’s costs of incremental production variability under outsourcing will outweigh his cost advantage. This will raise the equilibrium wholesale price above the manufacturer’s internal production costs, and the manufacturer will prefer to insource. Therefore, we predict that on average, higher demand variability is associated with less outsourcing.

We test this prediction using confidential data for 16,598 firms (97,903 firm-years) from the Turkish Annual Business Statistics Survey during 2003–2011. Prior studies (e.g., Novak and Eppington 2001; Baker and Hubbard 2004; McIvor 2009; Novak and Stern 2009; Rowley and Simcoe 2010) have been limited to small firm- or industry-specific samples due to lack of broad-based data on outsourcing. In contrast, our sample is representative of the entire manufacturing sector in Turkey and contains both public and private firms. The data includes production outsourcing costs, which reflect production activities subcontracted to third parties, along with accounting information and firm characteristics. To the best of our knowledge, this dataset is unique in its comprehensive coverage of outsourcing costs for a broad population of firms. Following Cachon et al. (2007), we use sales as an empirical proxy for demand, and measure demand variability for each firm as the standard deviation of log-changes in deflated sales.

The empirical results support our predictions. As expected, greater demand variability (using the standard deviation of log-changes in sales as a proxy) is associated with significantly less production outsourcing, which manifests both as a lower ratio of outsourcing costs to total costs and as a lower probability of outsourcing. The impact of demand variability is economically significant. For example, when demand variability rises from its bottom quartile to its top quartile, the ratio of outsourcing costs to total costs is reduced by about 8%, and the probability of outsourcing decreases by about 10%. The relation between demand variability and outsourcing varies predictably with firm characteristics, consistent with the theory. The results are robust to inclusion of additional control variables, alternative measures of demand variability and uncertainty, and various subsamples.

We next develop the analytical model in section 2, describe the data and the empirical model in section 3, present the empirical results in section 4, and conclude in section 5.
2. Analytical Model of Production Outsourcing

Our objective in this section is to develop a parsimonious analytical model that captures how the outsourcing decision may be affected by demand variability. We use the demand signal processing model of Lee et al. (1997) as a starting point. Lee et al. consider a firm (a “manufacturer” in our model) that faces an exogenously given wholesale price from the supplier and chooses optimal order amounts and inventory levels to meet uncertain demand in multiple periods. They show that optimal inventory planning can amplify downstream demand fluctuations, giving rise to the bullwhip effect. We extend their model in two ways. First, we add the manufacturer firm’s sourcing decision. In the initial period, the manufacturer makes a long-term choice between internal production (the insourcing scenario) and purchasing finished units from a supplier (the outsourcing scenario, which is identical to Lee et al.’s analysis). Second, we model how the equilibrium wholesale price arises, and how it is affected by demand variability and the supplier’s cost advantage.

The manufacturer’s sourcing choice in the initial period \( t = 0 \) determines her cost structure for all subsequent periods \( t = 1, \ldots, \infty \). In the insourcing scenario, the manufacturer’s total cost of making \( z \) finished units is \( C(z) = c_1 z + \frac{c_2}{2} z^2 \), following Anand and Mendelson (1997), where \( C(0) \) is normalized to zero and the marginal cost \( C'(z) = c_1 + c_2 z \) is positive. We assume that \( C'(z) \) is increasing in \( z \), i.e., the cost function is convex \( (C''(z) = c_2 > 0) \). This assumption is warranted when some of the production inputs are fixed in the short run, which limits production capacity and causes congestion at high output levels (e.g., Lee and Billington 1993; Aviv 2007; Chen and Lee 2009). Because the cost function is convex, production variability increases the expected costs. Lee et al. (1997) report that this effect of production variability is large in practice, causing excess costs in the range between 12.5% to 25% according to trade estimates.

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5 For simplicity, we assume that the entire production process is either performed in-house or outsourced. The model can also be interpreted as a single stage in a multi-stage production process, following Graves et al. (1998), with potentially different sourcing decisions in different stages.
In the outsourcing scenario, the manufacturer purchases finished units from a supplier at a wholesale price \( p \) per unit. We assume that in the initial period, multiple (and ex ante identical) suppliers compete for a contract to supply the manufacturer. The manufacturer-supplier relationship often requires significant relationship-specific capacity investment by the supplier (e.g., Netessine and Swinney 2011). Therefore, we assume that the contract is both long-term, to deter the hold-up problem (e.g., Klein et al. 1978), and exclusive, to avoid wasteful duplication of relationship-specific capacity.\(^6\) As a result of price competition among suppliers, the equilibrium wholesale price is reduced until the net present value (NPV) of expected profit for the winning supplier is zero (e.g., Shy 1995).\(^7\) In other words, the manufacturer captures all of the gains from the relationship, and the supplier has zero bargaining power due to competition. We make this assumption to isolate the effects of demand variability, because supplier’s bargaining power could potentially deter outsourcing (e.g., Van Mieghem 1999; Holcomb and Hitt 2007; Feng and Lu 2012) even when the demand is stable.

The supplier’s cost function in the outsourcing scenario is \( (1 - \delta)C(z) \), where \( z \) stands for the manufacturer’s production order from the supplier. The parameter \( \delta \geq 0 \) captures the supplier’s cost advantage over the manufacturer, which can arise due to economies of scale or scope, efficiency gains through specialization, or pooling of resources across multiple clients (e.g., Van Mieghem 1999; Cachon and Harker 2002; Holcomb and Hitt 2007; McIvor 2009; Feng and Lu 2012). Because a larger cost

\(^6\) A large literature examines sourcing from multiple suppliers, which is more relevant for standardized components that do not require relationship-specific investment. For example, Wang and Seidmann (1995) consider the impact of information technology on competition among suppliers, Honhon et al. (2012) examine optimal sourcing from several heterogeneous suppliers, while Lee and Whang (2002) and Mendelson and Tunca (2007) consider spot market trade as an additional source of supply.

\(^7\) If the net present value of profit for the winning supplier is positive, then another supplier will be willing to offer a slightly lower price to win the contract. Therefore, the equilibrium price is bid down until none of the potential suppliers has an incentive to undercut the current price. This zero-profit outcome can also arise if the manufacturer makes a take-it-or-leave-it offer of contract terms to a supplier (Cachon and Lariviere 2001). Because the wholesale price is fixed for the duration of the contract, the zero-profit condition is formulated in terms of the net present value of profit rather than profit in a single period. Economic profit incorporates the opportunity cost of all economic resources, including entrepreneurship (e.g., Mankiw 2014, p. 262); therefore, it is worthwhile for the supplier to bid despite zero profit.
advantage \( \delta \) reduces the convexity of the supplier’s cost function \( (1 - \delta)C(z) \), it not only reduces his total costs at any given production level but also improves his ability to cope with production variability.\(^8\)

After the sourcing choice has been made in the initial period \( t = 0 \), the demand and timing for periods \( t = 1, \ldots, \infty \) follow Lee et al. (1997). At the beginning of period \( t \), the manufacturer makes or buys \( z_t \) units. These units are added to inventory immediately, resulting in a total available stock of \( S_t \) units.\(^9\) Next, demand \( D_t \) is realized and fulfilled. When \( D_t > S_t \), excess demand is backlogged, and the manufacturer incurs a shortage penalty \( \pi \) for each backlogged unit. When \( D_t < S_t \), the manufacturer incurs a holding cost \( h \) for each unsold unit. The demand follows a first-order autoregressive process

\[
D_t = d + \rho D_{t-1} + u_t
\]

(1)

where the parameter \( \rho \) (\( 0 \leq \rho < 1 \)) determines demand persistence, and \( u_t \) is an independent identically distributed random variable drawn from a normal distribution \( N(0, \sigma^2) \). The parameter \( \sigma \) reflects demand variability \( SD\{D_t\} = \sigma/\sqrt{1 - \rho^2} \), which we measure as a standard deviation (rather than a variance) for consistency with our empirical specification.

We analyze the model in two steps. First, we examine the manufacturer’s optimal production and inventory choices in periods \( t = 1, \ldots, \infty \) under insourcing and outsourcing (§2.1). Second, we characterize the supplier’s equilibrium wholesale price \( p \) under outsourcing, which is set in period \( t = 0 \) based on the anticipated future distribution of production orders from step 1. We then examine how demand variability affects the wholesale price and the manufacturer’s expected costs under outsourcing relative to her expected costs in the case of insourcing, a tradeoff that determines her sourcing choice in the initial period (§2.2).

\(^8\) The supplier could potentially maintain his own inventory to further mitigate the costs of production variability. For simplicity, we do not model the supplier’s inventory, but his cost function can be viewed as a reduced form approximation incorporating this additional inventory.

\(^9\) We assume that both the manufacturer and the supplier have zero lead time. This constitutes a best-case scenario for outsourcing, which does not involve any delays (Jain et al. 2014) or information distortions (Lee and Whang 1999; Chen and Lee 2009) in the supply chain. These additional factors could further shift the results in favor of insourcing when demand variability is high. A large literature examines information sharing with the supplier as a way to mitigate the bullwhip effect (e.g., Graves 1999; Cachon and Fisher 2000; Chen et al. 2000; Lee et al. 2000; Raghunathan 2001; Aviv 2003, 2007; Gaur et al. 2005b; Chen and Lee 2009). Because the lead time is zero and the demand follows a simple autoregressive process, the supplier can fully infer the manufacturer’s demand information from her orders. Therefore, information sharing would not improve the outsourcing outcome in our model.
2.1. Optimal Production and Inventory Choices under Insourcing and Outsourcing

Under insourcing, in each period $t = 1, \ldots, \infty$ the manufacturer solves the following cost minimization

$$\min_{S_t} E_t \left\{ \sum_{t'=t}^{\infty} \beta^{t'-t} \left[ C(z_t) + g(S_t, D_t) \right] \right\}$$

(2)

where $C(z)$ is the production cost function, $g(S, D) = h \times \max\{S - D, 0\} + \pi \times \max\{D - S, 0\}$ is the shortage and holding cost, $S_t = S_{t-1} - D_{t-1} + z_t$ is the available stock in period $t$, and $\beta$ is the discount factor. The expectation $E_t$ is based on the information available at the beginning of period $t$, which does not include current demand $D_t$ as it is realized later in the period.

The first order condition with respect to $S_t$ is

$$C'(z_t) - \beta E_t \{C'(z_{t+1})\} + E_t \left\{ \frac{\partial g(S_t, D_t)}{\partial S_t} \right\} = 0$$

(3)

This condition represents a tradeoff between the net present value of the cost of adding a marginal inventory unit in the current period, $C'(z_t) - \beta E_t \{C'(z_{t+1})\}$, and the impact of this unit on the expected shortage and holding costs, $E_t \{\partial g(S_t, D_t) / \partial S_t\}$. Because the marginal cost $C'(z)$ is increasing with production quantity $z$, the present value of manufacturing costs can be reduced by shifting production from a period with high output (and high marginal costs) to a period with low output (and low marginal costs) until $C'(z_t) = \beta E_t \{C'(z_{t+1})\}$. This production smoothing incentive reduces production variability, using inventory as a buffer to absorb demand fluctuations (e.g., Graves et al. 1998; Balakrishnan et al. 2004). At the optimum, it is balanced against the inventory planning incentives, which are captured by $E_t \{\partial g(S_t, D_t) / \partial S_t\}$ and are discussed later. Condition (3) defines the optimal decision rules $z_t^{IN}(S_{t-1}, D_{t-1}), S_t^{IN}(S_{t-1}, D_{t-1})$ for the insourcing scenario, which do not have an analytical solution but can be solved numerically.

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10 If the manufacturer makes an extra unit in current period $t$, incurring a marginal cost $C'(z_t)$, production for the next period $t+1$ can be reduced equally, saving $C'(z_{t+1})$. Therefore, the net effect is $C'(z_t) - \beta C'(z_{t+1})$.  

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In the outsourcing scenario, the manufacturer solves a different cost minimization

$$\min_{(S_t)} E_t \left( \sum_{t=1}^{\infty} \beta^{t-1} [pz_t + g(S_t, D_t)] \right)$$

(4)

where \( p \) represents the supplier’s wholesale price, which was set in the initial period.

The first order condition is

$$p(1 - \beta) + E_t \left\{ \frac{\partial g(S_t, D_t)}{\partial S_t} \right\} = 0$$

(5)

Unlike (3) in the insourcing scenario, this condition does not lead to production smoothing. Whereas in the case of internal production the manufacturer has an increasing marginal cost \( C'(z) \), under outsourcing she faces a constant marginal cost \( p \). Therefore, she cannot reduce her total costs by shifting production orders from a period with a high \( z \) to a period with a low \( z \).

In other words, because the manufacturer faces a linear total cost function under outsourcing, versus a convex function under insourcing, she is not motivated to reduce the variability of her production orders from the supplier. Condition (5) defines the optimal decision rules \( z_t^{\text{OUT}}(S_{t-1}, D_{t-1}), S_t^{\text{OUT}}(S_{t-1}, D_{t-1}) \) for the outsourcing scenario. They have an analytical solution (Lee et al. 1997), presented in Appendix A.

The two scenarios include an identical inventory planning problem. It involves a tradeoff between the net present value of the cost of adding a marginal inventory unit, equal to \( C'(z_t) - \beta E_t \{ C'(z_{t+1}) \} \) in (3) or \( p(1 - \beta) \) in (5), and the impact of this marginal unit on the expected shortage and holding costs, \( E_t \{ \partial g(S_t, D_t) / \partial S_t \} \). Lee et al. (1997) show that when the demand is positively serially correlated (\( \rho > 0 \)), optimal inventory management amplifies demand fluctuations. In particular, to reduce the expected shortage and holding costs \( E_t \{ g(S_t, D_t) \} \), the available stock \( S_t \) should be matched to the anticipated demand \( E_t \{ D_t \} = d + \rho D_{t-1} \). Given \( \rho > 0 \), the anticipated demand \( E_t \{ D_t \} \) and the desired stock \( S_t \) are both increasing in \( D_{t-1} \). Therefore, when observed demand \( D_{t-1} \) rises, the firm acquires new units not only

11 The supplier has an increasing marginal cost \( (1 - \delta)C'(z) \). Therefore, the supplier’s total costs would be reduced by order smoothing. However, the manufacturer would not benefit from this cost reduction because she faces a predetermined wholesale price \( p \) from the supplier.

12 For example, under outsourcing, the optimal stock \( S_t^{\text{OUT}} \) is equal to the expected demand \( E_t \{ D_t \} \) plus a constant safety stock, which reflects an optimal balance between shortage, holding, and carrying costs (equation A.2 in the Appendix).
to replenish the $D_{t-1}$ units sold but also to increase the stock $S_t$. As a result, the desired production or order amount $z_t$ rises more than proportionately to the demand increase. This raises the variability of $z_t$ relative to that of demand, giving rise to the bullwhip effect.

Under insourcing, the bullwhip effect is counteracted by production smoothing. Therefore, the manufacturer’s production levels under insourcing ($z_t^{IN}$) are less sensitive to demand changes than are her production orders from the supplier under outsourcing ($z_t^{OUT}$). This reduces the variance of the manufacturer’s production under insourcing relative to the variance of the supplier’s production in the case of outsourcing. In other words, outsourcing causes incremental production variability relative to insourcing.

**Lemma 1.** The manufacturer’s internal production levels $z_t^{IN}$ under insourcing are less sensitive to demand fluctuations than are her production orders $z_t^{OUT}$ under outsourcing.

**Proof.** See Appendix B.

### 2.2. The Impact of Demand Variability on the Manufacturer’s Sourcing Choice

At the beginning of period $t = 0$, the potential suppliers anticipate the manufacturer’s future ordering behavior under outsourcing, summarized by the decision rules $z_t^{OUT}(S_{t-1}, D_{t-1})$, $S_t^{OUT}(S_{t-1}, D_{t-1})$ that arise from condition (5). Because in equilibrium the net present value of expected profit for the winning supplier is zero, the equilibrium wholesale price $p$ satisfies

$$E_0\{\sum_{\tau=1}^{\infty} \beta^\tau p z_{\tau}^{OUT} \} - E_0\{\sum_{\tau=1}^{\infty} \beta^\tau (1 - \delta)C(z_{\tau}^{OUT}) \} = 0$$

(6)

where $pz_{\tau}^{OUT}$ and $(1 - \delta)C(z_{\tau}^{OUT})$ represent the supplier’s revenues and costs, respectively. Therefore, the equilibrium wholesale price is

$$p = E_0\{\sum_{\tau=1}^{\infty} \beta^\tau (1 - \delta)C(z_{\tau}^{OUT}) \}/E_0\{\sum_{\tau=1}^{\infty} \beta^\tau z_{\tau}^{OUT} \}$$

(7)

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13 Bray and Mendelson (2013) show empirically that the bullwhip effect and production smoothing coexist, and that both phenomena have a large impact on production variability.
After substituting \( z_t^{\text{OUT}}, S_t^{\text{OUT}} \) and the equilibrium wholesale price (7) into the manufacturer’s objective function (4), the net present value of her expected total costs in the outsourcing scenario, evaluated when she makes her sourcing choice in the initial period, is

\[
NPV^{\text{OUT}} = E_0\{\sum_{t=1}^{\infty} \beta^t [C(z_t^{\text{OUT}}) + g(S_t^{\text{OUT}}, D_t)]\} \tag{8}
\]

In the case of insourcing, the net present value of the manufacturer’s expected total costs is

\[
NPV^{\text{IN}} = E_0\{\sum_{t=1}^{\infty} \beta^t [C(z_t^{\text{IN}}) + g(S_t^{\text{IN}}, D_t)]\} \tag{9}
\]

where \( z_t^{\text{IN}} \) and \( S_t^{\text{IN}} \) represent the optimal decision rules under insourcing, which arise from condition (3).

The manufacturer will outsource if \( \Delta NPV \equiv NPV^{\text{OUT}} - NPV^{\text{IN}} \) is negative and will insource otherwise. Because the sign of \( \Delta NPV \) cannot be fully characterized analytically, we first present the main intuitions and then validate them using numerical analysis.

Outsourcing has two opposing effects on the manufacturer’s costs relative to insourcing. From (8) and (9), \( \Delta NPV \) can be rewritten as a sum of two components

\[
\Delta^{\text{adv}} \equiv -\delta E_0\{\sum_{t=1}^{\infty} \beta^t C(z_t^{\text{OUT}})\} \tag{10}
\]

\[
\Delta^{\text{var}} \equiv E_0\{\sum_{t=1}^{\infty} \beta^t [C(z_t^{\text{OUT}}) + g(S_t^{\text{OUT}}, D_t)]\} - E_0\{\sum_{t=1}^{\infty} \beta^t [C(z_t^{\text{IN}}) + g(S_t^{\text{IN}}, D_t)]\} \tag{11}
\]

The first term, \( \Delta^{\text{adv}} \), is negative and captures the savings from the supplier’s cost advantage \( \delta \). The cost advantage reduces the supplier’s expected costs in (6). These savings are passed on to the manufacturer in the form of a lower equilibrium wholesale price (7), which in turn lowers the net present value of the manufacturer’s expected costs under outsourcing, \( NPV^{\text{OUT}} \) (8).

The second term, \( \Delta^{\text{var}} \), is positive\(^{14} \) and reflects the costs of incremental production variability for the supplier under outsourcing. The manufacturer does not have an incentive to smooth her production orders from the supplier but does have an incentive to smooth her own production in the case of insourcing (§2.1). Therefore, for the same magnitude of demand shocks, the manufacturer’s production orders from the

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\(^{14}\) The decision rules \( z_t^{\text{IN}}, S_t^{\text{IN}} \) minimize the conditional expectation (2) for each point of the state space in each period; therefore, they also minimize the unconditional version of this expectation in the initial period, \( E_0\{\sum_{t=1}^{\infty} \beta^t [C(z_t^{\text{IN}}) + g(S_t^{\text{IN}}, D_t)]\} \) in (11). Because the decision rules \( z_t^{\text{OUT}}, S_t^{\text{OUT}} \) solve a different conditional minimization problem (4), they yield a higher value of \( E_0\{\sum_{t=1}^{\infty} \beta^t [C(z_t^{\text{OUT}}) + g(S_t^{\text{OUT}}, D_t)]\} \) in (11). Therefore, \( \Delta^{\text{var}} \) must be positive.
supplier under outsourcing will fluctuate to a greater extent than the manufacturer’s internal production in the case of insourcing (Lemma 1). This causes incremental variability in the supplier’s production, relative to the variability in the manufacturer’s production in the corresponding insourcing scenario. Incremental production variability increases the supplier’s expected costs in (6). Because potential suppliers anticipate this when they compete for the long-term outsourcing contract in the initial period, the equilibrium wholesale price (7) rises commensurately. This in turn increases the net present value of the manufacturer’s expected costs $NPV^{OUT}$ (8) under outsourcing.\(^\text{15}\)

The manufacturer’s sourcing choice depends on the relative magnitudes of these two effects. If the supplier’s cost advantage $\delta$ is sufficiently large, then the associated savings $\Delta^{adv}$ dominate (i.e., $\Delta NPV = \Delta^{adv} + \Delta^{var} < 0$), and the manufacturer prefers to outsource in the entire relevant range of demand variability. If the supplier’s cost advantage $\delta$ is moderate, however, then the manufacturer’s sourcing choice depends on the level of demand variability. When demand variability is low, outsourcing does not lead to a significant increase in production variability. Therefore, production variability has a minimal impact on the supplier’s expected costs in (6), the equilibrium wholesale price (7), and the net present value of the manufacturer’s expected costs (8) under outsourcing. In other words, the costs of incremental production variability under outsourcing ($\Delta^{var}$) are small. In contrast, the supplier’s cost advantage reduces his total costs by a fraction $\delta$ even when the demand is stable, leading to a commensurate decrease in the wholesale price (7) and in the net present value of the manufacturer’s expected costs (8). Therefore, when demand variability is low, the savings from the supplier’s cost advantage ($\Delta^{adv}$) outweigh the costs of incremental production variability ($\Delta^{var}$), leading the manufacturer to outsource. When demand variability is high, however, outsourcing causes a large increase in production variability. This raises the supplier’s expected costs in (6) considerably, whereas the manufacturer’s expected production costs in the case of insourcing

\(^{15}\) In addition to incremental production variability, the two scenarios also have different levels of expected shortage and holding costs, and may have different expected production levels during the initial periods before convergence to the ergodic distribution. We include these additional effects in $\Delta^{var}$ because they arise from the difference in production smoothing behavior between insourcing and outsourcing.
are mitigated by production smoothing. Therefore, the costs of incremental production variability \((\Delta \text{var})\) are large, leading to a large increase in the equilibrium wholesale price (7) and, consequently, a large increase in the net present value of the manufacturer’s expected costs (8) under outsourcing. When demand variability is sufficiently high, this effect will outweigh the savings from the supplier’s cost advantage \((\Delta \text{adv})\), leading to insourcing.

Thus, depending on the cost advantage parameter \(\delta\), a sufficiently large increase in demand variability either induces a switch from outsourcing to insourcing or has no effect. Consequently, in a sample that contains some firms with a moderate \(\delta\), higher demand variability will be associated with less outsourcing on average.

We validate this argument using numerical analysis. The computational details are provided in Appendix C. We normalize the mean demand \(E\{D\} = d/(1 - \rho)\) to 100 units. We also normalize the cost function parameters \(c_1, c_2\) to maintain \(C(100) = \$100\) (i.e., \(c_1 = 1 - 50c_2\) and \(c_2 \leq 0.02\)), which corresponds to a unit production cost of \$1 at the expected production level.

We examine several main combinations of the parameter values. First, because the costs of production variability depend on the curvature of the cost function, determined by the parameter \(c_2\), we examine the cases \(c_2 = 0.01\) (a moderately convex cost function) and \(c_2 = 0.02\) (a highly convex cost function). Second, because the bullwhip effect amplifies demand variability, we examine the cases \(\rho = 0\) (no bullwhip effect) and \(\rho = 0.6\) (a strong bullwhip effect).\(^1\) We use the discount rate \(\beta = 0.95\), inventory holding cost \(h = 0.05\), and shortage cost \(\pi = 0.25\), but the results are robust to alternative parameter values.

Demand variability \(SD\{D_t\} = \sigma/\sqrt{1 - \rho^2}\) is capped at 40, so that the mean of demand \((E\{D\} = 100)\) is at

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\(^1\) The savings from the supplier’s cost advantage, \(\Delta \text{adv}\), also increase with demand variability, and could potentially outpace the increase in \(\Delta \text{var}\) if \(\delta\) is sufficiently large. In this case, outsourcing will become even more attractive when demand variability is high, and the manufacturer will outsource regardless of the level of demand variability. In other words, this can weaken the relation between demand variability and outsourcing but cannot reverse it.

\(^1\) Under outsourcing, order size variability is \(SD\{z\} = \sqrt{1 + 2\rho(1 - \rho^2)} \times SD\{D\}\) (equation (A.4) in Appendix A), where the multiplier \(\sqrt{1 + 2\rho(1 - \rho^2)}\) captures the bullwhip effect. The multiplier is equal to 1 (i.e., no variance amplification) when \(\rho = 0\), and is maximized when \(\rho = 1/\sqrt{3} \approx 0.58\).
least 2.5 standard deviations away from zero to ensure a negligible probability of negative demand realizations. We set the supplier’s cost advantage $\delta$ to 0%, 5%, and 10%.

Figure 1 presents production variability $SD\{z\}$ as a function of demand variability $SD\{D\}$. Consistent with Lemma 1, production variability is significantly higher under outsourcing than under insourcing. For example, at the maximum level of demand variability ($SD\{D\} = 40$), outsourcing increases production variability by 65–163% relative to insourcing. Notably, when demand variability increases, production variability under insourcing rises less than proportionately, i.e., production smoothing becomes relatively more prominent. Further, when the demand is sufficiently volatile, production variability under outsourcing is lower than demand variability even in the case of a strong bullwhip effect ($\rho = 0.6$), indicating that production smoothing can outweigh the bullwhip effect.

Figure 2 presents the equilibrium wholesale price under outsourcing and the manufacturer’s expected production cost (scaled by the expected production level)$^{18}$ under insourcing as a function of demand variability. When demand variability is low, the supplier’s wholesale price is less than the manufacturer’s internal production cost thanks to the supplier’s cost advantage $\delta$. The reduction in the wholesale price is approximately proportional to $\delta$. An increase in demand variability raises both the supplier’s wholesale price under outsourcing and the manufacturer’s internal production cost under insourcing. However, the wholesale price rises to a greater extent than the manufacturer’s production cost. For example, in the model with a strong bullwhip effect, a highly convex cost function, and a cost advantage of 10% ($\rho = 0.6$, $c_2 = 0.02$, and $\delta = 0.1$, respectively), an increase in demand variability from the lowest to the highest level in Figure 2 raises the wholesale price by 27%, whereas the manufacturer’s internal production cost under insourcing rises by just 7%. This reflects the incremental production variability under outsourcing, which has a greater impact on the supplier’s costs (and therefore, on the equilibrium wholesale price) when the demand is more volatile. When demand variability is sufficiently high, the wholesale price rises above the

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$^{18}$ To ensure that the price and the manufacturer’s expected production cost are directly comparable, we compute the latter as $E_0\{\sum_{t=1}^{\infty} \beta^t \cdot C(z_t^{IN})\}/E_0\{\sum_{t=1}^{\infty} \beta^t \cdot z_t^{IN}\}$, which is analogous to equation (7) for the price. It would be incorrect to compare the price to the expected unit cost $(E_0\{\sum_{t=1}^{\infty} \beta^t \cdot C(z_t^{IN})\}/E_0\{\sum_{t=1}^{\infty} \beta^t \cdot z_t^{IN}\})$, because the expected unit cost for a convex $C(z)$ does not fully capture the cost consequences of production variability.
manufacturer’s internal production cost, even when the supplier has a cost advantage $\delta$ of 10%.\textsuperscript{19} In other words, when the demand is highly volatile, the supplier is unable to offer an attractive wholesale price despite having a sizable cost advantage.

Figure 3 presents the difference in the net present value of the manufacturer’s expected total costs between outsourcing and insourcing, $\Delta NPV \equiv NPV^{OUT} - NPV^{IN}$ from (8) and (9), as a function of demand variability. A positive value of $\Delta NPV$ indicates that outsourcing increases the net present value of the manufacturer’s total costs relative to insourcing, in which case the manufacturer will prefer to insource. $NPV^{OUT}$ and $NPV^{IN}$ incorporate not only the costs of making or buying finished units, the focus of Figure 2, but also the shortage and holding costs incurred by the manufacturer ($g(S_T, D_T)$ in (8) and (9)). Under insourcing, the manufacturer uses inventory as a buffer to smooth production fluctuations, tolerating larger inventory-related costs in exchange for lower production variability. Therefore, the expected shortage and holding costs are larger in the case of insourcing than in the case of outsourcing. Notably, this implies that to make a good sourcing decision (even in a simple model that focuses on costs), it is not sufficient to just weigh the supplier’s wholesale price against the internal production costs under insourcing (Figure 2), because the sourcing choice also affects non-production-related costs.

When the supplier does not have a cost advantage ($\delta = 0$), the associated cost saving $\Delta adv$ (10) is zero, and the difference $\Delta NPV \equiv NPV^{OUT} - NPV^{IN}$ arises only from the costs of incremental production variability under outsourcing, $\Delta var$ (11). When demand variability is low, $\Delta NPV$ is positive but negligible, i.e., the manufacturer has only a weak preference for insourcing. $\Delta NPV$ increases with demand variability and becomes economically significant. For example, at the maximum level of demand variability in Figure 3, $\Delta NPV$ is equal to 4.4–13.7% of $NPV^{IN}$, i.e., outsourcing increases the net present value of the manufacturer’s expected costs considerably relative to insourcing. Therefore, in the absence of a cost advantage, the manufacturer has a strong preference for insourcing when demand variability is high.

\textsuperscript{19} The only exception is the case $\rho = 0$ (no bullwhip effect), $c_2 = 0.01$ (moderate convexity of the cost function), and $\delta = 0.1$ (a large cost advantage of 10%), in which the costs of incremental production variability are moderate and are insufficient to outweigh a 10% cost advantage even at the maximum level of demand variability.
The supplier’s cost advantage ($\delta = 0.05$ and $\delta = 0.1$ in Figure 3) makes outsourcing relatively more attractive. When demand variability is low, the cost advantage dominates (i.e., $\Delta NPV$ is negative). Outsourcing reduces the net present value of the manufacturer’s expected costs by more than 4.1% (9.2%) for $\delta = 0.05$ ($\delta = 0.1$) relative to insourcing. Therefore, the manufacturer strictly prefers to outsource when demand variability is low. An increase in demand variability lowers the net cost savings from outsourcing (i.e., $\Delta NPV$ becomes less negative), indicating that the costs of incremental production variability under outsourcing ($\Delta^\text{var}$) rise more quickly than the gains from the supplier’s cost advantage ($\Delta^\text{adv}$).

When demand variability is high, the manufacturer either switches to insourcing or continues to outsource, depending on the size of the supplier’s cost advantage $\delta$ and the parameter values $c_2$ and $\rho$, which affect the costs of production variability and the strength of the bullwhip effect, respectively. If the supplier has a moderate cost advantage of 5% ($\delta = 0.05$ in Figure 3), in three cases out of four $\Delta NPV$ becomes positive when demand variability is sufficiently high. In other words, for these parameter values outsourcing would increase the manufacturer’s total costs relative to insourcing, despite the supplier’s cost advantage.\(^{20}\) This leads to insourcing at high levels of demand variability. Even when the supplier’s cost advantage is increased to 10%, in one case out of four the manufacturer will insource when demand variability is high. For the remaining combinations of parameter values, $\Delta NPV$ is negative even at the maximum level of demand variability, i.e., the manufacturer will continue to outsource in the entire relevant range of demand variability.\(^{21}\) As the scenarios in Figure 3 illustrate, this outcome is more likely to arise when (1) the supplier’s cost advantage parameter $\delta$ is larger, which increases the gains from outsourcing, (2) the cost function is less convex (a lower $c_2$), which reduces the costs of incremental production variability under outsourcing.

\(^{20}\) Notably, one of these cases includes zero bullwhip effect ($\rho = 0$). Thus, even when the bullwhip effect is absent, production variability in a decentralized supply chain can be too high, increasing costs considerably.

\(^{21}\) In two of these scenarios ($\rho = 0, c_2 = 0.01, \delta = 0.05$ and $\rho = 0, c_2 = 0.02, \delta = 0.1$), the manufacturer prefers to outsource (i.e., $\Delta NPV < 0$) at the maximum level of demand variability even though the supplier’s wholesale price is slightly higher than the manufacturer’s production cost under insourcing (Figure 2). As we explain earlier, outsourcing lowers the manufacturer’s expected shortage and holding costs; in these two scenarios, the reduction in expected shortage and holding costs outweighs the effect of a slightly higher wholesale price. This underscores the importance of taking into consideration the non-production costs when making a sourcing decision.
variability under outsourcing, or (3) the bullwhip effect is weaker (a lower $\rho$), which reduces the magnitude of incremental production variability under outsourcing.

We conduct additional sensitivity checks for various combinations of the parameter values.\(^{22}\) In all cases, we obtain consistent results. When the supplier has a moderate cost advantage $\delta$ (where the upper limit for $\delta$ varies predictably with the parameters $c_2$ and $\rho$), a sufficiently large increase in demand variability leads to a switch from outsourcing to insourcing. When the supplier has a large cost advantage, the manufacturer always prefers to outsource, regardless of demand variability. Because empirical tests focus on situations with meaningful variation in outsourcing, which cannot arise if the supplier has a large cost advantage relative to all firms in the sample, the former scenario is relevant for many firms. Therefore, on average, demand variability will be associated with less outsourcing.

**PROPOSITION 1:** Higher demand variability is associated with less outsourcing.

### 3. Data and Empirical Models

#### 3.1. Sample Selection and Descriptive Statistics

We use confidential Annual Business Statistics Survey data from the Turkish Statistical Institute.\(^{23}\) The sample is representative of the full universe of firms with 10 or more employees in Turkey, including both public and private firms. The data is an unbalanced firm-level panel from 2003 to 2011. It contains financial information and additional firm characteristics such as the number of employees.

Crucially, the data includes production outsourcing costs for all manufacturing firms. These costs represent production activities that are subcontracted to third parties. The outsourcing costs do not include off-the-shelf components that can be purchased from suppliers in an open market, or outsourced non-production activities such as janitorial or security services. To the best of our knowledge, no other dataset world-wide has a comparably broad coverage of firms’ outsourcing costs.

\(^{22}\) We generate 1,000 random draws of the parameters $\delta$, $\rho$, $c_2$, $h$, $\beta$, and $\pi$. For each combination of parameters, we solve the model for the full range of demand variability from $SD\{D\} = 4$ to $SD\{D\} = 40$.

\(^{23}\) Survey details and summary statistics are publicly available at http://www.turkstat.gov.tr/PreTablo.do?alt_id=1035. The confidential firm-level data can be accessed only at the research data centers of the Turkish Statistical Institute.
We restrict the sample to firms in the manufacturing sector. We require at least 6 annual observations per firm during 2003–2011 for the computation of demand variability at the firm level, and discard the top and bottom 1% of extreme values for all continuous regression variables. All financial variables are deflated to control for inflation. The final estimation sample comprises 97,903 firm-year observations for 16,598 firms from 2003 to 2011 (in some specifications, the sample is smaller because of data requirements for additional variables).

Following Cachon et al. (2007), we use sales as an empirical proxy for demand, and measure demand variability for firm \( i \) as a standard deviation of deflated log-changes in sales for all observations of that firm, \( SD\{\Delta \ln SALES\}_i \). Demand can differ from sales due to stock-outs and backlogs (e.g., Chen 2010). However, Cachon et al. find, using data for industries for which they observe both sales and demand (total orders), that sales and demand have similar volatilities in most cases.

Table 1 presents the descriptive statistics for the full sample (Panel A) and for the subsamples of outsourcing and non-outsourcing firms (Panel B). The average ratio of outsourcing costs to total costs \( (OUTS\_RATIO) \) for the full sample is 2.2%; the median is zero. 34.5% of firms have positive outsourcing costs; among these firms, outsourcing costs account for 6.4% of total costs on average, and the median is 3.2%. Consistent with Proposition 1, outsourcing is associated with lower values of our proxy for demand variability, the standard deviation of log-changes in sales \( SD\{\Delta \ln SALES\}_i \). The mean \( SD\{\Delta \ln SALES\} \) is 0.379 for the outsourcing firms versus 0.411 for the non-outsourcers, and the median is 0.312 versus 0.332,

\(^{24}\) Cachon et al. (2007) document that the sales series typically follows a random walk (i.e., it has a stochastic trend), which implies that the variance of untransformed sales series depends on the time horizon (and the unconditional variance over an infinite horizon is undefined due to non-stationarity). Therefore, they use the log-change transformation to remove the stochastic trend, and use the variance of log-changes as a measure of variability. We replace variance with standard deviation to improve the scaling of this variable in regression analysis. The use of the standard deviation of log-changes as a measure of variability is also standard in the economics literature (e.g., Stock and Watson 2002; Comin and Philippon 2005; Comin and Mulani 2006; Davis and Kahn 2008). Because Cachon et al. focus on the ratio of demand variability to production variability as a metric of the bullwhip effect, they adjust sales for margin to obtain cost of sales, a measure that is directly comparable to their production proxy (=cost of sales + change in inventory). Bray and Mendelson (2012) use cost of goods sold (i.e., sales adjusted for the gross margin) for the same reason. Because we focus on absolute demand variability, as opposed to relative variability of demand versus production in Cachon et al. and Bray and Mendelson, we do not need to margin-adjust sales. Similarly, Netessine and Rumyantsev (2007) do not adjust sales for margin in computing their measure of demand variability, the standard deviation of sales after controlling for a linear trend (which we remove using the first-difference transformation) and seasonal dummies (which are irrelevant in our annual data).
respectively; both differences are significant at the 1% level. The outsourcing firms are larger in terms of total employees (EMP), sales revenue (SALES), and fixed assets (ASSETS), and have higher wages per employee (WAGE). They also have a lower ratio of total employees to sales (EMPINT) but a higher ratio of fixed assets to sales (ASINT). This suggests that the outsourced activities tend to be labor-intensive but not capital-intensive.

[Insert Table 1 here]

### 3.2. Empirical Specification

We use the following main model

\[
OUTS\_RATIO_{i,t} = \beta_0 + \beta_1 \times SD\{\Delta lnSALES\}_i + controls_{i,t} + \epsilon_{i,t}
\]  

(12)

where \(OUTS\_RATIO_{i,t}\) is the ratio of production outsourcing costs to total costs for firm \(i\) in year \(t\); \(SD\{\Delta lnSALES\}_i\) is a measure of demand variability, the standard deviation of log-changes in sales for all annual observations of firm \(i\); \(controls_{i,t}\) is the vector of control variables; and \(\epsilon_{i,t}\) is the error term. Proposition 1 predicts that \(\beta_1\) is negative, i.e., greater demand variability is associated with less outsourcing.

We control for several factors. First, the extent of outsourcing may vary over time and across industries. Therefore, we include year effects and industry fixed effects, defined at the two-digit NACE level.\(^{25}\) Second, larger firms have a greater ability to manage complex contractual arrangements with suppliers, and the associated transaction costs are relatively small compared to the scale of their purchases. Therefore, they are more likely to outsource. We control for firm size using total employees in year \(t−1\) (\(EMP_{i,t−1}\)) as a proxy.\(^{26}\) Third, firms that face higher internal labor costs likely benefit more from outsourcing. Therefore, we control for the average wage per employee in firm \(i\) in year \(t−1\) (\(WAGE_{i,t−1}\)). Because a firm’s total outsourcing costs likely co-vary with sales, we also control for the concurrent log-change in sales

\(^{25}\) NACE industry classification is used in Europe and is similar in function to the SIC and NAICS classifications in the U.S. The two-digit NACE industry level is comparable to three-digit NAICS.

\(^{26}\) We use lagged firm characteristics as controls because their year \(t\) values may be influenced by the concurrent outsourcing choices (the dependent variable). The results are similar when we use lagged sales or lagged assets as an alternative size proxy. We log-transform most of the control variables to improve their scaling.
(ΔlnSALES$_{i,t}$). We include a differential slope for sales decreases ($DEC_{i,t} \times \Delta\lnSALES_{i,t}$, where $DEC_{i,t}$ is a sales decrease dummy) because a firm may prefer to reduce outsourcing rather than cut internal resources when sales decrease. In the full model, we control for additional firm-level factors that may influence outsourcing: lagged asset intensity ($ASINT_{i,t-1}$), lagged employee intensity ($EMPINT_{i,t-1}$), and lagged profit margin ($PM_{i,t-1}$).

4. Empirical Results

Table 2 presents the estimates of the relation between the empirical proxy for demand variability, $SD\{\Delta\lnSALES\}$, and outsourcing intensity, measured as the ratio of production outsourcing costs to total costs ($OUTS\_RATIO$), for various combinations of controls. The standard errors are clustered two-way by firm and year to control for cross-sectional and time-series correlation and heteroskedasticity in the error term. To facilitate the interpretation of the coefficients, $OUTS\_RATIO$ is measured in percentage points on a scale from 0 to 100. All of the control variables have the expected signs. For example, outsourcing intensity increases significantly with firm size (using total employees $EMP_{i,t-1}$ as a proxy) and with average wage per employee ($WAGE_{i,t-1}$), consistent with our argument in section 3.2. Outsourcing intensity is also significantly lower in more asset- and employee-intensive firms ($ASINT_{i,t-1}$ and $EMPINT_{i,t-1}$, respectively) and in more profitable firms ($PM_{i,t-1}$), as expected.

The main parameter of interest is the coefficient $\beta_1$, which captures the relation between the demand variability measure, $SD\{\Delta\lnSALES\}$, and outsourcing intensity, $OUTS\_RATIO$. Consistent with Proposition 1, in all specifications the relation between demand variability and outsourcing intensity is negative and statistically significant at the 1% level. To illustrate the economic significance of this effect, we compare predicted outsourcing intensity for a firm at the top quartile of demand variability

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27 These factors partly reflect technological and financial constraints on outsourcing. For example, a firm that has a complex capital- and labor-intensive manufacturing process is likely less able to outsource. Conversely, a firm that has low profitability is likely to be reluctant to commit major internal resources and will prefer to use more outsourcing. However, these variables may partly reflect the consequences of past outsourcing decisions. Therefore, we exclude these variables from some of the empirical specifications to ensure the robustness of our findings.
\( SD\{\Delta \ln SALES\} = 0.486 \) from Table 1) relative to a firm at the bottom quartile of demand variability \( (SD\{\Delta \ln SALES\} = 0.221) \), holding all other firm characteristics constant. This change in demand variability is associated with a reduction of 0.13–0.22 percentage points in outsourcing intensity \( (= \beta_1 \times (0.486 - 0.221) \)\), where \( \beta_1 \) ranges from –0.834 in column 1 of Table 2 to –0.483 in column 3), a decrease that is equivalent to 5.8–10.0% of the average outsourcing intensity in the sample (2.2% from Table 1). Thus, contrary to the traditional intuition but in agreement with our Proposition 1, higher demand variability is associated with significantly less outsourcing.\(^{28}\)

We conduct multiple untabulated robustness checks. Because the impact of demand variability may differ across industries, we estimate the models in columns (1)–(3) of Table 2 for each of the 20 two-digit NACE industries in the sample. In all specifications, the demand variability proxy \( (SD\{\Delta \ln SALES\}) \) has a negative impact on outsourcing for 16 industries out of 20, consistent with Proposition 1, and a majority of these estimates are significant at the 10% level. When we aggregate the industry-specific coefficients using the Fama-Macbeth (1973) approach, the resulting pooled estimate of \( \beta_1 \) in all specifications is negative and significant at the 1% level, as expected. Because firms’ outsourcing behavior may evolve over time, we also estimate the model year-by-year. The coefficient on \( SD\{\Delta \ln SALES\} \) has the expected sign for all years in the data, and most of these estimates are individually significant at the 1% level. Our sample includes both small private firms with as few as 10 employees and large publicly-traded firms, which may differ in their outsourcing behavior. Therefore, we partition the sample by quartiles of firm size, finding a significant negative relation between \( SD\{\Delta \ln SALES\} \) and outsourcing in all four quartiles. The results also continue to hold when we control for the ratio of R&D employees to total employees (a proxy for technological complexity and physical asset specificity, which could deter outsourcing, e.g., Shelanski and Klein 1995)

\(^{28}\) Because \( OUTS\_RATIO \) cannot be negative, we also estimate the model using censored (Tobit) regression with bootstrapped standard errors. These untabulated estimates are consistent with the ordinary least squares (OLS) estimates presented in Table 2, and indicate a significant negative relation between demand variability and outsourcing intensity. The results also hold when we estimate the models in Table 2 using maximum likelihood following Gaur et al. (2005a).
and the ratio of software spending to total costs (a proxy for IT capability, which could facilitate outsourcing, e.g., Bardhan et al. 2006).  

In Table 3, we examine the impact of demand variability on the probability of outsourcing. We set the dependent variable to 1 if a firm has positive outsourcing costs (i.e., $O U T S _ { R A T I O } > 0$) and zero otherwise, and estimate the model using a probit regression with firm random effects. All of the control variables have the expected signs. Consistent with Proposition 1, higher demand variability $S D \{ Δ l n S A L E S \}$ reduces the probability of outsourcing ($β_1 < 0$). In all specifications, this effect is statistically significant at the 1% level. To assess its economic significance, we compare the predicted probability of outsourcing for a firm at the top quartile of demand variability relative to a firm at the bottom quartile of demand variability ($S D \{ Δ l n S A L E S \} = 0.486$ and $S D \{ Δ l n S A L E S \} = 0.221$, respectively, from Table 1), holding all other variables constant and using the marginal effects computed at the mean of the independent variables. Based on the estimates from column 1 of Table 3, a change in $S D \{ Δ l n S A L E S \}$ from its bottom quartile to the top quartile reduces the probability of outsourcing by 4.4 percentage points ($= (0.486 − 0.221) \times (−0.165)$, where $−0.165$ is the marginal effect of $S D \{ Δ l n S A L E S \}$), a decrease of 12.7% relative to the average probability of outsourcing (34.5% from Table 1). For the estimates in columns 2 and 3, the corresponding reduction in the probability of outsourcing is 3.3 percentage points and 2.8 percentage points, respectively ($= (0.486 − 0.221) \times (−0.126)$ and $(0.486 − 0.221) \times (−0.104)$, respectively), which is equivalent to a decrease of 9.7% and 8.0% relative to the average probability of outsourcing, respectively. We also conduct the robustness checks described earlier, finding a significant negative effect of $S D \{ Δ l n S A L E S \}$ on the probability of outsourcing in all cases (untabulated).

[Insert Table 3 here]

As an additional sensitivity analysis, we decompose the overall demand variation into its predictable and unpredictable components, using the decomposition approach from McConnell and Perez-Quiros

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29 We do not include these controls in our main models because they reduce the sample size due to missing data, and have a statistically insignificant effect.
30 We include the random effects because the error term in outsourcing outcomes is likely to be persistent. The results continue to hold when we remove the random effects.
We first estimate a first-order autoregression $\Delta \ln \text{SALES}_{i,t} = \alpha_0 + \alpha_1 \Delta \ln \text{SALES}_{i,t-1} + u_{i,t}$ for each two-digit industry, where $\alpha_0 + \alpha_1 \Delta \ln \text{SALES}_{i,t-1}$ and $u_{i,t}$ represent the predictable and unpredictable components of $\Delta \ln \text{SALES}_{i,t}$, respectively. For each firm $i$, we then compute the standard deviations $SD_{i}^{\text{RED}} = SD\{\alpha_0 + \alpha_1 \Delta \ln \text{SALES}_{i,t-1}\}$ and $SD_{i}^{\text{UNPRED}} = SD\{u_{i,t}\}$ to characterize the variation in these two components. $SD_{i}^{\text{UNPRED}}$ can be interpreted as a proxy for demand uncertainty.\(^{31}\) Chen and Lee (2009) show analytically that uncertainty in order revisions affects the supplier’s costs to a greater extent than total order variability. Similarly, the costs of production variability, the key driver of our theoretical argument, are likely to be influenced more by the unpredictable demand variation than by the predictable demand variation, because firms and their suppliers have more time to adapt to the latter. Consistent with this argument, Bray and Mendelson (2013) document that firms smooth production uncertainty to a greater extent than they smooth production variability. Therefore, we expect that the negative relation between demand variability and outsourcing is driven primarily by the unpredictable component $SD_{i}^{\text{UNPRED}}$.

The estimates are presented in Table 4. As expected, the relation between the unpredictable component of demand variability ($SD_{i}^{\text{UNPRED}}$) and the ratio of outsourcing costs to total costs is negative and significant at the 1% level. In contrast, the impact of the predictable component ($SD_{i}^{\text{RED}}$) generally is insignificant and has the opposite sign.\(^{32}\) The only exception is the model without firm-level controls in column (1), in which $SD_{i}^{\text{RED}}$ has a significant negative effect. However, this estimate becomes positive and insignificant when we add firm-level controls in columns (2) and (3). This suggests that the negative significant coefficient on $SD_{i}^{\text{RED}}$ in column (1) captures the effect of these firm characteristics, which are likely correlated with the firm-level determinants of predictable sales changes (such as a firm’s ability to

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\(^{31}\) Aviv (2007), Chen and Lee (2009), and Bray and Mendelson (2012, 2013) distinguish between demand variability (i.e., unconditional variance of demand) and demand uncertainty (i.e., conditional variance). Bray and Mendelson (2012) decompose total demand variation by information lead time; however, we cannot use their approach due to the short time series dimension of our data. Padmanabhan et al. (2010) distinguish between uncertainty about market size and uncertainty about consumers’ valuations, both of which affect demand uncertainty.

\(^{32}\) Although the coefficients on $SD_{i}^{\text{RED}}$ and $SD_{i}^{\text{UNPRED}}$ appear to be comparable in magnitude, the latter has a much greater impact on outsourcing because cross-sectional variation in $SD_{i}^{\text{UNPRED}}$ dwarfs that in $SD_{i}^{\text{RED}}$. For example, the interquartile range of $SD_{i}^{\text{UNPRED}}$ is 0.233, versus just 0.019 for $SD_{i}^{\text{RED}}$ (untabulated), implying that the impact of $SD_{i}^{\text{UNPRED}}$ on outsourcing is an order of magnitude larger than that of $SD_{i}^{\text{RED}}$. 

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sustain sales growth). Notably, adding the firm-level controls does not have a large impact on the estimates for the unpredictable component $SD_{i}^{\text{UNPRED}}$, which suggests that $SD_{i}^{\text{UNPRED}}$ primarily reflects the fundamental properties of demand in a firm’s market rather than internal, firm-specific factors. Thus, consistent with the logic of our theoretical model, the relation between demand variability and outsourcing primarily reflects the impact of unpredictable demand fluctuations.

[Insert Table 4 here]

4.1. Moderating Factors in the Relation between Demand Variability and Outsourcing

As we show in section 2, when demand variability increases, the costs of incremental production variability under outsourcing are partly offset by the supplier’s cost advantage, which improves his ability to cope with a more variable production schedule. Therefore, the negative impact of demand variability on outsourcing is expected to be weaker when outside suppliers have a greater cost advantage relative to the firm. Because we do not observe firms’ suppliers, we only focus on the manufacturer firm’s characteristics, assuming that all firms within an industry have access to a similar set of potential suppliers on average. We use two firm-level proxies, firm size and average wage. Because larger firms benefit from economies of scale and scope, the suppliers’ cost advantage likely decreases with manufacturer firm’s size. Conversely, the suppliers’ advantage is likely to be greater when the manufacturer faces higher wages per employee. Therefore, the negative relation between demand variability and outsourcing should be stronger (i.e., more negative) for larger firms and should be weaker for firms with higher wages.

Firms that have a more complex asset- and employee-intensive production process likely face more significant technological constraints on outsourcing. This limits the production activities that can potentially be outsourced, even when demand variability is low. Therefore, the impact of demand variability on outsourcing is likely weaker in manufacturer firms that have higher asset and employee intensity.

To test these predictions, we interact the demand variability measure $SD\{\Delta \ln \text{SALES}\}$ with our proxy for firm size, $\ln(EMP_{t-1})$, wage per employee $\ln(WAGE_{t-1})$, asset intensity $\ln(ASINT_{t-1})$, and employee intensity $\ln(EMPINT_{t-1})$, using the following model
\[ \text{OUTS\_RATIO}_{i,t} = \beta_0 + \beta_1 \times SD\{\Delta \ln \text{SALES}\}_i + \delta_1 \times SD\{\Delta \ln \text{SALES}\}_i \times \ln(\text{EMP}_{i,t-1}) \]
\[ + \delta_2 \times SD\{\Delta \ln \text{SALES}\}_i \times \ln(\text{WAGE}_{i,t-1}) + \delta_3 \times SD\{\Delta \ln \text{SALES}\}_i \times \ln(\text{ASINT}_{i,t-1}) \]
\[ + \delta_4 \times SD\{\Delta \ln \text{SALES}\}_i \times \ln(\text{EMPINT}_{i,t-1}) + \text{controls}_{i,t} + \epsilon_{i,t} \]  

(13)

where all variables were defined previously. The coefficients \( \delta_1 \ldots \delta_4 \) capture the moderating effect of firm characteristics on the relation between \( SD\{\Delta \ln \text{SALES}\} \) and outsourcing intensity. A positive (negative) \( \delta \) indicates that the corresponding firm characteristic weakens (strengthens) the negative impact of \( SD\{\Delta \ln \text{SALES}\} \) on outsourcing.

The estimates are presented in Table 5. The coefficient \( \delta_2 \) on the interaction term \( SD\{\Delta \ln \text{SALES}\} \times \ln(\text{EMP}_{t-1}) \) is negative and significant while the coefficient \( \delta_2 \) on \( SD\{\Delta \ln \text{SALES}\} \times \ln(\text{WAGE}_{t-1}) \) is positive and significant. This indicates that the negative relation between demand variability and outsourcing is stronger (i.e., more negative) in larger firms and is weaker (i.e., less negative) in firms with higher internal wages, as expected. The coefficient on the interaction term \( SD\{\Delta \ln \text{SALES}\} \times \ln(\text{EMPINT}_{t-1}) \) is positive and significant, as expected, while the coefficient on \( SD\{\Delta \ln \text{SALES}\} \times \ln(\text{ASINT}_{t-1}) \) has the expected sign but is insignificant. Thus, the relation between demand variability and outsourcing varies systematically across firms, and is generally consistent with the theory.

5. Conclusion

We examined the relation between demand variability and firms’ production outsourcing decisions. The traditional intuition asserts that the manufacturer benefits from shifting production variability onto a supplier. For example, Van Mieghem (1999) analyzes a manufacturer who maintains internal production capacity and has an option to outsource additional production to a supplier when realized demand is high. The value of this real option increases with demand variability. Similarly, Jack and Raturi (2002) and Holcomb and Hitt (2007) emphasize the value of the supplier’s ability to absorb demand fluctuations. While these papers focus on how outsourcing can help firms cope with a given level of production variability, we
argued that outsourcing can increase production variability, an additional first-order effect. The incremental production variability under outsourcing arises because the manufacturer does not have an incentive to smooth her production orders from the supplier. In contrast, under insourcing she has a strong incentive to smooth her own production; further, as Cachon and Fisher (2001) point out, smoothing the physical flow of goods can generate large cost savings. Incremental production variability under outsourcing raises the supplier’s costs, even if he has a superior ability to absorb production fluctuations relative to the manufacturer, leading to an increase in the equilibrium wholesale price. This effect deters outsourcing, and is stronger when the demand is more variable. Therefore, we predicted that higher demand variability is associated with less outsourcing, contrary to the traditional intuition.

We formalized this argument in a simple analytical model, which is based on the seminal demand signal processing model of Lee et al. (1997). While the Lee et al. model has been widely used to investigate the bullwhip effect (and has been validated empirically in that context), it is useful beyond its original purpose, providing insights about firms’ outsourcing behavior.

We tested our prediction using confidential firm-level data from the Turkish Annual Business Statistics survey, a dataset that is unique in its comprehensive coverage of production outsourcing costs for a broad representative sample of firms. Consistent with our theoretical argument, demand variability (measured as the standard deviation of log-changes in sales following Cachon et al. 2007) has a negative effect on both the extent and the probability of outsourcing. This effect is highly significant both statistically and

---

33 Because Van Mieghem (1999) considers a single-period model without inventory, production is determined only by the concurrent demand realization subject to capacity constraints, and production smoothing is impossible. Therefore, outsourcing in his model does not increase production variability. Jack and Raturi (2002) and Holcomb and Hitt (2007) do not use an analytical model; however, an implicit assumption in their verbal argument is that outsourcing does not affect production variability. Notably, prior research in transaction costs economics has recognized that the opposite of the traditional intuition may hold. For example, Walker and Weber (1984, 1987) argue that unexpected production volume changes increase the transaction costs because of mid-contract renegotiation with the supplier, and can be managed more efficiently in the case of insourcing. Using a proprietary sample of 60 make-versus-buy decisions in a large U.S. auto manufacturer, they find that greater demand variability increases the probability of insourcing, consistent with their argument.

34 Randall et al. (2006) find that online retailers are more likely to outsource fulfillment capabilities to a wholesaler when the demand is more volatile. Notably, this finding is consistent with our argument, because outsourcing by a retailer implies insourcing of downstream fulfillment activities by the wholesaler. Similar to our analysis for the manufacturer, this can mitigate the bullwhip effect, resulting in a positive relation between demand variability and insourcing (outsourcing) by the wholesaler (retailer).
economically, and is robust to alternative model specifications, alternative measures of demand variability, and various subsamples. The negative relation between demand variability and outsourcing varies systematically with firm characteristics, as expected.

The conventional wisdom asserts that outsourcing allows firms to transfer variability to the suppliers, who are better able to handle variability, and views this as one of the key attractions of outsourcing (e.g., Jack and Raturi 2002; Holcomb and Hitt 2007; McIvor 2009). However, as our analytical example illustrates, such variability transfer can also remove the manufacturer’s incentive to limit variability, raising the supply chain costs. Our empirical results suggest that firms recognize this pitfall of outsourcing, and act contrary to the traditional intuition (but consistent with our predictions).

References


Appendix A: Derivations for the Outsourcing Scenario

The derivations follow Lee et al. (1997, page 550). $E_t \{ \partial g / \partial S_t \}$ in (5) is equal to

$$E_t \{ \partial g / \partial S_t \} = h Pr_t \{ D_t < S_t \} - \pi Pr_t \{ D_t = S_t \} = (\pi + h) \Phi \left( \frac{S_t - d - \rho D_{t-1}}{\sigma} \right) - \pi \quad (A.1)$$

where $\Phi$ is the cumulative distribution function of the standard normal distribution, $d + \rho D_{t-1}$ is the expected demand $E_t \{ D_t \}$, and $\sigma^2$ is the conditional variance of demand. Therefore, (5) can be rewritten as

$$\Phi \left( \frac{S_t - d - \rho D_{t-1}}{\sigma} \right) = \frac{\pi - p(1-\beta)}{\pi + h} \quad (A.2)$$

where $\Phi^{-1}$ is the inverse cumulative distribution function of the standard normal distribution.

Optimal production $z^*_{t+1}$ is

$$z^*_{t+1} = S^*_{t+1} - S^*_{t-1} + D_{t-1} = D_{t-1} + \rho \Delta D_{t-1} \quad (A.3)$$

Production variability is

$$SD \{ z^*_{t+1} \} = SD \{ D_{t-1} + \rho \Delta D_{t-1} \} = \sqrt{1 + 2\rho(1-\rho^2)} \times SD \{ D \} \quad (A.4)$$

Appendix B: Proof of Lemma 1

Suppose that lagged demand $D_{t-1}$ is perturbed by $\Delta D$. From (A.2) and (A.3), the optimal amounts under outsourcing will change as follows:

$$\Delta z^*_{t+1} = (1 + \rho) \Delta D \quad (B.1)$$

$$\Delta E_t \{ z^*_{t+1} \} = (\rho + \rho^2 - 1) \Delta D \quad (B.2)$$

$$\Delta S^*_{t+1} = \rho \Delta D \quad (B.3)$$

Let $z_t^*, E_{t+1}^*, S_t^*$ represent the optimal values under insourcing for a given point of the state space $(S_{t-1}, D_{t-1})$. These values satisfy the first order condition (3). Suppose that when $D_{t-1}$ is perturbed by $\Delta D$, we adjust the optimal $z_t^*, E_{t+1}^*, S_t^*$ by $\Delta z^*_{t+1}$, $\Delta E_t \{ z^*_{t+1} \}$, and $\Delta S^*_{t+1}$, respectively, from the outsourcing solution (B.1)–(B.3). At these adjusted values, the left-hand side of the first order condition (3) under insourcing can be rewritten as:

$$c_2 \Delta z^*_{t+1} - \beta c_2 E_t \{ z^*_{t+1} \} + (\pi + h) \Phi \left( \frac{S^*_{t+1} + \Delta S^*_{t+1} - d - \rho D_{t-1} - \rho \Delta D}{\sigma} \right) - (\pi + h) \Phi \left( \frac{S^*_{t+1} - d - \rho D_{t-1}}{\sigma} \right) = \frac{[(1 + \rho)(1 - \beta \rho) + \beta] c_2 \Delta D}{2}$$

Because $|\rho| < 1$ and $0 < \beta < 1$, the term $[(1 + \rho)(1 - \beta \rho) + \beta] c_2$ is positive. Therefore, when $\Delta D$ is positive, the left-hand side of (3) is positive, which indicates that $z_t^* + \Delta z^*_{t+1}$ is above the optimal level in cost minimization (2). When $\Delta D$ is negative, the left-hand side of (3) is negative, which indicates that $z_t^* + \Delta z^*_{t+1}$ is below the optimal level in cost minimization (2).

---

35 To obtain the first line of this expression, we first substitute $C'(z) = c_1 + c_2 z$ and $E_t \{ \partial g / \partial S_t \}$ from (A.1), and then subtract $C'(z_{t+1}) - \beta E_t \{ C'(z_{t+1}) \}$ from (A.1), which is equal to zero due to (3).
\( \Delta z_t^{\text{OUT}} \) is below the optimal level. Thus, for any demand change \( \Delta D \), the optimal production level \( z_t^{*\text{IN}} \) under insourcing changes to a lesser extent than \( z_t^{*\text{OUT}} \) under outsourcing.

**Appendix C: Computational Details of the Numerical Solution**

Conditional on the wholesale price \( p \), the outsourcing scenario has an analytical solution presented in Appendix A. To obtain the equilibrium price, we solve numerically for the value of \( p \) that satisfies the zero profit condition (6) for the supplier.

The insourcing scenario is solved numerically using the policy function iteration approach (Coleman 1991). We first define a discrete grid for the state variables \((S_{t-1}, D_{t-1})\) and form an initial guess for the decision rules \( z_t^{\text{IN}}(S_{t-1}, D_{t-1}), S_t^{\text{IN}}(S_{t-1}, D_{t-1}) \). We use the outsourcing solution (Appendix A) as the initial guess, but the results are robust to alternative starting values. In each iteration, for each point of the state space we solve numerically for the values \( z_t^{*}, S_t^{*} \) that satisfy the first order condition (3), assuming that \( z_{t+1} \) in (3) follows the decision rule \( z_t^{\text{IN}}(S_{t-1}, D_{t-1}) \). We then update \( z_t^{\text{IN}}(S_{t-1}, D_{t-1}), S_t^{\text{IN}}(S_{t-1}, D_{t-1}) \) based on the optimal \( z_t^{*}, S_t^{*} \) from the current iteration. Coleman (1991) proves that this iterative process converges to a unique optimal solution. We iterate until convergence to obtain the optimal decision rules \( z_t^{*\text{IN}}(S_{t-1}, D_{t-1}), S_t^{*\text{IN}}(S_{t-1}, D_{t-1}) \) for the insourcing scenario. We then compute the present value of the manufacturer’s expected costs using numerical integration.\(^{36}\)

\(^{36}\) In both insourcing and outsourcing scenarios, we assume that the firm starts with zero stock in the initial period, and incorporate the (potentially gradual) transition from this initial condition to the ergodic distribution in computing the present value of expected costs.
Strong bullwhip effect ($\rho = 0.6$), moderate convexity ($c_2 = 0.01$)

No bullwhip effect ($\rho = 0$), moderate convexity ($c_2 = 0.01$)

Strong bullwhip effect ($\rho = 0.6$), high convexity ($c_2 = 0.02$)

No bullwhip effect ($\rho = 0$), high convexity ($c_2 = 0.02$)

Figure 1. Production Variability under Insourcing and Outsourcing
Figure 2. The Impact of Demand Variability on the Equilibrium Wholesale Price under Outsourcing and on the Manufacturer’s Expected Production Cost under Insourcing

Note: $\delta$ represents the supplier’s cost advantage over the manufacturer. The manufacturer’s expected production cost in the insourcing scenario does not depend on $\delta$. The expected production cost is scaled by the expected production volume.
Figure 3. Demand Variability and the Impact of Outsourcing on the Net Present Value of the Manufacturer’s Expected Costs

Note: $\Delta$NPV on the vertical axis is the net present value of the manufacturer’s expected total costs under outsourcing, $NPV^{OUT}$ (8), less the net present value of her expected total costs under insourcing, $NPV^{IN}$ (9). A positive value indicates that outsourcing increases costs relative to insourcing. $\delta$ represents the supplier’s cost advantage over the manufacturer.
Table 1. Descriptive Statistics

**Panel A: Pooled Sample**

<table>
<thead>
<tr>
<th>Variable</th>
<th>mean</th>
<th>s.d.</th>
<th>p25</th>
<th>median</th>
<th>p75</th>
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<tbody>
<tr>
<td>OUTS_RATIO (×100)</td>
<td>2.215</td>
<td>5.462</td>
<td>0.000</td>
<td>0.000</td>
<td>0.978</td>
</tr>
<tr>
<td>I{OUTS_RATIO &gt; 0}</td>
<td>0.345</td>
<td>0.475</td>
<td>0.000</td>
<td>0.000</td>
<td>1.000</td>
</tr>
<tr>
<td>SD{ΔlnSALES}</td>
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<td>0.267</td>
<td>0.221</td>
<td>0.324</td>
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</tr>
<tr>
<td>EMP</td>
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<td>107.400</td>
<td>29.000</td>
<td>43.000</td>
<td>81.000</td>
</tr>
<tr>
<td>SALES (million TL)</td>
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<td>12.420</td>
<td>1.477</td>
<td>3.371</td>
<td>8.247</td>
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<td>ASSETS (million TL)</td>
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<td>0.003</td>
<td>0.077</td>
<td>0.370</td>
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<td>0.001</td>
<td>0.021</td>
<td>0.074</td>
</tr>
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<td>EMPINT</td>
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<td>18.850</td>
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<td>14.040</td>
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<td>0.431</td>
<td>-0.140</td>
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<td>0.252</td>
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**Panel B: Outsourcing versus Non-Outsourcing Firms**

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<th>OUTS_RATIO = 0</th>
<th>difference</th>
</tr>
</thead>
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<td>Variable</td>
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<td>median</td>
<td>mean</td>
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<td>EMP</td>
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<td>SALES (million TL)</td>
<td>9.951</td>
<td>4.837</td>
<td>6.615</td>
</tr>
<tr>
<td>ASSETS (million TL)</td>
<td>0.557</td>
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<td>0.380</td>
</tr>
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<td>WAGE (thousand TL)</td>
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<td>ASINT</td>
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<td>0.023</td>
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<td>PM</td>
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<td>ΔlnSALES</td>
<td>0.048</td>
<td>0.048</td>
<td>0.056</td>
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</table>

*, **, *** indicates significance at 10%, 5%, and 1% level, respectively, in t-test for the means or Wilcoxon rank-sum test for the medians. The average exchange rate during the sample period (2003–2011) was 1.45 Turkish Lira (TL) per U.S. dollar (source: http://data.worldbank.org/indicator/PA.NUS.FCRF)

Variable definitions:

- **OUTS_RATIO**<sub>i,t</sub> = ratio of outsourcing costs to total costs for firm <i>i</i> in year <i>t</i>;
- **SD{ΔlnSALES}<sub>i</sub>** = demand variability, computed as the standard deviation of log-changes in sales for all observations of firm <i>i</i>;
- **EMP<sub>i,t</sub>** = total employees of firm <i>i</i> in year <i>t</i>;
- **SALES<sub>i,t</sub>** = total sales (in million Turkish Lira [TL]) of firm <i>i</i> in year <i>t</i>;
- **ASSETS<sub>i,t</sub>** = total fixed assets (in million TL) of firm <i>i</i> in year <i>t</i>;
- **WAGE<sub>i,t</sub>** = average annual wage per employee (in thousand TL) in firm <i>i</i> in year <i>t</i>;
- **ASINT<sub>i,t</sub>** = asset intensity, computed as the ratio of fixed assets to sales for firm <i>i</i> in year <i>t</i>;
- **EMPINT<sub>i,t</sub>** = employee intensity, computed as the ratio of total employees to sales (in million TL) for firm <i>i</i> in year <i>t</i>;
- **PM<sub>i,t</sub>** = profit margin, computed as the ratio of operating income to sales for firm <i>i</i> in year <i>t</i>;
- **ΔlnSALES<sub>i,t</sub>** = log-change in sales for firm <i>i</i> in year <i>t</i>. 

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36
Table 2. The Relation between Demand Variability and the Ratio of Outsourcing Costs to Total Costs

Dependent variable: Ratio of outsourcing costs to total costs ($OUTS\_RATIO_{i,t}$)

<table>
<thead>
<tr>
<th>Exp. sign</th>
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<th>(2)</th>
<th>(3)</th>
</tr>
</thead>
<tbody>
<tr>
<td>$SD{∆lnSALES}$</td>
<td>$-0.834^{***}$</td>
<td>$-0.592^{***}$</td>
<td>$-0.483^{***}$</td>
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<tr>
<td></td>
<td>(0.057)</td>
<td>(0.064)</td>
<td>(0.070)</td>
</tr>
<tr>
<td>$ln(EMP_{t-1})$</td>
<td>$+0.248^{***}$</td>
<td>$0.235^{***}$</td>
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</tr>
<tr>
<td></td>
<td>(0.024)</td>
<td>(0.024)</td>
<td>(0.03)</td>
</tr>
<tr>
<td>$ln(WAGE_{t-1})$</td>
<td>$+1.315^{***}$</td>
<td>$0.631^{***}$</td>
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<tr>
<td></td>
<td>(0.048)</td>
<td>(0.049)</td>
<td>(0.06)</td>
</tr>
<tr>
<td>$ln(ASINT_{t-1})$</td>
<td>$-0.084^{***}$</td>
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<td></td>
<td>(0.009)</td>
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<td>$ln(EMPINT_{t-1})$</td>
<td>$-1.089^{***}$</td>
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<tr>
<td>$PM_{t-1}$</td>
<td>$-0.182^{***}$</td>
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<td>(0.07)</td>
</tr>
<tr>
<td>$∆lnSALES$</td>
<td>$+0.320^{***}$</td>
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<tr>
<td></td>
<td>(0.074)</td>
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<td>(0.11)</td>
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<tr>
<td>$DEC×∆lnSALES$</td>
<td>$+0.230^{*}$</td>
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<td></td>
<td>(0.118)</td>
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<tr>
<td>Industry Effects</td>
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</tr>
</tbody>
</table>

| N      | 97,903 | 81,736 | 81,734 |
| Adj. $R^2$ | 17.6% | 19.1% | 21.8% |

*, **, *** indicates significance at 10%, 5%, and 1% level, respectively. We estimate the models using ordinary least squares (OLS) with two-way clustering by firm and year. The numbers in parentheses are the standard errors. The variable definitions are provided in Table 1.
Table 3. The Relation between Demand Variability and the Probability of Outsourcing

<table>
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<tr>
<td>$SD{\Delta \ln \text{SALES}}$</td>
<td>–</td>
<td>-0.610***</td>
<td>-0.448***</td>
<td>-0.369***</td>
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<td></td>
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<td>(0.051)</td>
<td>(0.054)</td>
<td>(0.054)</td>
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<tr>
<td>$\ln(\text{EMP}_{t-1})$</td>
<td>+</td>
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<td>0.399***</td>
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<td>(0.015)</td>
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</tr>
<tr>
<td>$\ln(\text{WAGE}_{t-1})$</td>
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<td>0.485***</td>
<td>0.317***</td>
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<tr>
<td></td>
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<td>(0.029)</td>
<td>(0.029)</td>
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<tr>
<td>$\ln(\text{ASINT}_{t-1})$</td>
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<td>-0.007*</td>
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<td>$\ln(\text{EMPINT}_{t-1})$</td>
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<tr>
<td>$\text{PM}_{t-1}$</td>
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<td>(0.018)</td>
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<tr>
<td>$\Delta \ln \text{SALES}$</td>
<td>+</td>
<td>0.301***</td>
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<td>DEC* $\Delta \ln \text{SALES}$</td>
<td>+</td>
<td>0.086*</td>
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<tr>
<td></td>
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<td>(0.052)</td>
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<td>$\ln(\sigma_{\tilde{RE}}^2)$</td>
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<td>0.801***</td>
<td>0.781***</td>
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<td>(0.024)</td>
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<td>Industry Effects</td>
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<td>Marginal effect of $SD{\Delta \ln \text{SALES}}$</td>
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<td>-0.165***</td>
<td>-0.126***</td>
<td>-0.104***</td>
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<td>(0.014)</td>
<td>(0.015)</td>
<td>(0.015)</td>
</tr>
<tr>
<td>N</td>
<td>97,903</td>
<td>81,736</td>
<td>81,734</td>
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<tr>
<td>Pseudo R²</td>
<td>5.0%</td>
<td>6.6%</td>
<td>7.9%</td>
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</table>

*, **, *** indicates significance at 10%, 5%, and 1% level, respectively. We estimate the models using probit with firm random effects and bootstrapped standard errors. The numbers in parentheses are the standard errors. The variable definitions are provided in Table 1.
Table 4. The Relation between Variability in the Unpredictable Component of Demand and the Ratio of Outsourcing Costs to Total Costs

Dependent variable: Ratio of outsourcing costs to total costs \((OUTS\_RATIO_{i,t})\)

<table>
<thead>
<tr>
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<th>(3)</th>
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<tbody>
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<td>(SD^{UNPRED})</td>
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<td>-0.773***</td>
<td>-0.723***</td>
<td>-0.668***</td>
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<td>(0.095)</td>
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<td>0.492</td>
<td>0.975</td>
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</tr>
<tr>
<td></td>
<td></td>
<td>(0.766)</td>
<td>(0.864)</td>
<td>(0.876)</td>
</tr>
<tr>
<td>(\ln(EMP_{t-1}))</td>
<td>+</td>
<td>0.248***</td>
<td>0.240***</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.024)</td>
<td>(0.024)</td>
<td></td>
</tr>
<tr>
<td>(\ln(WAGE_{t-1}))</td>
<td>+</td>
<td>1.348***</td>
<td>0.664***</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.049)</td>
<td>(0.049)</td>
<td></td>
</tr>
<tr>
<td>(\ln(ASINT_{t-1}))</td>
<td>–</td>
<td></td>
<td>-0.081***</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>(0.009)</td>
<td></td>
</tr>
<tr>
<td>(\ln(EMPINT_{t-1}))</td>
<td>–</td>
<td></td>
<td>-1.093***</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>(0.026)</td>
<td></td>
</tr>
<tr>
<td>(PM_{t-1})</td>
<td>–</td>
<td></td>
<td>-0.177***</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>(0.060)</td>
<td></td>
</tr>
<tr>
<td>(\Delta\lnSALES)</td>
<td>+</td>
<td></td>
<td>0.374***</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>(0.076)</td>
<td></td>
</tr>
<tr>
<td>(DEC*\Delta\lnSALES)</td>
<td>+</td>
<td></td>
<td>0.122</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>(0.125)</td>
<td></td>
</tr>
<tr>
<td>Year Effects</td>
<td>included</td>
<td>included</td>
<td>included</td>
<td>included</td>
</tr>
<tr>
<td>Industry Effects</td>
<td>included</td>
<td>included</td>
<td>included</td>
<td>included</td>
</tr>
<tr>
<td>(N)</td>
<td>97,903</td>
<td>81,736</td>
<td>81,734</td>
<td></td>
</tr>
<tr>
<td>Adj. R²</td>
<td>17.5%</td>
<td>19.0%</td>
<td>21.7%</td>
<td></td>
</tr>
</tbody>
</table>

\*\*\*\*** indicates significance at 10%, 5%, and 1% level, respectively. We estimate the models using ordinary least squares (OLS) with two-way clustering by firm and year. The numbers in parentheses are the standard errors. The variable definitions are provided in Table 1. To decompose overall variation in demand into its unpredictable and predictable components \((SD^{UNPRED} \text{ and } SD^{PRED}, \text{ respectively})\), we first estimate a first-order autoregression model \(\Delta\lnSALES_{i,t} = \alpha_0 + \alpha_1\Delta\lnSALES_{i,t-1} + u_{i,t}\) for each two-digit industry, and then compute the predictable component for firm \(i\) as \(SD^{PRED}_{i,t} = SD\{\alpha_0 + \alpha_1\Delta\lnSALES_{i,t-1}\}\) and the unpredictable component as \(SD^{UNPRED}_{i,t} = SD\{u_{i,t}\}\).
Table 5. Moderating Factors in the Relation between Demand Variability and Outsourcing

Dependent variable: Ratio of outsourcing costs to total costs ($OUTS\_RATIO_{i,t}$)

<table>
<thead>
<tr>
<th></th>
<th>Exp. sign</th>
<th>(1)</th>
<th>(2)</th>
</tr>
</thead>
<tbody>
<tr>
<td>$SD{\Delta \ln \text{SALES}}$</td>
<td>-</td>
<td>-0.603***</td>
<td>-0.480***</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.065)</td>
<td>(0.071)</td>
</tr>
<tr>
<td>$\ln (\text{EMP}_{t-1})$</td>
<td>+</td>
<td>0.321***</td>
<td>0.288***</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.040)</td>
<td>(0.039)</td>
</tr>
<tr>
<td>$SD{\Delta \ln \text{SALES}} \times \ln (\text{EMP}_{t-1})$</td>
<td>-</td>
<td>-0.187**</td>
<td>-0.141*</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.076)</td>
<td>(0.076)</td>
</tr>
<tr>
<td>$\ln (\text{WAGE}_{t-1})$</td>
<td>+</td>
<td>1.273***</td>
<td>0.406***</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.079)</td>
<td>(0.082)</td>
</tr>
<tr>
<td>$SD{\Delta \ln \text{SALES}} \times \ln (\text{WAGE}_{t-1})$</td>
<td>+</td>
<td>0.098</td>
<td>0.525***</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.159)</td>
<td>(0.166)</td>
</tr>
<tr>
<td>$\ln (\text{ASINT}_{t-1})$</td>
<td>-</td>
<td>-0.088***</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.017)</td>
<td></td>
</tr>
<tr>
<td>$SD{\Delta \ln \text{SALES}} \times \ln (\text{ASINT}_{t-1})$</td>
<td>+</td>
<td>0.009</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.032)</td>
<td></td>
</tr>
<tr>
<td>$\ln (\text{EMPINT}_{t-1})$</td>
<td>-</td>
<td>-1.283***</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.039)</td>
<td></td>
</tr>
<tr>
<td>$SD{\Delta \ln \text{SALES}} \times \ln (\text{EMPINT}_{t-1})$</td>
<td>+</td>
<td>0.440***</td>
<td></td>
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<tr>
<td></td>
<td></td>
<td>(0.072)</td>
<td></td>
</tr>
<tr>
<td>$PM_{t-1}$</td>
<td>-</td>
<td>-0.158***</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.057)</td>
<td></td>
</tr>
<tr>
<td>$\Delta \ln \text{SALES}$</td>
<td>+</td>
<td>0.261***</td>
<td></td>
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<td></td>
<td></td>
<td>(0.074)</td>
<td></td>
</tr>
<tr>
<td>$DEC^*\Delta \ln \text{SALES}$</td>
<td>+</td>
<td>0.258**</td>
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<tr>
<td></td>
<td></td>
<td>(0.118)</td>
<td></td>
</tr>
<tr>
<td>Year Effects</td>
<td>included</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Industry Effects</td>
<td>included</td>
<td></td>
<td></td>
</tr>
<tr>
<td>N</td>
<td>81,736</td>
<td>81,734</td>
<td></td>
</tr>
<tr>
<td>Adj. $R^2$</td>
<td>19.1%</td>
<td>21.9%</td>
<td></td>
</tr>
</tbody>
</table>

*, **, *** indicates significance at 10%, 5%, and 1% level, respectively. We estimate the models using ordinary least squares (OLS) with two-way clustering by firm and year. The numbers in parentheses are the standard errors. The variable definitions are provided in Table 1.